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Method of vibration signal processing and load-type identification of a mill based on ACMD-SVD

Introduction

The development and utilization of mine resources play a significant role in the development of human beings. The development of many emerging technology industries requires the use of mineral resources (Yun et al. 2020). As key equipment for the development and utilization of ore resources, the internal load change of the mill will directly affect the production safety and efficiency of the entire grinding industry (Ting et al. 2021a; Xu et al. 2022). Mill efficiency is highest when the mill load is at its optimum; however, the mill load is difficult to measure directly (Yang and Cai 2021). Mill load parameters (material-ball ratio, grinding concentration, filling ratio, etc.) are important parameters in the ore-grinding process (Li 2020) which are closely related to product quality and production efficiency in the grinding process. The real-time detection of these parameters is one of the key factors for realizing the optimal control of the beneficiation process (Lu 2017).

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Researches show that the vibration signal of the mill is an important indicator to reflect the mill load (Luo; Cai et al. 2020). The vibration signal generated by the mill during the grinding process is correlated with the load, and using the vibration signal to reflect the load state is an effective way to identify the load of the ball mill (Wang et al. 2021b). Many investigators obtain the feature information related to the mill load through vibration signals.

The mill vibration signal contains a lot of noise which causes non-stationarity. Therefore, it is important to pre-process the vibration signal to extract potential features and construct an identification model to predict the mill load. Many traditional feature extraction algorithms have been used for mill vibration signal processing, but the effectiveness of the processing still needs further study. Ping et al. (Ping et al. 2005), in view of the fact that it is difficult to obtain the load status of the mill in the actual industry, used D-S evidence theory and neural networks to achieve the offline load detection of the mill. Tang et al. (Tang et al. 2014) applied empirical mode decomposition (EMD) to process the vibration and grinding sound signals of the mill and extracted the features of the mill load by the mutual information method, which can determine which modal components contain abundant information on mill load parameters. Liu et al. (Liu et al. 2015) extracted the load characteristics of the mill by combining EMD and PCA methods, and their results showed the effectiveness of using this method to identify the load.

Zhao et al. (Zhao et al. 2014) applied ensemble empirical modal decomposition (EEMD) to process the vibration signal of the mill and extracted the spectral features of modal components by interval partial least squares (I PLS), which can remove irrelevant and redundant components in the spectrum of modal components. Cai et al. (Cai et al. 2019) applied complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to process the vibration signal of the mill and extracted the load features of the mill with cloud model feature entropy, which can eliminate the difficulties caused by parameter selection and avoid the problems caused by uncertainty. Qing et al. (Qing et al. 2020) used adaptive variational modal decomposition (VMD) to process vibration signals and estimate mill load features with an improved power spectrum. The above-mentioned mill feature-extraction methods have achieved good results on some occasions, but there are also decomposition defects, such as the D-S theory requires a lot of expertise to assist in solving the problem, the EMD decomposition has the modal mixing problem, the EEMD decomposition has a large reconstruction error, the first two order modal components of CEEMDAN contain a lot of noise and the VMD decomposition effect is affected by the setting parameters.

To predict the load state of the mill, Tang et al. (Tang et al. 2010) used principal component analysis (PCA) and least squares support vector machine (LSSVM) to establish the mill load soft-sensing model, which can simplify the dimension of the mill load feature vector and ensure the prediction accuracy of the model. Luo et al. (Luo et al. 2019) used SVM to establish the mill load parameter-prediction model and the prediction accuracy increases with the increase of evidence. Gao et al. (Gao et al. 2020) used the improved stacked cyclic neural network to establish the mill load prediction model, which can quickly and accurately

identify the load state of the mill. He et al. (He et al. 2019) used multi-task least squares support vector machine (MTLS-SVM) to establish the mill load prediction model, and realized the effective prediction of the mill load state after changing working conditions.

Wang et al. (Wang et al. 2015) proposed a soft-sensing method for ball mill load based on the least squares support vector machine (LS-SVM) and grey model (GM). The above methods have achieved good results in some aspects. However, SVM is sensitive to the selection of the kernel function and the recurrent neural network is prone to gradient dissipation, which makes it have some limitations in mill load forecasting.

