Multistage noise reduction processing for vibration signal of hydropower units

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Abstract—In actual field testing environments of hydropower units, unit vibration signals are often contaminated with noise. In order to obtain the real vibration signal, a multi-stage vibration signal denoise method SG-SVD-VMD is proposed for the guide bearing nonlinear and non-stationary vibration signals. And the root mean square error (RMSE) and signal to noise ratio (SNR) are used to evaluate the noise reduction ability of eight methods. The results show that the noise-canceling ability of this proposed method has improved to some extent. It can effectively suppress the noise of the hydropower units vibration signals. This method can effectively identify the shaft track and the running state of hydropower units.

1. Introduction
The operating environment of the hydroelectric unit is harsh, especially the frequent change of working conditions of pumped-storage generating units, which leads to strong nonlinear and non-stationarity vibration of the unit, meanwhile, there is strong noise in the process of shafting vibration data collection. How to quickly and effectively extract the characteristics of such signals has always been a key and difficult point in the field of signal processing[1].

In recent years, many experts and scholars have done a lot of research on the noise reduction of vibration signals of hydropower units and achieved remarkable results. Wavelet transform[2,3] essentially is a band-pass filter. It is more suitable for the decomposition of linear and steady-state signals. For the non-linear and non-stationary vibration signals of hydropower units, the effect of noise reduction by using wavelets is not particularly desirable. Empirical mode decomposition (EMD) [4,5] has high-frequency resolution and adaptive decomposition characteristics, but there are some defects of model mixing and end effect. In order to overcome the problem of different mode aliasing in EMD, Dragomiretskiy et al. [6] proposed variational mode decomposition(VMD) method based on optimal to solve the variational problem, the given signal is decomposed into finite bandwidth component sets. Singular value decomposition [7] (SVD) is different from the above method in principle. It reconstructs the signal and achieves nonlinear filtering through orthogonal decomposition of high dimensional Hankle matrix and effective singular value screening. The core idea of Savitzky Golyay(SG) Filter is also to perform weighted filtering on the data in the window, but its weight is obtained by least square fitting of a given high-order polynomial. The advantage of this method is that it can keep the change information of signal more effectively while filtering and smoothing. To improve the analysis accuracy of the pendulum signal of hydropower units, the characteristic frequency components are extracted. Thus, a multi-stage noise reduction method SG-SVD-VMD is proposed for the vibration monitoring data of the upper, lower, and water guide bearings, and verify its effectiveness.
2. SG-SVD-VMD fusion signal denoising principle

2.1. SG smoothing filtering
SG smoothing filter[8] is widely used in data stream smoothing and noise reduction, it is using the least square method to fit the signal sequence by moving the window in the time domain, which can effectively remove the noise without changing the shape and width of the original signal. First, a window array with $2M + 1$ sampling points centered on $x_i$ is constructed, and then a p-order polynomial $q(n)$ is constructed to fit the array:

$$q(n) = \sum_{k=0}^{p} a_k n^k, \quad -M \leq n \leq M, \quad p \leq 2M + 1$$

Defined function:

$$C = \sum_{n=-M}^{M} (q(n) - x(n)) = \sum_{n=-M}^{M} \left( \sum_{k=0}^{p} a_k n^k - x(n) \right)$$

When Eq (1) gets the minimum value, the filtering effect is the best, and then all the fitting points of the original data can be obtained by moving the window array. In the process of filtering, the noise part that deviates too much from the normal trend curve is eliminated, which plays the role of smooth filtering, to reduce the signal to deal with the noise. The signal obtained after smooth filtering is as follows:

$$f(i) = \sum_{k=-M}^{M} h(k) y(x-k)$$

where $f(i)$ is the filtered signal, $h(k)$ is the sampling response of the smoothing filter, $y(x)$ is a group of data in the original signal, $x = -N, \cdots, 0, N$.

2.2. Singular Value Decomposition (SVD)
As an orthogonalization decomposition method, the key to SVD noise reduction lies in the construction of the Hankel matrix and the selection of effective singular values[9].

Given a signal sequence of $\{v_i\}$, Hankel matrix is constructed as follows:

$$H = \begin{bmatrix} v(1) & v(2) & \cdots & v(q) \\ v(2) & v(3) & \cdots & v(q+1) \\ \vdots & \vdots & \ddots & \vdots \\ v(d) & v(d+1) & \cdots & v(N) \end{bmatrix}$$

where $N = d + q - 1, \quad d > q, \quad N$ is the length of the acquired signal.

