The Accumulative Component Kurtosis in the SVD Based De-noising of the Fault Diagnosis for Rolling Element Bearing of Generator

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Abstract. Rolling bearings are important load-bearing components that are prone to failure, so it is necessary to reveal their failure mechanisms. As the singular value mainly reflect the energy of the decomposed singular components (SCs), the singular value decomposition (SVD) de-noising tend to preserve the significant-energy SCs and ignoring the neglected one, thus weaken singular has the ability to detect the incipient fault of the mechanical systems. In this paper, accumulative component kurtosis based SVD reconstitution scheme is proposed for mechanical signal de-noising to detect the incipient fault of the generator systems. With the kurtosis index, the decomposed SCs can be evaluated and sorted not only according to their energy but also the contribution to the de-noising effect. In this way, the sensitive SCs could be taken into calculation effectively. The advantages of the ACK-SVD over traditional approaches are verified by both simulated signals and real vibration data from the rolling element bearing rig. The results proved the incipient fault feature even with heavy background noise could be extracted successfully.

1. Introduction
The generator is the core component of the military general mobile electric power plant and bearings are critical elements of the generator. When the rolling bearing fails, a periodic pulse signal appears in the vibration waveform, but because the waveform is more complicated, it is difficult to extract the characteristic information therein. Rolling bearing is one of the most common and most vulnerable parts in rotating machinery. It is important to detect the early failure of bearing in time to prevent accidents. Therefore, the effective extraction of the characteristics of its fault signal is of great significance for bearing fault diagnosis [1].

The noise reduction methods commonly used in the literature mainly include Wavelet Transform (WT), Spectral Kurtosis, EMD, EEMD, LMD, principal component analysis and stochastic resonance. According to the different ways of improving the signal-to-noise ratio of weak signals, they can be roughly divided into two categories: pure noise de-noise method and noise reduction method [2-6]. The above method reduces the noise to a certain extent, but at the same time reduces the fault characteristic information while reducing the noise, resulting in the result of "neither side gains " and
does not consider the trend of the fault characteristics of the rolling bearing throughout the whole life cycle, resulting in low accuracy and accuracy of fault diagnosis and damage assessment [7].

Singular value decomposition (SVD) is a very important matrix decomposition method in linear algebra, and it also has a good effect on singular value decomposition in feature information separation and weak signal extraction. Xiong et al. used EMD and kurtosis to filter out trends and noise components, and to guide the assessment of the type of failure and damage to rolling bearings under different loads[8]. Dbala et al. used the EMD method to decompose the IMF component of the original signal into three combined mode functions, and obtained three parts of the signal noise part, the signal part and the trend part, and extracted the fault-related features [9]. Guo et al. proposed an improved EMD analysis method based on multi-objective optimization to extract the outer ring and inner ring fault characteristics of rolling bearings [10].

Based on the analysis of the whole life trend of rolling bearing operation, a more effective method for fault feature extraction and damage degree evaluation of rolling bearings are proposed. Cui et al. used the accumulative component kurtosis in the SVD de-noising method extracted the bearing fault. However, the fault diagnosis of large bearings such as generators has not been further analysed [11]. The de-noising technique based on SVD belongs to one of the subspace algorithms. In simple terms, we want to decompose the noisy signal vector space into two subspaces dominated by pure signal and noise signals, and then estimate the pure signal by simply removing the noisy signal vector components that fall in the “noise space”. Accumulative Component Kurtosis in the SVD Based De-noising method can extract bearing fault characteristic signals more efficiently and quickly [12]. The generator set operates under complex conditions, and its bearing fault characteristics are more likely to be submerged in complex vibration signals. Envelope spectrum analysis is more widely used in rotating machinery fault diagnosis signal processing [13]. The numerical simulation ACK-SVD method is used to obtain the fault characteristics of the generator bearing.

2. Principle of SVD

2.1 Principle of SVD

Singular value decomposition is a very important matrix decomposition method in linear algebra, and it also has a good effect on singular value decomposition in feature information separation and weak signal extraction. The singular value decomposition of the matrix $A \in \mathbb{R}^{m \times n}$ is defined as:

$$A = U \Sigma V^T$$

Where, $U = [u_1, u_2, \ldots, u_m] \in \mathbb{R}^{m \times m}$, $V = [v_1, v_2, \ldots, v_n] \in \mathbb{R}^{n \times n}$, $\Sigma = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_q), O)$ or its transposition, which is decided by whether $m < n$ or $m > n$. $\Sigma \in \mathbb{R}^{m \times m}$, $O$ is zero matrix, and $q = \min(m, n)$. These parameters $\{\sigma_i\} (i = 1, 2, \ldots, q)$ are defined singular values (SVs) of $A$, and $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_q > 0$.