ACMD is a signal-processing method with high resolution for time-frequency distribution, which can solve the problem that VMD is not effective in processing multi-component signals with overlapping frequencies and does not need to set the signal modal number in advance so it has been widely used in the field of fault diagnosis. Chen et al. (Chen et al. 2019) used ACMD for fault diagnosis of the rotor-stator system and achieved good results. Ma et al. (Ma et al. 2021) used the particle swarm optimization algorithm and ACMD to perform fault diagnosis of variable speed rolling bearings, and the results showed that the method is practical. Yao et al. (Yao et al. 2022) used the ACMD algorithm with the sparrow search algorithm to optimize the BiLSTM network and improved the accuracy of short-term load prediction. Yang et al. (Yang et al. 2020) combined wavelet transform and ACMD methods to perform fault diagnosis of circuit breakers. The minimum distance classifier (MDC) is a classifier that classifies each input vector in the dataset by calculating the distance from the class centroid. The advantage of this classifier is that the feature variability is very small and easy to calculate, but it is not sensitive to data containing noise, which will lead to error classification (Liao et al. 2008).

The standardized variable distance classifier (SVD) is an improved version of the average distance classifier. SVD is a kind of classifier that is more sensitive to data. Considering the influence of standard deviation and standardized variable factors on feature vectors, it has a good classification performance even when the feature vectors have little variability. Elen et al. (Elen et al. 2021) used a variety of public data sets to verify the high component accuracy of SVD. Wang et al. (Wang et al. 2022) proposed a bearing fault health monitoring method based on HSSCEn and ISVD to diagnose the bearing fault mode, the superiority of the scheme is verified by experiments.

Based on the above analysis, a signal-processing method combining ACMD and SVD is proposed. ACMD is used to extract the feature information related to the mill load state and compared with EMD, EEMD, and VMD to verify the processing capability of ACMD for mill vibration signals. Adaptive chirp mode decomposition probabilistic neural network (ACMD-PNN), adaptive chirp mode decomposition back propagation (ACMD-BP) neural network, and adaptive chirp mode decomposition K-nearest neighbor (ACMD-KNN) are then selected to compare with ACMD-SVD for identification of the mill load and the superiority of the proposed method is verified by grinding experiments.

1. Materials and methods

1.1. Basic principle of ACMD

ACMD uses the recursive framework of an iterative algorithm to adaptively extract signal components one by one, and its model is as follows:

$$\min_{\{p_i(t), q_i(t), \tilde{f}_i(t)\}} \left\{ \|p_i''(t)\|_2^2 + \|q_i''(t)\|_2^2 + \alpha \|y(t) - y_i(t)\|_2^2 \right\} \quad (1)$$

where $\|\cdot\|_2$ is the L2 norm used to represent the distance, $p_i''(t)$ and $q_i''(t)$ are the second derivative of the demodulation operators, α is the weighting coefficient, $y(t)$ is the input signal, $y_i(t)$ is the extracted target component and $\|y(t) - y_i(t)\|_2^2$ represents the residual energy.

$$y_i(t) = a_i(t) \cos \left(2\pi \int_0^t \tilde{f}_i(\tau) d\tau \right) + b_i(t) \sin \left(2\pi \int_0^t \tilde{f}_i(\tau) d\tau \right) \quad (2)$$

where $a_i(t)$ and $b_i(t)$ are the demodulated signals, \tilde{f}_i is the frequency function of the demodulation operator, and $\cos \left(2\pi \int_0^t \tilde{f}_i(\tau) d\tau \right)$ and $\sin \left(2\pi \int_0^t \tilde{f}_i(\tau) d\tau \right)$ are the two demodulation operators.

$$\begin{cases} a_i(t) = A_i(t) \cos \left(2\pi \int_0^t (f_i(\tau) - \tilde{f}_i(\tau)) d\tau + \theta_i \right) \\ b_i(t) = -A_i(t) \sin \left(2\pi \int_0^t (f_i(\tau) - \tilde{f}_i(\tau)) d\tau + \theta_i \right) \end{cases} \quad (3)$$

where $A_i(t)$, $f_i(t)$, and θ_i respectively represent the instantaneous amplitude, instantaneous frequency, and the initial phase of the i th component.

$$A_i(t) = \sqrt{a_i^2(t) + b_i^2(t)} \quad (4)$$

The signal discretization is expressed as:

$$\min_{\{\{v_i\}, \{f_i\}\}} \left\{ \|\Theta v_i\|_2^2 + \alpha \|y - G_i v_i\|_2^2 \right\} \quad (5)$$

where $\Theta = \begin{bmatrix} \Omega & 0 \\ 0 & \Omega \end{bmatrix}$, Ω is the second order difference matrix; $v_i = [p_i^T, q_i^T]^T$;

$y = [y(t_0), \dots, y(t_{N-1})]^T$; $G_i = [C_i, S_i]$; $C_i = \text{diag}[\cos(\varphi_i(t_0)), \dots, \cos(\varphi_i(t_{N-1}))]$;
 $S_i = \text{diag}[\sin(\varphi_i(t_0)), \dots, \sin(\varphi_i(t_{N-1}))]$; $\varphi_i(t) = 2\pi \int_0^t \tilde{f}_i(\tau) d\tau$.