By SVD of the matrix $H$, we can get:

$$H = U \Delta V^T = \sum_{i=1}^{q} \theta_i u_i v_i^T$$

in Eq(5), $u_i$ and $v_i$ are orthogonal vectors $U \in \mathbb{R}^{d \times d}$ and $V \in \mathbb{R}^{q \times q}$, respectively. $\theta$ is the singular value of $H$; The expression of the diagonal matrix $\Delta$ is as follows:

$$\Delta = diag(\theta_1, \theta_2, \ldots, \theta_q)$$

in Eq(6): $\theta_i$ satisfies $\theta_1 \geq \theta_2 \geq \cdots \theta_q \geq 0$.

For noise-free signals, the diagonal matrix $\Delta$ is full rank. For a noisy signal, the effective singular values are usually concentrated in a larger part. After the Hankel matrix is obtained, the noise reduction effect of SVD is only affected by the effective singular value screening. Commonly used effective
singular value screening methods include median filtering, mean filtering, differential spectral filtering, etc[10-11]. In this paper, we choose to mean filtering for noise reduction.

2.3. Variational mode decomposition (VMD)

VMD is an adaptive, non-recursive variational mode decomposition method proposed by Dragomiretskiy et al. in 2014, which can decompose the signal into the sum of finite IMF components. The main steps of VMD are as follows [12]:

For each mode function $u_k(t)$, the Hilbert transform is used to calculate the corresponding analytic signal, and then its one-sided spectrum is obtained.

$$ f_s = \left[ \delta(t) + \frac{j}{\pi t} \right] * u_k(t) $$

(7)

For each mode function $u_k(t)$, the spectrum of each mode is modulated to the corresponding baseband by aliasing the exponential term of its corresponding center frequency

$$ B = \left\{ \left[ \delta(t) + \frac{j}{\pi t} \right] * u_k(t) \right\} e^{-j\omega t} $$

(8)

The Gaussian smoothing method of demodulation signals is used to estimate the bandwidth of each modal signal, i.e. the gradient square norm, and then solve the variational problem with constraints. The constrained variational expression is

$$ \left\{ \min \left\{ \sum_{k} \left\| \hat{\delta}(t) \left[ \delta(t) + \frac{j}{\pi t} \right] * u_k(t) \right\|_2^2 \right\} \right\} $$

s.t. $\sum_{k} u_k = f(t)$

(9)

in Eq(9), $\{u_k\} = \{u_1 \cdots u_k\}$ is K IMF components obtained by decomposition, $\{\omega_k\} = \{\omega_1 \cdots \omega_k\}$ is the frequency center of each component, $*$ is the convolution, $\hat{\delta}(t)$ is the derivative of the function at time $t$, $\delta(t)$ is the unit impulse function.

The quadratic penalty factor $\alpha$ and the Lagrange multiplication operator $\lambda(t)$ are used to solve the solution of Eq (9), and the constrained variational problem is turned into an unconstrained problem, i.e:

$$ L\{u_k, \{\omega_k\}, \lambda\} = \alpha \sum_{k} \left\| \left[ \delta(t) + \frac{j}{\pi t} \right] * u_k(t) \right\|_2^2 + \left\| f(t) - \sum_{k} u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_{k} u_k(t) \right\rangle $$

(10)

The alternative direction multiplier method is adopted to solve the above variational problem, and the extended Lagrangian saddle point is sought by alternatively updating $u_k$, $\omega_k$ and $\lambda_{n+1}$. The solution of the variational problem is as follows:

$$ \hat{u}_{k+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i=1}^{k} \hat{u}(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha (\omega - \omega_k)^2} $$

(11)

Similarly, the updating method of the center frequency is

$$ \hat{\omega}_{k+1} = \frac{\int_{0}^{\infty} \omega |\hat{u}(\omega)|^2 d\omega}{\int_{0}^{\infty} |\hat{u}(\omega)|^2 d\omega} $$

(12)

The iteration stop criterion is as follows:
Finally, K IMF components are obtained according to the frequency domain characteristics of the actual signal. When the signal is denoised by VMD, the preset value of mode number K and the selection of effective modes after VMD decomposition affect the denoising effect of the final signal. In this paper, the minimum Babitt distance (MBD) method is used to determine the optimal K value by calculating the MBD between the modal components after VMD decomposition under different K values. Further, the effective component is determined according to the mutual correlation between each component and the original signal, and the effective component is fused to obtain the denoised signal.

2.4. SG-SVD-VMD fusion signal denoising

In order to filter out the noise components of shafting vibration data and improve the signal-to-noise ratio of the data, we proposed a multi-level noise reduction method combining SG, SVD, and VMD, and the specific process is shown in Fig. 1.

