RV Reducer Torque Signal Denoising Research Based VMD

Weiwen Wu [1, a], Zhenxing Zheng [2,b], Lei Song [3, c], Zhijun Ye [3,d] and Siqi Xiong [3,e]

[1]Guangzhou MingSen Science and Technology Co. LTD, Guangzhou, 510640, China;

[2] Industrial Training Center, Guangdong Polytechnic Normal University, Guangzhou, 510635, China

[3] School of Mechatronic Engineering, Guangdong Polytechnic Normal University, Guangzhou, 510635, China

[a] Jason@mingsen.com.cn, [b] zhengzhenxing@sina.com, [c] s_forrest@126.com,

[d] 2087646271.@qq.com, [e] 1282858347@qq.com

Abstract. The RV reducer is a core component in industrial robots, but its performance is facing higher demands due to the expanding application scenarios. Accurately obtaining the torque signal is crucial for achieving precise control of the RV reducer, as torque is an important performance indicator. In this paper, a VMD-based noise reduction method for RV reducer torque signals is proposed, in which the VMD algorithm is used to decompose the original signal, and the IMFs are selected for signal reconstruction by fusing the correlation index and sample entropy. Experimental results show that the proposed method achieves higher SNR and lower MSE after noise reduction, demonstrating its effectiveness. This method provides a foundation for the precise control of RV reducers.

Keywords: RV reducer; signal denoising; VMD.

1. Introduction

The Rotate Vector (RV) reducer is a precise two-stage reduction drive device and a core component of industrial robots, with particularly wide application in heavy-duty industrial robots [1]. However, robots have placed higher performance requirements on RV reducers to meet the operational requirements of various scenarios [2]. Some researchers have attempted to improve the transmission performance of RV reducers through design and optimization from the perspective of manufacturing processes, but with limited success and high costs. Analyzing the various performance parameters of RV reducers using signal processing techniques can provide data support for the precise control of RV reducers.

Torque is an important performance indicator of RV reducers, but the collected torque signals often contain a significant amount of noise due to environmental factors and exhibit non-linear and non-stationary characteristics. Wavelet thresholding and Empirical Mode Decomposition (EMD) [3] denoising methods have been extensively used by researchers for vibration signal denoising in rotating machinery, with good results [4-5]. However, wavelet thresholding methods suffer from the difficulty in selecting optimal thresholds, while EMD denoising methods have difficulty achieving good denoising performance in low signal-to-noise ratio conditions. Variational Mode Decomposition (VMD) [6] is a non-recursive signal processing method that can adaptively determine the frequency and bandwidth of each local mode function during the decomposition process of a random signal, effectively avoiding mode mixing and improving the accuracy and stability of the decomposition [7-8]. In this paper, the VMD algorithm is used to decompose the torque signals of RV reducers, and the corresponding signal components are selected through correlation indexs and sample entropies for signal reconstruction. This method can effectively remove noise from the signal while preserving the main features of the signal, thereby better reflecting the transmission performance of the RV reducer.

2. Materials and methods

2.1 Experimental Study of Torque Signal Acquisition for RV Reducer

In this experiment, the RV40E reducer with a transmission ratio of 121 was selected as the test object, and its torque signal was measured on a dedicated testing platform. The input torque signal was measured using a Kistler 4502A50RA sensor between the input shaft of the RV reducer and the driving motor. The output torque signal was measured using a Kistler 4503A1KLA10000 sensor between the output end of the RV reducer and the load. The driving motor in this experiment was operated at a speed of 1000 rpm, and both sensors were sampled at a rate of 1000 Hz for signal acquisition. Fig. 1 shows the torque signal at the input end, and Fig. 2 shows the torque signal at the output end.