The instantaneous frequency of the signal is obtained and the vector v_i is solved by m iterations with the following result:

$$v_i^m = \left(\frac{1}{\alpha} \Theta^T \Theta + (G_i^m)^T G_i^m \right)^{-1} (G_i^m)^T y \quad (6)$$

where α is a weighting factor, G_i^m consists of a frequency function, and T is a transpose sign.

The corresponding signal components y_i^m are as follows:

$$y_i^m = G_i^m v_i^m \quad (7)$$

The remaining signal components are as follows:

$$r_{i+1} = r_i - y_i \quad (8)$$

When the remaining signal components are less than the threshold value, the iterative computation is stopped and the signal satisfies:

$$y = \sum_{i=1}^m y_i + r_{i+1} \quad (9)$$

1.2. Basic principle of SVD

The SVD is based on the optimization obtained on the mean distance classifier (MDC). Assume that the input matrix is v_X , $v_X \in R^{m \times n}$. The specific description steps of SVD principle are as follows:

$$v_Y = [y_0, y_1, \dots, y_m] \quad (10)$$

$$c = \{ \exists a \in v_Y : (p(a) \wedge \forall b \in v_Y : p(b) \rightarrow a = b) \} \quad (11)$$

where the output matrix $v_Y \in R^m$, m represents the number of samples, n represents the number of attributes. Each type of label is determined by the input matrix and is the value range of the class label.

The average of the input vectors is calculated for each class label and the obtained prime class matrix is:

$$\mu V = \sum_{a=0}^k \sum_{j=0}^n \mu V[a, j] \quad \mu V \in R^{k \times n} \quad (12)$$

where, k represents the number of labels, and $\mu V[a, j]$ represents the j -th attribute of the a -th vector of the centroid class matrix μV .

The distance of each input vector to the center-of-mass class matrix is

$$dX = \sum_{i=0}^k \{dX[i] = \text{distance}(X, \mu V[i, *]), X | X \in v_X\} \quad (13)$$

where k represents the number of labels, X is the input vector, $\text{distance}(X, \mu V[i, *])$ can be solved by using Euclidean, Manhattan, Minkowski, Chebyshev or Hellinger distance methods.

Next, calculate the standard deviation matrix of the input vector:

$$\sigma V = \left\{ \sqrt{\sum_{i=0}^m \left\{ \left(x_{i,j} - \mu V[a, j] \right)^2 \right\}}, \quad c_a = y_i / \sum_0^m \{1, \quad c_a = y_i \right. \quad (14)$$

where, $x_{i,j}$ represents the j -th attribute of the i -th sample in the input vector, represents the output value of the i -th sample and c_a is the class label.

Finally, calculate the similarity score of each input vector:

$$Decision = \underset{i}{\operatorname{argmin}}(i | i \in c, dX[i]Z[i]) \quad (15)$$

$$Z = \sum_{i=0}^k Z[i] = \left\{ \sum_{j=0}^n \frac{|X_j - \mu V[i, j]|}{\sigma V[i, j]}, \quad X | X \in v_X \right. \quad (16)$$

where $i \in c$ represents the class label; X_j represents the j -th attribute of the input vector in the data set; n represents the number of attributes in the input vector; k represents the number of classes; Z represents the standard deviation from each prime vector. The standard deviation between Z and a certain center-of-mass vector converges to 0, indicating that the input sample converges more closely to this class of labels.

1.3. ACMD-SVD method and implementation steps

The process of mill vibration signal processing and load-type identification based on ACMD-SVD is shown in Figure 1.

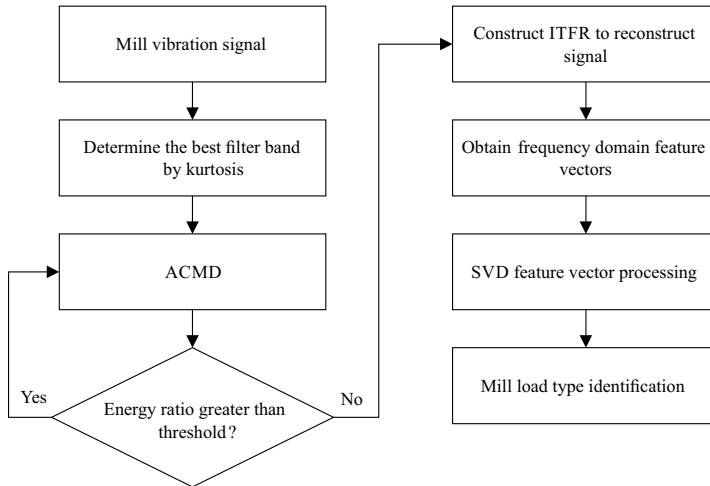


Fig. 1. Flow chart of mill vibration signal processing and load-type identification based on ACMD-SVD