In this paper, we set the polynomial order of the SG smoothing filter as 5 and the length of the moving window as 41. Meanwhile, set the number of rows for the reconstructed Hankel matrix to 8.

In order to reveal the performance of the proposed method in noise reduction, we selected the SNR and RMSE as evaluation criteria. The measured data of shafting vibration of a power station were denoised at multiple levels. As can be seen from Table 1, after SG-SVD-VMD denoising, the shafting vibration data has higher SNR and smaller RMSE, and the data before and after de-noising were shown in Fig. 2, and the spectrum diagram before and after shafting vibration denoising are shown in Fig. 3. Meanwhile, As can be seen from Fig. 2 and Fig. 3, the Shafting vibration condition monitoring data by
SG-SVD-VMD multi-stage noise reduction, some noise components have been filtered out. In conclusion, it can be seen that the SG-SVD-VMD fusion multi-stage noise reduction method has a good noise reduction effect and universality.

Table 1 The SNR and RMSE of each signal denoise method

| Method         | $X_3$   | $Y_3$   | $X_4$   | $Y_4$   | $X_5$   | $Y_5$   |
|----------------|---------|---------|---------|---------|---------|---------|
| VMD            | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.6353 | 0.0818  | 16.0648 | 0.0810  | 19.7347 | 0.0570  |
|                | 0.0863  | 0.1828  | 0.1828  | 0.2108  | 5.9473  | 4.8077  |
| MG-VMD         | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 16.0114 | 0.0987  | 14.1497 | 0.0956  | 15.2229 | 0.1118  |
|                | 0.1010  | 0.1911  | 0.1911  | 0.2086  | 14.1068 | 5.5645  |
| SVD-VMD        | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.5892 | 0.0823  | 16.0299 | 0.0791  | 16.8659 | 0.0864  |
|                | 0.0813  | 0.1362  | 0.1362  | 0.2093  | 16.3438 | 8.5060  |
| SVD-SVMD       | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 16.0286 | 0.0985  | 13.7879 | 0.1053  | 13.2089 | 0.1205  |
|                | 0.1010  | 0.1912  | 0.1912  | 0.2087  | 14.0245 | 5.5583  |
| SVD-SG-VMD     | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.6333 | 0.0819  | 16.0305 | 0.0571  | 19.7115 | 0.0861  |
|                | 0.0894  | 0.1840  | 0.1840  | 0.2117  | 16.3774 | 5.8921  |
| SVD-SV-MG      | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.5842 | 0.0823  | 16.0022 | 0.0572  | 19.6979 | 0.0866  |
|                | 0.0816  | 0.1851  | 0.1851  | 0.2114  | 16.3266 | 5.8383  |
| SVD-SV-MG      | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.6131 | 0.0821  | 15.9934 | 0.0569  | 19.7435 | 0.0864  |
|                | 0.0817  | 0.1849  | 0.1849  | 0.2118  | 16.3497 | 5.8492  |
| SVD-SV-MG      | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 17.5872 | 0.0823  | 15.9790 | 0.0572  | 19.6888 | 0.0867  |
|                | 0.0818  | 0.1857  | 0.1857  | 0.2116  | 16.3201 | 5.8118  |
| SG-SV-MG       | SNR     | RMSE    | SNR     | RMSE    | SNR     | RMSE    |
|                | 18.7629 | 0.0719  | 16.7913 | 0.0745  | 19.7437 | 0.0568  |
|                | 16.3663 | 0.0862  | 6.2178  | 0.1772  | 4.9064  |
|                | 2.085   | 2.085   | 2.085   | 2.085   | 2.085   | 2.085   |

The upper guide bearing vibration

The lower guide bearing vibration

real signals
De-noised signal
Fig. 2 shafting vibration before and after de-noising

(a) Spectrum diagram before shafting vibration denoising
3. Conclusion

In this paper, a multi-stage noise reduction method SG-SVD-VMD for vibration signal of hydropower units is proposed. Firstly, the SG filter was used to smooth the filtering, and then SVD was used to de-noise and reconstruct the filtered signals. Finally, the reconstructed signal is decomposed by VMD, the number of decomposition is determined by the MBD and the effective components are determined by the coefficient of correlations between the decomposed signal and the original signal to obtain the real vibration signal of the unit. The results show that the parameters of SNR and RMSE for the SG-SVD-VMD method have an enhancement to some extent compared with the other denoising methods. Real vibration signals of hydropower units demonstrate the proposed method’s performance of noise reduction. It can effectively remove the noise to timely and accurately obtain the true state of the unit. The proposed method provides a new tool for rotor system fault diagnosis, has good application prospects.

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