2.2 the theory of SVD based de-noising

Since SVD needs to process signals in a matrix, it is first necessary to construct the signal sequence into a matrix of a certain structure. The Hankel matrix is often used for the construction of one-dimensional sequences. However, the next row of data of the Hankel matrix lags one data point from the previous row. The adjacent two rows have correlation and the constructed matrix is an ill-conditioned matrix for the noiseless signal. After the singular value decomposition, the first $k$ singularities are obtained. The value is large and fast decremented, the subsequent singular values are close to zero, and the singular value is obviously divided into two levels. The adjacent two rows have no correlation and the singular value of the constructed matrix will slowly decrease, therefore, there are obvious mutations for the noise signal. Useful information and noise can be distinguished by changes in singular values. In general, the useful information exists only in the first level, that is, the larger singular value in the front, and we can refer to the singular value in the first level as the effective singular value. By means of the differential spectrum, the hierarchical nodes can be found quickly and easily to find effective singular values.

Bearing fault signal is obtained by a sensor mounted in the housing. from the REBs housing usually Because the sensor obtains the bearing vibration signal is more complicated, it cannot characterize the
fault characteristics of the bearing and has a time series. The SVD method does not directly extract the fault signal. For the rolling bearing fault monitoring and diagnosis, in order to extract the singular value more reasonably and effectively when applying SVD to feature extraction, the characteristics of the singular value of the acquired signal under the Hankel matrix should be analyzed first [14]. The SVD de-noise process is shown in Fig. 1.

Figure 1 the process chart of the SVD

3. The ACK-SVD de-noising method
The SVD de-noising method is combined to propose a composite de-noising method based on optimized ACK-SVD. For the selection problem of matrix effective rank (eigenvalue) in singular value decomposition and noise reduction, the eigenvalues are optimized from the perspective of structural risk minimization; the key role of ACK-SVD threshold de-noising is based on the difference of the crucial step. The approximation signal and the detail signal adaptively determine the noise reduction threshold. There are two problems to be considered in the SVD de-noising method: the formation of the matrix $A$ and the selection of the eigenvalues. In terms of matrix formation, for a signal with quasi-periodicity, a method of evenly segmenting the signal is adopted, so that $n$ is equal to the length of its period; and for non-periodic or unknown. In combination with practical experience, the lengths of $m$ and $n$ should be as close as possible. In terms of matrix effective rank selection, the commonly used methods are mean method, median method and mutation method. The theoretical basis of these methods is not complete, and the application risk is unknown. How to effectively select the eigenvalue is a problem still to be studied. Selecting the eigenvalue problem is an optimization problem, and ideally, the actual risk of selection is minimized. Statistical learning theory shows that the actual risk consists of two parts from the perspective of function set learning performance: empirical risk and confidence range. Hence, the accumulative constructed kurtosis (ACK) is proposed as showed in Figure.

The analysis process based on the ACK-SVD method can be described as follows:
(1) Applying SVD to decompose the signal, obtain the singular components $X$.
(2) Using the kurtosis of $X$ component add the variation $K$.
(3) Application of Hilbert Envelope Analysis to Study Vibration Fault Signals.

4. Simulation Validation

4.1 Vibration model for rolling element bearing
In order to verify the validity of accumulative component kurtosis in the SVD singular value decomposition (ACK-SVD), the effectiveness of the algorithm is verified by constructing a simulation signal. The constructed simulation signal is shown in equation (2). Therefore, the sensor excitation signal installed in the bearing housing $s_i(t)$ can be expressed as:

$$s_i(t) = e^{-B_i t} \cos(2\pi f_i t + \varphi_i)$$

Where, $f_i$ is the resonant frequency, $B_i$ is the coefficient and $\varphi_i$ is the phase.
In order to verify the validity of the ACK combined with the singular value decomposition technique, the effectiveness of the algorithm is verified by constructing a simulation signal. The constructed simulation signal is shown in equation (3).