Rys. 1. Schemat blokowy przetwarzania sygnału drganiowego młyna i identyfikacji rodzaju obciążenia na podstawie ACMD-SVD

According to Figure 1, the concrete steps of vibration signal processing and load-type identification of the mill based on ACMD-SVD are as follows:

1. Collect the original vibration signal of the mill under different load states.
2. Find the optimal filter band for the vibration signal based on the kurtosis of the signal.
3. Set threshold, decompose vibration signal by ACMD, and obtain instantaneous amplitude and instantaneous frequency of each modal component.
4. Construct a high-resolution signal extractor (ITFR) to reconstruct the signal based on the instantaneous amplitude and instantaneous frequency of each modal component.

$$ITFR(t, \omega) = \sum_{i=1}^K A_i(t) \cdot \delta(\omega - \varphi'_i(t)) \quad (17)$$

where δ represents the Dirac function and K represents the number of modal components, $A_i(t)$ represents the instantaneous amplitude, $\varphi'_i(t)$ represents the instantaneous frequency.

5. The frequencies corresponding to the ten largest peaks in the frequency domain of the reconstructed signal are extracted as feature vectors.
6. Input the feature vector into the SVD model for training recognition and obtain the mill load type.

2. Results and discussion

2.1. Mill barrel vibration signal acquisition and processing

In this paper, the tungsten ore used in the experiment was selected from a mine in Ganzhou and a wet mill with a Bond work index was used to perform experiments to validate the proposed mill vibration signal processing and load identification method. The DH5922N dynamic data acquisition instrument and DH131 vibration acceleration sensor were selected as the experimental equipment. The sampling frequency was set at 10 kHz, and the shell vibration signals underload, normal load, and overload were collected. The length of each vibration signal is 10,000. Fifty groups of shell vibration signals under each mill load state were selected as experimental data so there was a total of 150 groups. The vibration acceleration sensor and its location on the mill is shown in Figure 2.

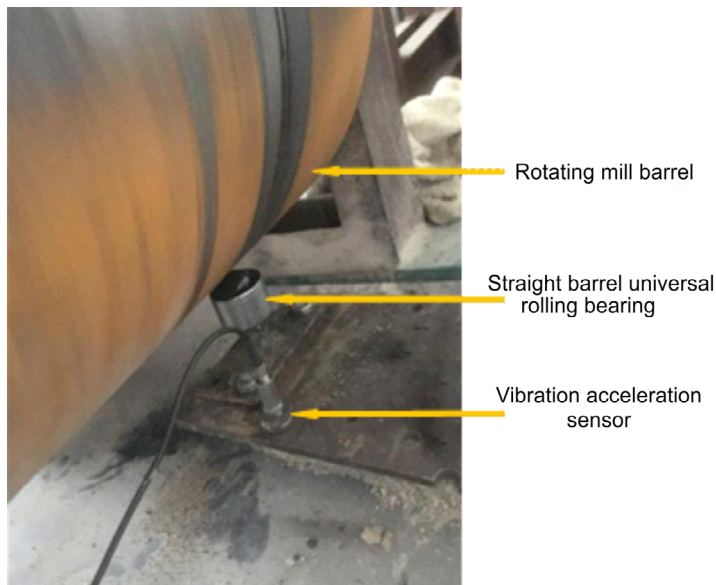


Fig. 2. The vibration acceleration sensor and its location on the mill

Rys. 2. Czujnik przyspieszenia drgań i jego umiejscowienie na młynie

The original shell vibration signals under three load states were selected from the grinding experiments, as shown in Figure 3.

In Figure 3, the peak positions of the shell vibration signals under three load states represent the acceleration generated when the steel balls hit the liner. There are certain differences in the amplitude of the shell vibration signals in the time domain under the three load states. However, due to a large amount of noise in shell vibration signals, the variation law

is not obvious and it is difficult to judge the mill load state through the time domain peak information. Therefore, the frequency spectrum information of vibration signals is obtained by Fourier transform, as shown in Figure 4.