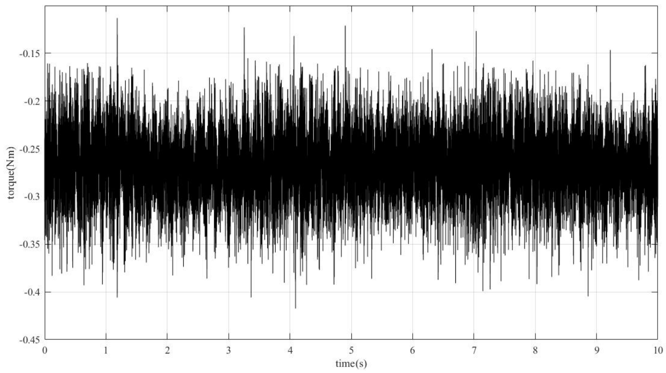


Fig. 1 Input torque signal

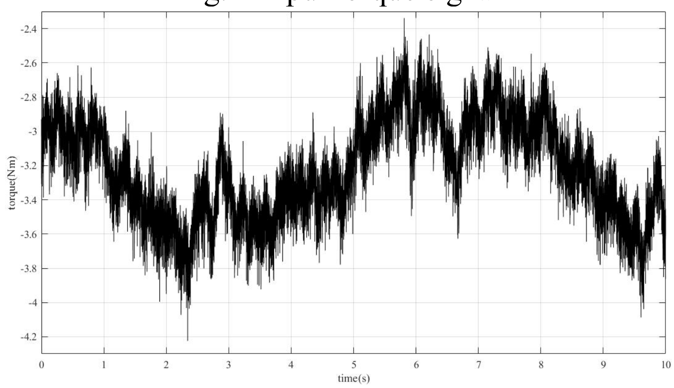


Fig. 2 Output torque signal

2.2 VMD-Based Denoising Method for Torque Signals of RV Reducers

The proposed denoising method based on VMD utilizes the VMD algorithm to decompose non-stationary random signals. The Intrinsic Mode Functions (IMFs) obtained from the decomposition are effectively distinguished based on their correlation indexs and sample entropies, and signal components that contain information are selected for reconstruction. The essence of the VMD decomposition algorithm is to decompose the original signal $f(t)$ into a series of IMFs, where each IMF varies within a narrow frequency band, and the frequency and bandwidth adaptively change as the decomposition process proceeds. Therefore, VMD decomposition is actually searching for the optimal solution in a constrained variational model to obtain the center frequency of each IMF. The constrained variational model of VMD is shown in Formula 1.

$$\begin{cases} \min\limits_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_l [(\delta(t) + \frac{j}{\pi t}) \bullet u_k(t)] e^{-j\omega_k t} \right\|_2^2 \right. \\ s.t. \sum_k u_k = f \end{cases} \qquad (1)$$

Here, $u_k(t) = A_k(t)\cos(\phi_k(t))$ represents the k-th IMF, $\omega_k(t) = \phi_k^{'}(t)$ denotes the center frequency of the k-th IMF, and $\delta(t)$ represents the pulse function.

In this study, the fusion of correlation index and sample entropy was used as a criterion for selecting signal components. The correlation index is a measure of the degree of correlation between two signals, with a higher index indicating a stronger correlation and vice versa. Sample entropy is used to evaluate the self-similarity and complexity of signal sequences, and it is independent of the length of the signal sequence, thereby exhibiting high anti-interference and robustness. The fusion of these two criteria can effectively distinguish noise components from information components among the IMFs, further improving the effectiveness of signal reconstruction. The steps involved in this process are shown in Fig. 3.

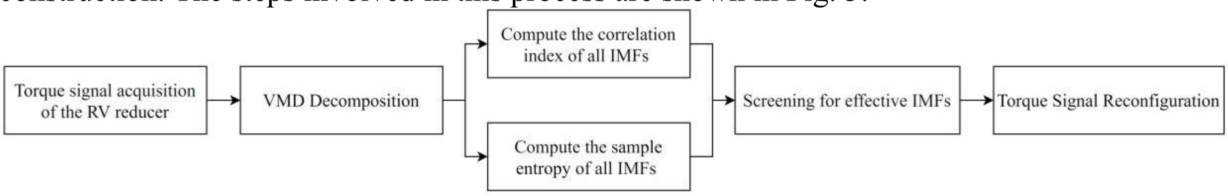


Fig. 3 Steps of the VMD-Based Denoising Method for Torque Signals of RV Reducers

3. Results and Discussions

By decomposing the collected torque signals using VMD, the non-linear and non-stationary signals were decomposed into a series of IMFs. The decomposition results of the torque signals at the input and output ends are shown in Fig. 4 and Fig. 5, respectively.