\[ x(t) = \sum_{i=1}^{N} (A_d + A_i \cos(2\pi f_i t + \phi))s_i(t - iT_0 - t_i) + n(t) \]  

(3)

Where, \( f_i \) is the rotating frequency, \( T_0 \) is the nominal time, \( t_i \) is random variable the random \( t_i \) usually accounts for 1-2\% of \( T_0 \), \( A_d \) and \( A_i \) represent the amplitude due to the static load and the unbalance load of the rotator, respectively. The last part represents background noise including the shaft, gear meshing, etc. components so that the Gaussian distributed white noise used to represents \( n(t) \).

4.2 Simulation result analysis

It can be seen from equation (2) that the frequency of the composite signal included in the constructed simulation signal is: the frequency of outer race is 105.5Hz, the sampling frequency is 12kHz, resonant frequency is 10Hz, and the rotating speed is 1772rpm is 199Hz. Set the sampling time to \( T = 0.1s \) and the Gaussian noise with SNR-7dB. The simulation signal is shown in Fig.2.

Based on the above analysis, after the original excitation signal is mixed with the noise, it is relatively difficult to separate the fault signal. The first application of the SVD method eliminates noise and separates the vibration signal. The traditional SVD method eliminates noise as shown in Fig.3. The amplitude fluctuation of each component signal after SVD noise de-noising is significantly reduced. When the appropriate filtering threshold is selected, the component signal after SVD processing is significantly smooth and the sharp fluctuation is significantly reduced.

To further illustrate the ACK-SVD method’s ability to analyse complex signals with noisy aliasing, the signal de-noise law when comparing DSSV is shown in Fig.4. It can be seen from the graphs that the ACK varies from order to 4th and 6th, and reaches maximum at 5th. but compared with SVD, the algorithm reduces noise more thoroughly. The kurtosis is more sensitive to the signal, the results show that a peak occurs at 5th and causes the ACK to appear at its maximum.

During the actual operation of the bearing, random signals are unavoidable, which directly leads to the weak peak signal. Then the processing of accumulated signals is especially important. In general,
loading Gaussian noise will cause the random transient excitation signal to keep unchanged. In fact, the peak value of the accumulative signal is attenuated as the more singular components are added.

Fig. 3 Signal amplitude and spectrum

Fig. 4 The kurtosis of the accumulative singular

Fig. 5 (a) and (b) show the waveform and envelope spectrum of the simulated signal by DSSV method. The impact signal is submerged in the noise signal. The signal frequency and period cannot be found. The characteristic frequency of the fault cannot be accurately found from the envelope spectrum. The ACK-SVD method is used to process the fault signal and the envelope spectrum as shown in the Fig. 5(c) and (d). From this analysis, it can be seen that in the traditional SVD method, the high-order peaks in the Hilbert envelope map are basically submerged. Therefore, the noise of the fault signal is difficult to separate. However, the ACK-SVD overcomes the shortcomings of the traditional method. As can be seen from the figure, the method is well separated from the noise signal, and the determination of the fault signal is more obvious.

Fig. 5 The recovered signal:
(a) recovered signal by DSSV;
(b) the envelope spectrum in (a);
(c) format of recovered signal by ACK-SVD;
(d) the envelope spectrum in (c).

We can see that the ACK varies from order to 4th and 6th, and reaches maximum at 5th. The ACK-SVD method can achieve a more complete decomposition of the signal, and obtain the kurtosis of
accumulative signal from the high frequency to the low frequency band. It is a complete decomposition. After the signal is decomposed by the ACK-SVD, the fault can be better obtained. Therefore, ACK-SVD is superior and effective to the traditional SVD de-noise method.

5. Conclusions
In this paper, a new method based on ACK-SVD for bearing fault diagnosis is proposed. The effectiveness of the method is verified by simulation and experimental data using the new method. The vibration signal is adaptively divided into multiple component signals, and the calculation speed is fast, which avoids the modal aliasing and end effect existing in the EMD method. The SVD method exhibits better stability when processing matrix information and can suppress noise to some extent. Combining the two, it can clearly decompose the frequency values contained in each component, and has good noise reduction performance. It is more effective for complex signal analysis with noise, and has high reliability and strong in actual engineering signal decomposition.

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