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Research on Speech Denoising Algorithm for Equipment Trains in Fully Mechanized Mining Working Faces based on CEEMDAN High and Low Frequency Filtering

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Abstract: This paper proposes a high and low frequency filtering denoising algorithm based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). CEEMDAN to address the issue of noise in speech signals obtained in the environment of fully mechanized mining face equipment trains. This algorithm first decomposes speech signals into multiple Intrinsic Mode Functions (IMFs) in different frequency domains through CEEMDAN, then uses Hilbert-Huang Transform (HHT) to obtain the instantaneous frequency and amplitude of IMFs, calculates the Euclidean distance between IMFs, normalizes it to obtain the average distance between IMFs, and divides the IMFs components into high and low frequency categories based on the average distance. Next, Optimally Modified Log Spectral Amplitude (OMLSA) algorithm and Kalman filtering algorithm are used for the high-frequency and low-frequency IMF components, respectively. Finally, the processed IMF components are reconstructed to obtain a denoised signal. After comparative experiments, the noise reduction algorithm proposed in this paper significantly improves the Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Mean Square Error (RMSE), and Mean Absolute Distance (MAE) of speech signals obtained in the environment of fully mechanized mining face equipment trains compared to other commonly used noise reduction algorithms.

Keywords: CEEMDAN; Intrinsic Mode Function; Hilbert-Huang Transform; OMLSA; Kalman Filter.

1. Introduction

The coal industry is one of the important pillar industries of my country's national economy and provides the main energy guarantee for my country's economic construction [1, 2, 3]. However, during coal in the process of mining, safety cannot be guaranteed due to various reasons [4,5]. With the continuous advancement of voice communication technology, ensuring smooth communication between the surface and underground and monitoring underground conditions from the ground have played a vital role in safe production underground [6,7].

At present, the common noise reduction methods in coal mines are mainly depend on the equipment itself [8] and for specific underground environments. The noise reduction technology of the equipment itself mainly involves studying the noise reduction structure of the equipment [9] and adding sound insulation equipment [10], which is not applicable to the designed equipment and tunnel layout, but the applicability to specific environments is poor. For example, literature [11] combines the improved fruit fly algorithm and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to solve coal and rock cutting noise. The adaptability is poor, and the coal and rock cutting noise is single. Document [12] applies wavelet threshold denoising to underground voice communication systems. Document [13] applies wavelet threshold to underground received signals. Document [14] applies wavelet threshold to denoising metal rope signals of coal mine crane adjustment. Although wavelet transform to achieve noise reduction in specific environments, it is necessary to manually select the wavelet base and noise reduction threshold according to the differential noise in different environments, which lacks adaptability. Literature [15] uses EMD decomposition and wavelet noise reduction for acoustic detection of underground geological structures. Although the quality of the processed speech signal has been improved to a certain extent, aliasing will occur if the signal does not fully meet the definition of white noise.

Based on the above analysis, in view of the characteristics of underground coal mine fully mechanized mining working face equipment trains that any machines and equipment, high power, narrow working space, large reflective surface, easy to form mixed noise with high intensity and high sound level [16,17], this paper proposes A high frequency and low frequency filtering algorithm for coal mines based on CEEMDAN is proposed. The algorithm uses CEEMDAN and Hilbert-Huang Transform (HHT) to adaptively decompose the original speech signal into intrinsic mode function (IMFs) components of high-frequency and low-frequency. According to the noise characteristics of different frequency domains, the optimal improved log spectral amplitude estimation (OMLSA) algorithm and the Kalman filter (kalman) algorithm are used respectively, and the final denoised signal is obtained by reconstructing the processed IMFs components.

2. Basic Theory

2.1. CEEMDAN Algorithm Principle

The CEEMDAN algorithm is a complete integrated empirical mode decomposition algorithm with adaptive white noise proposed by Torres [18] based on empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD). The method borrows the idea of adding Gaussian noise in the EEMD method and canceling the noise through multiple superpositions and averages. After the first-order IMF component, the overall average calculation is performed, and the IMF component containing auxiliary noise after EMD decomposition is added, and the third-order IMF component is obtained. After the first-order IMF component, the overall average calculation is performed to obtain the final first-order IMF component, and then the above operation is repeated for the remaining part. CEEMDAN reduces the number of screenings and effectively solves the problem of white noise transfer from high frequency to low frequency [19].