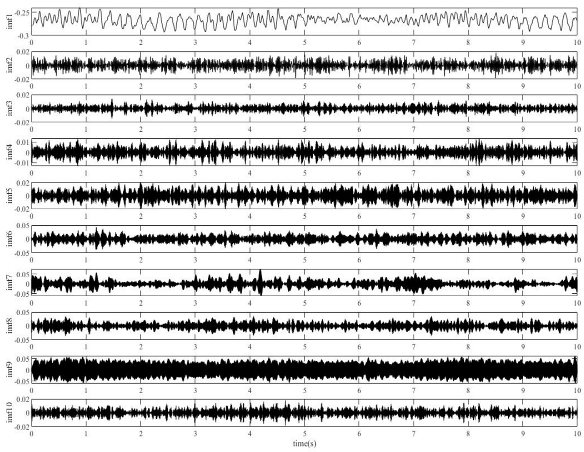


Fig. 4 VMD decomposition of input torque signal

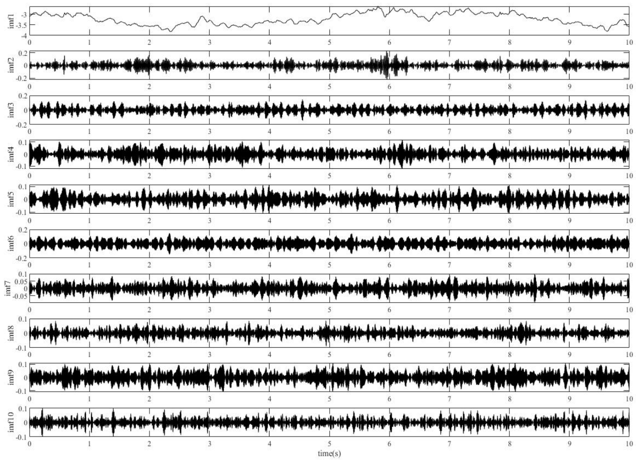
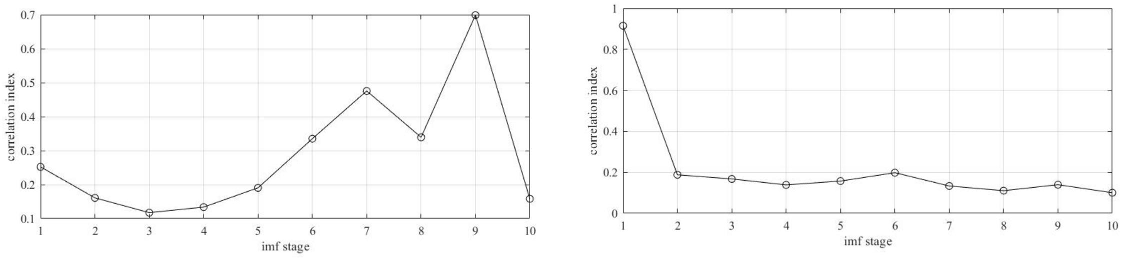


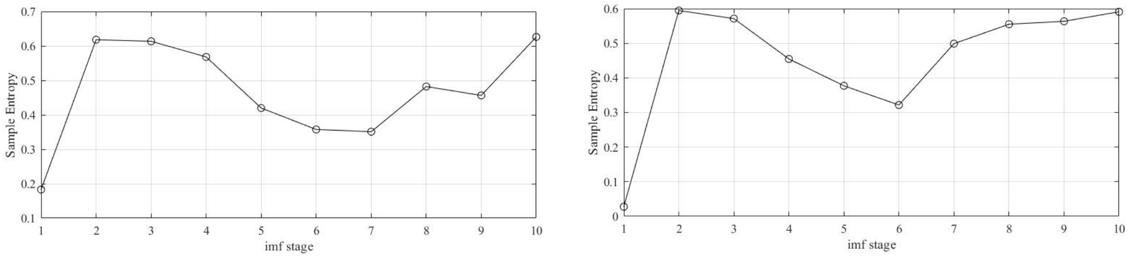
Fig. 5 VMD decomposition of output torque signal

To select effective IMFs, the correlation indexs and sample entropies of each order of IMF were calculated. Fig. 6 shows the results of the correlation index calculations for the input and output torque signals. The values of the 1st, 6th, 7th, and 8th order IMFs in the input signal, as well as the 1st order IMF in the output signal, are all greater than 0.2, indicating a strong correlation with the original signal. Therefore, they are considered as key components in the signal reconstruction process. Fig. 7 shows the results of the sample entropy calculations for the input and output torque signals. The values of the 1st and 6th order IMFs in the input signal, and the 1st, 5th, and 6th order IMFs in the output signal, are all less than 0.4, indicating low complexity and self-similarity. These IMFs are also considered as key components in the signal reconstruction process.



