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Dynamic unbalance detection of Cardan shaft in high-speed train applying double decomposition and double reconstruction method

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ABSTRACT

The unbalance of Cardan shaft compromises operations of high-speed train. A new method is proposed to detect the unbalance by applying DDDR (double decomposition and double reconstruction method). The vibration acceleration of gearbox was decomposed into eight scale wavelet coefficients through wavelet packet decomposition. The eight single scale vibration signals were reconstructed by the corresponding scale wavelet coefficients. Hankel matrices in different scales were constructed through the reconstructed vibration signals in wavelet domain. SVD (singular value decomposition) of Hankel matrices was executed, and critical singular values were selected based on the maximum change of singular values. Those selected singular values were used to reconstruct the single scale vibration signal. So far, DDDR processing of signal has been completed. Fourier spectrum of signal acquired by DDDR processing was used to detect dynamic unbalance of high-speed train Cardan shaft. The validity of this method is supported by experimental data collected on dynamic unbalance experiments. The results show that this method can effectively extract the vibration characteristics of fundamental, multiplier, and divider frequencies. With comparison to the traditional wavelet decomposition, wavelet singularity value decomposition, the clarity and sensitive force have been significantly improved.

1. Introduction

The key component of any high-speed train is its bogie. It plays an important role in load bearing, motion guide, structural support and power transmission, and directly determines the running safety and quality of a train. Within the bogie, Cardan shaft is the critical power transmission component. In the special service surroundings of the Cardan shaft in high-speed train 5 shown in Fig. 1, the traction motor is a body-hung installation structure on the car-body, the gearbox is installed on the wheel set by means of a nose-suspension structure, and the cardan shaft is installed between the traction motor and the gearbox via two universal joints. So, Cardan shaft not only transfers traction torque but also coordinates the complex motion relationship between two universal joints. In addition, both bending and torsion stiffness of Cardan shaft are small due to its elongated structure. As a result, Cardan shafts easily deform and produce eccentric loads over the long service life of high-speed train. Other factors, which contribute to worsening eccentricity over time, include the gap to the rear of the shaft between the axis of the universal joint and the looseness of the balance slide blocks. Eccentricity quickly creates additional dynamic unbalance torques and gives rise to excessive vibrations, which lead to rapid damage of power transmission components such

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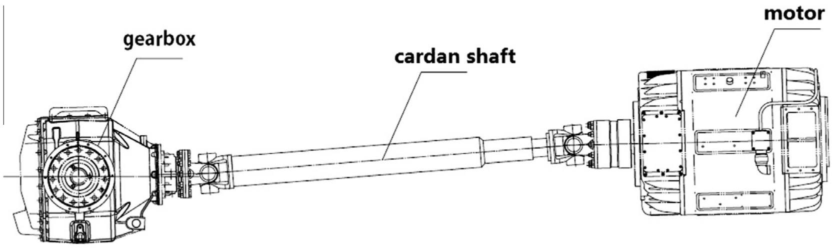

Fig. 1. Installation structure of Cardan shaft.

as bearings and universal joints. In severe cases, the unbalance of Cardan shaft will cause major accidents such as power interruption, component damage, and even crashes. Thus, it is necessary and urgent to carry out research on detecting dynamic unbalance of cardan shaft to the end of ensuring safe operation and effective power transmission.

Wavelet transformation is a powerful tool to process non-stationary signals and has been widely applied to mechanical fault diagnosis such as bearing fault diagnosis, gearbox fault diagnosis, and rotor unbalance detection [1–5]. In those studies, the time–frequency characteristics of wavelet decomposition have been made full use of to extract the fault feature under the different scales. Wavelet transform has also been used in reducing noise level to highlight fault features. While effective for small quantities, wavelet decomposition of large data volumes often leads to difficulty in judging the data processing result in practice. Therefore, post-processing methods of wavelet decomposition such as wavelet scale energy statistical analysis [6–8], wavelet fractal analysis [9–12], and wavelet singular value decomposition [13–16] have been fully developed. Because wavelet singular value decomposition has unique advantages in de-noising and eliminating correlations of signals, it has widely been used in fault diagnosis and image processing. But under the traditional combination model of wavelet decomposition and SVD, wavelet transformation and traditional wavelet singular value decomposition can not efficiently seize the vibration features of fundamental, multiplier, or divider frequencies when applied to detect unbalance faults in cardan shafts of high-speed trains.