CEEMDAN steps are as follows:

1. Add white noise $\omega^i[n]$ to realize $r_1[n]+\varepsilon_0\omega^i[n]$, where $\varepsilon=0.02$ is the standard error, and the first modal component obtained through EMD decomposition is:

$$\widetilde{IMF}_1[n]=\frac{1}{I}\sum_{i=1}^{I}IMF_1^i[n]=\overline{IMF_1}[n] \tag{1}$$

2. At the first time $(k=1)$, calculate the first residual $r_1[n]$, that is $r_1[n]=x[n]-\widetilde{IMF}_1[n]$.

3. Add white noise $E_1(\omega^i[n])$, EMD decomposition $r_1[n]+\varepsilon_1E_1(\omega^i[n]), i=1,\cdots,I$, until their first-order EMD modal component are achieved, and define the second EMD modal component as:

$$\widetilde{IMF}_2[n]=\frac{1}{I}\sum_{i=1}^{I}E_1(r_1[n]+\varepsilon_1E_1(\omega^i[n])) \tag{2}$$

4. When $k=2,\cdots,K$, the kth residual is calculated as:

$$r_k[n]=r_{(k-1)}[n]-\widetilde{IMF}_k[n] \tag{3}$$

5. Add white noise $E_k(\omega^i[n])$ in sequence, decompose $r_k[n]+\varepsilon_kE_k(\omega^i[n]), i=1,2,\cdots,I$, until their first-order EMD modes are achieved component, and define the (k+1)th modal component as:

$$\widetilde{IMF}_{k+1}[n]=\frac{1}{I}\sum_{i=1}^{I}E_1(r_k[n]+\varepsilon_kE_k(\omega^i[n])) \tag{4}$$

6. Repeat step 4 to k times until the residuals cannot be decomposed. The final remaining residual is:

$$R[n]=x[n]-\sum_{k=1}^{K}\widetilde{IMF}_k \tag{5}$$

2.2. OMLSA Algorithm Principle

The OMLSA algorithm is a commonly used single-channel noise reduction algorithm proposed by Cohen [20]. The algorithm uses the minimum controlled recursive average (MCRA) algorithm to estimate the prior signal-to-noise ratio and posterior signal-to-noise ratio, and calculate the speech existence probability, and then the effective gain of the noise is calculated to achieve the estimation of the noise.

The OMLSA algorithm essentially minimizes the logarithmic spectrum amplitude [21], that is:

$$E\left(\left(\log A(k,l)-\log \hat{A}(k,l)\right)^2\right) \tag{6}$$

Where $A(k,l)$ represents the spectrum speech amplitude, and $\hat{A}(k,l)$ represents the spectrum speech optimization estimate.

$$\hat{A}(k,l)=\left(G_{H_1}(k,l)\left|Y(k,l)\right|\right)^{p(k,l)}\times\left(G_{\min}(k,l)\left|Y(k,l)\right|\right)^{1-p(k,l)} \tag{7}$$

Where $p(k,l)$ represents the posterior probability of the presence of speech, $G_{H_1}(k,l)$ represents the conditional gain function, $G_{\min}(k,l)$ represents the spectral gain Hall when speech does not exist, and its size is Depends on subjective standards.

$$\begin{aligned}
G_{H_1}(k,l)&=\frac{\xi(k,l)}{1+\xi(k,l)}\exp\left(\frac{1}{2}\int_{v(k,l)}^{\infty}\frac{e^{-t}}{t}dt\right)\\
p(k,l)&=\left(1+\frac{q(k,l)}{1-q(k,l)}\left(1+\xi(k,l)\right)\times\exp(-v(k,l))\right)\\
v(k,l)&=\frac{\gamma(k,l)\xi(k,l)}{1+\xi(k,l)}
\end{aligned} \tag{8}$$

Where $\xi(k,l)$ represents the prior signal-to-noise ratio, and $\gamma(k,l)$ represents the posterior signal-to-noise ratio.

2.3. Kalman Filter Algorithm Principle

The Kalman filter algorithm is a relatively classic estimation algorithm. It is an algorithm that uses the minimum mean square error as the best criterion for estimation to find a set of recursive estimation algorithms [22]. The algorithm uses the state space model of signal and noise, uses the estimated value at the previous moment and the observed value at the current moment to update the estimate of the state variable, and obtain the estimated value at the current moment. The classic Kalman filter algorithm consists of five formulas, the formulas are as follows:

Predict the equation of state:

$$\begin{aligned}
\hat{x}_t^- &= A\hat{x}_{t-1}+BU\\
P_{t+1}^- &= AP_tA^T+Q
\end{aligned} \tag{9}$$

Where $\hat{x}_t^-$ is the state prediction value, and $\hat{x}_t$ is the state estimate value. *A* is called the transformation matrix, *B* is called the control matrix, and *U* is the system input at the current moment. P_t^-, P_t are the covariance matrices of the a priori error and the posterior error respectively, *Q* is Gaussian noise with a mean value of 0 and a covariance matrix of *Q*.