(a) Correlation index of input torque signal imfs (b) Correlation index of output torque signal imfs

Fig. 6 Calculation of correlation index



(a) Sample entropy of input torque imfs (b) Sample entropy of output torque imfs

Fig. 7 Calculation of sample entropy

Due to the presence of significant noise components in the collected input torque signals, IMF components with a correlation index greater than 0.2 and a sample entropy less than 0.4 were selected for signal reconstruction, which includes the 1st, 6th, and 7th order IMFs. In the case of the output torque signals, IMF components with a correlation index greater than 0.2 or a sample entropy less than 0.4 were selected for signal reconstruction, which includes the 1st, 5th, and 6th order IMFs. The reconstructed input torque signal is shown in Fig. 8, and the reconstructed output torque signal is shown in Fig. 9.

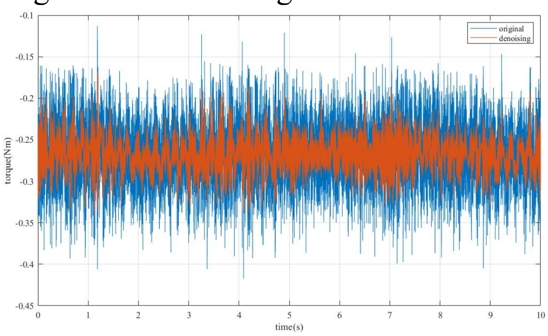


Fig. 8 Denoising signal of input torque

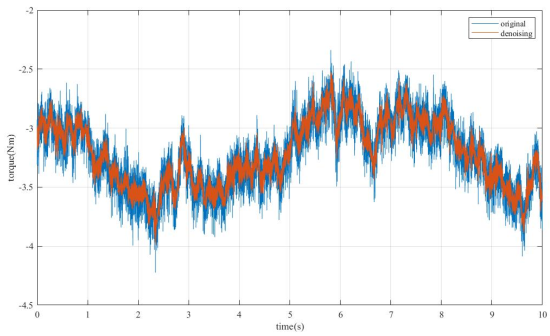


Fig. 9 Denoising signal of output torque

To further demonstrate the denoising effectiveness, SNR and MSE were used as evaluation criteria, which are listed in Table 1 (the values in parentheses indicate the change between the denoised and original signals). The denoised signals exhibit higher SNR and lower MSE, indicating the effectiveness of the proposed denoising algorithm in this study.

Table 1. The SNR and RMSE for denoising algorithm

	Original SNR/db	Denoising SNR/db	Original MSE	Denoising MSE
Input torque signal	16.0797	20.9956 (+4.9163)	0.0730	0.0713 (-0.0017)
Output torque signal	20.7802	21.3463 (+0.5661)	10.4333	10.3469 (-0.0864)

4. Conclusions

In this paper, a VMD-based denoising method for torque signals of RV reducers was proposed. Firstly, the collected torque signals were decomposed using the VMD algorithm, and the correlation indexs and sample entropies of each order of IMF were calculated. Based on the combination of these two criteria, effective signal components were selected and used for signal reconstruction. The denoised signals exhibited higher SNR and lower MSE, indicating the effectiveness of the proposed algorithm. In future research, algorithm optimization and control strategies will be combined to achieve precise control of RV reducers, thereby improving their transmission performance.

References

[1] Wang H, Shi Z Y, Yu B, et al. Transmission performance analysis of RV reducers influenced by profile modification and load[J]. Applied sciences, 2019, 9(19): 4099.

[2] Yang M, Zhang D, Cheng C, et al. Reliability-based design optimization for RV reducer with experimental constraint[J]. Structural and Multidisciplinary Optimization, 2021, 63: 2047-2064.

[3] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis[J]. Proceedings A, 1998, 454(1971):903-995.

[4] Jiang K, Li Z, Zhou Y, et al. Transient waveform matching based on ascending multi-wavelets for diagnostics and prognostics of bearing deterioration[J]. ISA transactions, 2022, 120: 330-341.

[5] Zheng J, Pan H. Mean-optimized mode decomposition: An improved EMD approach for non-stationary signal processing[J]. ISA transactions, 2020, 106: 392-401.

[6] Dragomiretskiy K, Zosso D.Variational Mode Decomposition[J]. IEEE Transactions on Signal Processing, 2014, 62(3):531-544 .

[7] Li J, Chen Y, Qian Z, et al. Research on VMD based adaptive denoising method applied to water supply pipeline leakage location[J]. Measurement, 2020, 151: 107153.

[8] Li Y, Li Y, Chen X, et al. Research on ship-radiated noise denoising using secondary variational mode decomposition and correlation coefficient[J]. Sensors, 2017, 18(1): 48.