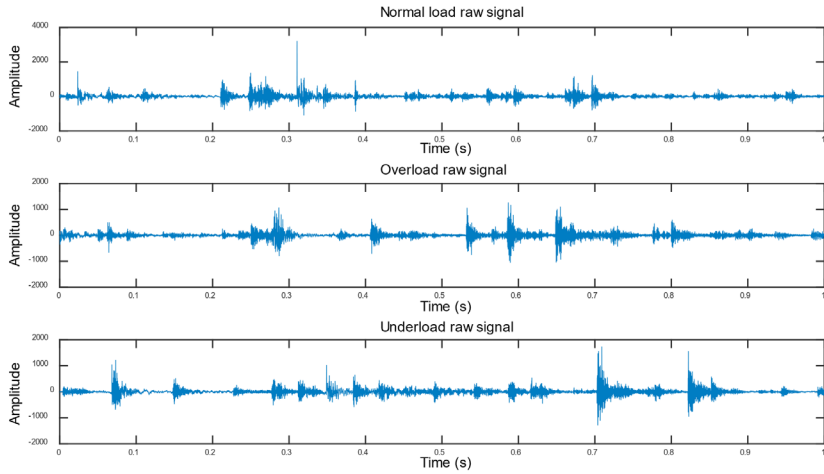


Fig. 3. Vibration signals of the shell under three load states

Rys. 3. Sygnały drganiowe płaszczka w trzech stanach obciążenia

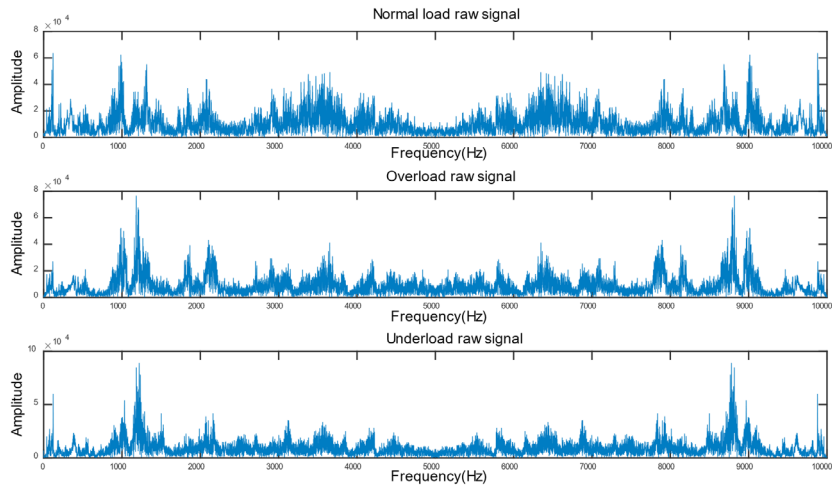


Fig. 4. Frequency spectrum of shell vibration signal under three load states

Rys. 4. Widmo częstotliwości sygnału drgań powłoki w trzech stanach obciążenia

In Figure 4, there are some differences in the frequency spectrum of shell vibration signals under three load states. The main frequency band of a normal load is the middle frequency band, the main frequency band of the overload is at the full frequency band, and the main frequency band of underload is at the low frequency band and the high frequency band. It can be seen that the frequency domain information can indirectly reflect the mill load state. However, due to the existence of a large amount of noise, it is impossible to accurately extract the frequency domain features. Therefore, the signal is processed by ACMD and the threshold is set by the ratio of the residual signal energy to the original signal energy. When the ratio is less than 1%, the operation is stopped to obtain high-resolution time-frequency distribution signals. The ACMD decomposition times and the ratio of the residual signal energy to the original signal energy are shown in Table 1.

Table 1. ACMD decomposition times and the energy ratio

Tabela 1. Czasy rozkładu ACMD i wskaźnik energii

Decomposition times	Energy ratio (%)	Decomposition times	Energy ratio (%)
1	44.8778	6	4.4621
2	20.3888	7	3.1161
3	10.0616	8	2.3263
4	8.4970	9	1.6512
5	6.2998	10	1.0849

In Table 1, each decomposition takes the peak frequency of the original signal as the initial frequency of ACMD, and the reconstructed modal components are obtained by ACMD. With the increase of decomposition times, the ratio of residual signal energy to original signal energy decreases continuously until it is less than the threshold value and the calculation is then stopped. The frequency spectrum of the reconstructed vibration signal of the shell under three load states after ACMD processing is shown in Figure 5.