To improve upon these methods, this paper presents the new combined mode of wavelet decomposition and SVD to detect the dynamic unbalance of Cardan shafts. The complete course includes four steps. Firstly, the vibration acceleration is decomposed into different scale wavelet coefficients, which were traditionally used to construct a matrix to compute its singular value [13–16]. Secondly, the single scale vibration signal is reconstructed via inverse wavelet transformations of single scale wavelet coefficients. Thirdly, The Hankel matrices were created with the only single reconstructed vibration signals and their singular values computed. Finally, the key singular values were chosen and the final reconstruction signals were obtained through the inverse singular value transformation. The four processing steps consist of DDDR method of detecting the Cardan shaft dynamic unbalance.

In this paper, the newly combination of the wavelet decomposition and SVD was applied to detect Cardan shaft dynamic unbalance.In the second section of this paper, the relational theory of the DDDR is discussed. The usefulness of this detection method is supported through experimentation and verified by test data in the third section. The results obtained by DDDR are compared with ones drawn by traditional wavelet decomposition and classical wavelet singular value decomposition in the fourth section of the paper. Lastly, the results of the completed studies are presented and further research has been programmed.

2. The basic theory of DDDR processing

2.1. Wavelet decomposition and its reconstruction

The fast algorithm of wavelet transforms is as following [17].

$$\begin{cases} \boldsymbol{A}_j(n) = \sum_{k\in\mathbf{Z}} \boldsymbol{h}(k-2n)\boldsymbol{A}_{j-1}(n-1) \\ \boldsymbol{D}_j(n) = \sum_{k\in\mathbf{Z}} \boldsymbol{g}(k-2n)\boldsymbol{A}_{j-1}(n-1) \end{cases} \tag{1}$$

where $\boldsymbol{A}_{j-1}(n-1)$ is the approximate signal, $\boldsymbol{D}_{j-1}(n-1)$ is detail signals, $\boldsymbol{h}(n)$ is the low-pass filter for approximate signals, and $\boldsymbol{g}(n)$ is the high-pass filter for signal details, j indicates the wavelet decomposition level. When j is just equal to 1, $\boldsymbol{f}(n) = \boldsymbol{A}_0(n)$, and $\boldsymbol{f}(n)$ shows the vibration signal of gearbox.

The relationship between $\boldsymbol{h}(n)$ and $\boldsymbol{g}(n)$ is stated below.

$$\boldsymbol{g}(n) = (-1)^n\overline{\boldsymbol{h}(1-n)} \tag{2}$$

In which, n is the sample time point.

In order to improve the resolution of decomposition signals, wavelet packet transformations for approximate signals and detail signals are executed as following.

$$\begin{cases} \boldsymbol{x}_j^{2i-1}(n) = \sum_{k\in\mathbf{Z}} \boldsymbol{h}(k-2n)\boldsymbol{x}_{j-1}^{2i-1}(n-1) \\ \boldsymbol{x}_j^{2i}(n) = \sum_{k\in\mathbf{Z}} \boldsymbol{g}(k-2n)\boldsymbol{x}_{j-1}^{2i-1}(n-1) \end{cases} \tag{3}$$

In which, $i = 1, 2, \ldots, j^2$ expresses the wavelet packets number corresponding to wavelet decomposition level j, and $\boldsymbol{f}(n) = \boldsymbol{x}_0^1(n)$ with $j = 1$.

The different scale wavelet packets in different wavelet decomposition levels were obtained through Formula (3). Single scale vibration signals were obtained through single