In Figure 5, after ACMD processing, the features of the shell vibration signal in the frequency domain at high amplitude are strengthened, while those at low amplitude are weakened. ACMD effectively removes the interference of noise, which makes the frequency domain features of the mill vibration signal more obvious. As the frequency distribution of shell vibration signals is different under the three load states, the frequency domain information of shell vibration signals processed by ACMD can be used to identify the mill load state.

To evaluate the effectiveness of ACMD, the signal-to-noise ratio (SNR) is selected as a quantitative comparison index, and ACMD is compared with the current mainstream signal-processing algorithms (EMD, EEMD, and VMD). According to reference (Luo 2019), setting the VMD parameter $K = 6$, the standard deviation parameter of EEMD Gaussian

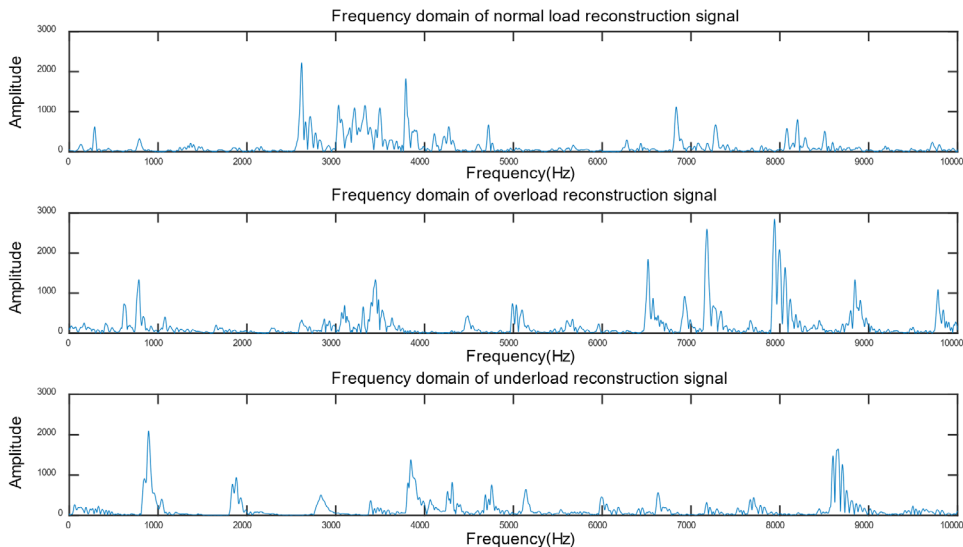


Fig. 5. Frequency spectrum of the reconstructed vibration signal of the shell under three load states

Rys. 5. Widmo częstotliwościowe zrekonstruowanego sygnału drgań powłoki w trzech stanach obciążenia

white noise is 0.2, and the noise count parameter to 100 times. After being processed by four methods, the SNR results of the vibration signal of the mill shell are shown in Table 2.

Table 2. Comparison of the denoising effects of mill vibration signals

Tabela 2. Porównanie efektów odzsumiania sygnałów drgań młyna

		ACMD	VMD	EEMD	EMD
SNR	Normal load	19.9164	16.6562	12.5185	10.6058
	Overload	19.2276	16.3530	13.1190	12.3610
	Underload	22.5409	17.7943	12.5934	11.1414

In Table 2, the signal-to-noise ratio (SNR) of the vibration signals of the mill shell processed by ACMD under three load states is the highest, far exceeding the results processed by other methods, indicating that ACMD has better noise robustness. After ACMD processing, the frequency distribution of shell vibration signals under three load states is obviously different, and the mill load state can be indirectly obtained through frequency spectrum analysis, so the frequencies corresponding to ten frequency domain peaks obtained during iterative decomposition are used as feature vectors. The frequencies corresponding to ten

frequency domain peaks of shell vibration signals obtained by ACMD under three load states are shown in Table 3.

Table 3. ACMD obtains the corresponding frequencies at ten frequency domain peaks

Tabela 3. ACMD uzyskuje odpowiednie częstotliwości w dziesięciu pikach w dziedzinie częstotliwości

Serial number	Normal load	Overload	Underload
1	2,616.28	783.78	893.66
2	2,712.73	3,447.68	1,880.11
3	3,032.59	4,990.84	3,845.68
4	3,212.06	6,515.68	4,310.82
5	3,329.26	6,928.33	4,685.63
6	3,497.74	7,179.83	4,755.21
7	3,789.52	7,940.42	5,141.01
8	6,834.33	8,060.06	6,629.22
9	7,277.49	8,846.29	8,655.84
10	8,199.24	9,780.24	8,752.28

In Table 3, the frequencies corresponding to the maximum peak of the normal load vibration signal are mainly concentrated in the middle frequency band, the frequencies corresponding to the maximum peak of overload vibration signal are mainly concentrated in the middle frequency band and the high frequency band, and the frequencies corresponding to the maximum peak of under load vibration signal are mainly concentrated in the low frequency band and the middle frequency band. This shows that the frequency domain distribution of shell vibration signals under three load states after ACMD processing is quite different, and the frequencies corresponding to the ten frequency domain peaks obtained by ACMD can be used as the load features of the mill.

2.2. Application of the signal-processing method based on ACMD-SVD in mill load identification

The obtained 150 groups of mill feature parameters are input into the SVD model for testing. Each group of load state is trained by thirty samples and tested by twenty samples. These samples are processed by ACMD, and the frequencies corresponding to the ten frequency domain peaks of iterative decomposition are obtained as feature vectors. The test results are shown in Figure 6.

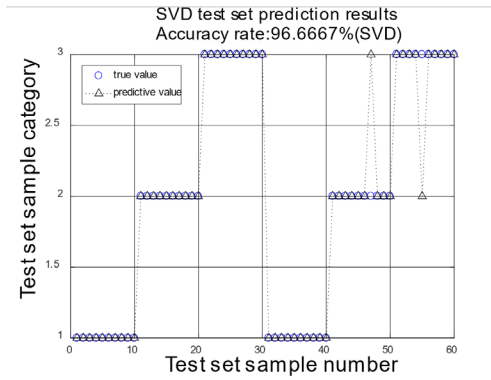


Fig. 6. Test results based on ACMD-SVD

Rys. 6. Wyniki badań na podstawie ACMD-SVD

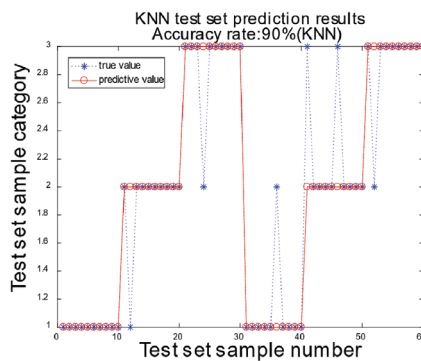
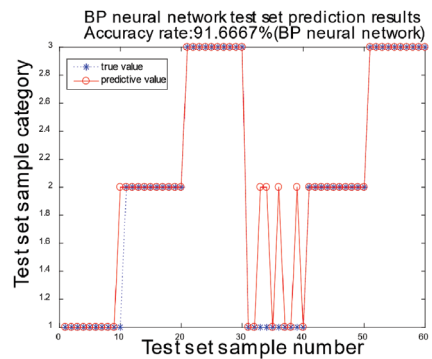
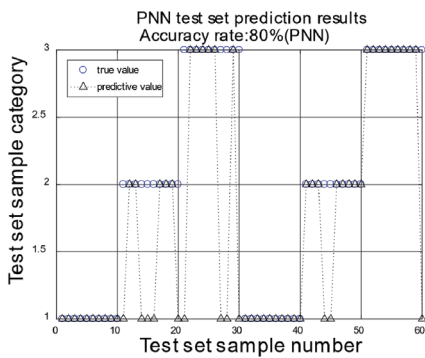


Fig. 7. Identification results of test samples of each method

Rys. 7. Wyniki identyfikacji próbek testowych każdej metody

In Figure 6, label 1 indicates the normal load type, label 2 indicates the overload type and label 3 indicates the underload type. The prediction results of mill load state show that all normal loads are correctly predicted, while only one prediction error is found in under-load and over-load states. The prediction accuracy rate of the ACMD-SVD model for the mill load state is 96.6667%. This shows that ACMD-SVD can better predict the load state of the mill. To verify the effectiveness of the method, ACMD-PNN, ACMD-BP neural network, and ACMD-KNN are selected for comparative study with ACMD-SVD. Among them, set the number of BP neural network iterations to 1,000, the expected error to 0.001, the learning rate to 0.01, and the KNN parameter to $k = 9$, and use the Euclidean distance metric. The prediction results are shown in Figure 7.

In Figure 7, mill load state identification can also be achieved by PNN, BP neural network, and KNN, with correct prediction rates of 80%, 91.6667%, and 90% respectively, while the ACMD-SVD has a higher prediction accuracy of 96.6667% compared with other methods. Therefore, the method of mill vibration signal processing and load-type identification based on ACMD-SVD has a good denoising effect and a high accuracy of load identification.

Conclusions

In this paper, a method of mill vibration signal processing based on ACMD-SVD is proposed, which is applied to identify the load state of the mill, and the following conclusions are obtained.

1. ACMD is used to extract the feature of mill vibration signals, and SNR is used as the evaluation index, which is compared with EMD, EEMD, and VMD signal processing algorithms. The results show that the frequency-domain features of the vibration signals under the three load states are more obvious and the denoising effect is good after ACMD processing, which provides a new idea for mill load feature signal extraction.
2. ACMD-SVD is used to predict the load state of the mill, and the accuracy rate reaches 96.6667%. Compared with ACMD-PNN, the prediction accuracy rate increased by 16.6667%; compared with ACMD-BP neural network, it increased by 5.6667%; compared with ACMD-KNN, it increased by 6.6667%. The prediction accuracy of ACMD-SVD shows a large degree of improvement.
3. The method of mill vibration signal processing and load-type identification based on ACMD-SVD has excellent performance, which provides an accurate and reliable basis for improving grinding efficiency.

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METHOD OF VIBRATION SIGNAL PROCESSING AND LOAD-TYPE IDENTIFICATION OF A MILL BASED ON ACMD-SVD

Keywords

feature information, mill load, ACMD, SVD, feature vector

Abstract

Green mine construction is the main melody of mining development and problems such as safe production, energy saving and consumption reduction need to be solved urgently. The working conditions of the mill are complex in the process of grinding. Aiming at the problems existing in the feature extraction and load prediction of the mill, a signal-processing method based on adaptive chirp mode decomposition (ACMD) and a standardized variable distance classifier (SVD) is proposed. Firstly, the recursive framework of the ACMD method is used to obtain the initial frequency of mill vibration signals. Secondly, the initial frequency is used to reconstruct the high-resolution component of the mill vibration signal through the iterative frame in the ACMD method. The frequency corresponding to the frequency domain peak of the reconstructed signal is then selected as the mill load feature vector. Finally, with consideration to the influence of standard deviation and standardized variable factors on the feature vectors, a standardized variable distance classifier is proposed. The feature vectors of the mill load are input into the SVD model for training, and the state types of the mill load are obtained. The method is applied to the grinding experiment and the results show that the frequency-domain features obtained by the mill vibration signal-processing method based on ACMD-SVD are obvious, which has high accuracy in the identification of mill load types, and provides a new idea for the extraction of mill load features and prediction of the mill load.

**METODA PRZETWARZANIA SYGNAŁU DRGANIOWEGO I IDENTYFIKACJI
TYPU OBCIĄŻENIA MŁYNA NA PODSTAWIE ACMD-SVD****Słowa kluczowe**

informacja o cechach, obciążenie młyna, ACMD, SVD, wektor cech

Streszczenie

Budowa zielonej kopalni jest główną melodią rozwoju górnictwa, a problemy takie jak: bezpieczna produkcja, oszczędność energii i redukcja zużycia wymagają pilnego rozwiązania. Warunki pracy młyna w procesie mielenia są złożone. Mając na celu rozwiązanie problemów występujących w ekstrakcji cech i przewidywaniu obciążenia młyna, zaproponowano metodę przetwarzania sygnału opartą na dekompozycji w trybie adaptacyjnym ACMD (*Adaptive Chirp Made Decomposition*) i znormalizowanym klasyfikatorze zmiennej odległości SVD (*Variable Distance Classifier*). Po pierwsze, rekurencyjna struktura metody ACMD jest wykorzystywana do uzyskania początkowej częstotliwości sygnałów drgań młyna. Po drugie, częstotliwość początkowa jest wykorzystywana do rekonstrukcji wysokorozdzielczej składowej sygnału drgań młyna poprzez ramkę iteracyjną w metodzie ACMD. Częstotliwość odpowiadająca pikowi w dziedzinie częstotliwości rekonstruowanego sygnału jest następnie wybierana jako wektor cech obciążenia młyna. Na koniec, biorąc pod uwagę wpływ odchylenia standardowego i standaryzowanych czynników zmiennych na wektory cech, zaproponowano standaryzowany klasyfikator odległości o zmiennej długości. Wektory cech obciążenia młyna są wprowadzane do modelu SVD w celu uczenia i uzyskiwane są typy stanu obciążenia młyna. Metodę zastosowano w eksperymencie mielenia, a wyniki pokazują, że cechy w dziedzinie częstotliwości uzyskane za pomocą metody przetwarzania sygnału drgań młyna opartej na ACMD-SVD są oczywiste, co ma wysoką dokładność w identyfikacji typów obciążeń młyna i zapewnia nowy pomysł na ekstrakcję cech obciążenia młyna i predykcję obciążenia młyna.