Update equation:

$$\begin{aligned}
\hat{x}_t &= \hat{x}_t^-+K_t\left(z_t-H\hat{x}_t^-\right)\\
P_t &= \left(I-K_tH\right)P_t^-\\
K_t &= P_t^-H^T\left(HP_t^-H^T+R\right)^{-1}
\end{aligned} \tag{10}$$

Where K_t becomes the Kalman gain, z_t is the measurement value at the current moment, *H* is called the measurement matrix, and *R* is Gaussian noise with a mean of 0 and a covariance of *R*.

2.4. High and Low Frequency Filtering and Noise Reduction Algorithm based on CEEMDAN

The flow chart of the noise reduction algorithm based on CEEMDAN high and low frequency filtering is shown in Figure 1. The specific algorithm is described as follows:

(1) Use the OMLSA algorithm to filter out the environmental noise of the original signal of the equipment train before CEEMDAN decomposition.

(2) Decompose the noisy signal in step 1 into IMFs components of n frequency domain segments IMF_n through CEEMDAN.

(3) Perform HHT on all IMFs components and calculate the instantaneous frequency and instantaneous amplitude of all components.

(4) Calculate and normalize the Euclidean distance between IMFs components, calculate the average distance between IMF components, and adaptively divide the IMFs components into high frequency and low frequency.

(5) Use the OMLSA algorithm to reduce noise for high-

frequency IMF components, and use Kalman filtering for low-frequency IMF components.

(6) Reconstruct all filtered IMFs components to obtain the final denoised signal.

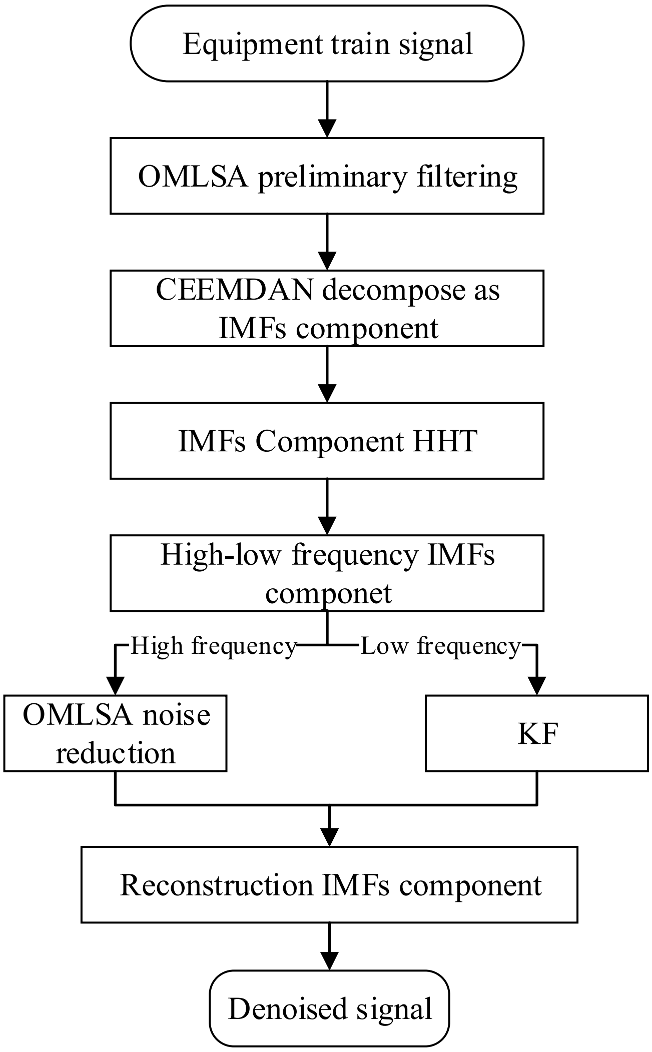

Figure 1. Flow Chart of CEEMDAN High-low Frequency Filtering Algorithm

3. Experimental Results and Analysis

In order to verify the effectiveness of the high and low frequency filtering noise reduction algorithm proposed in this article based on CEEMDAN, the train voice signals of the fully mechanized mining face equipment in Shaqu Coal Mine, Luliang City, Shanxi Province were collected for experimental analysis. On the basis of the noise reduction results of the algorithm in this article, the noise reduction results of OMLSA combined with Kalman filter algorithm, CEEMDAN combined with full-frequency OMLSA algorithm, CEEMDAN combined with full-frequency Kalman filter algorithm, CEEMDAN combined with high-frequency Kalman filter and low-frequency OMLSA algorithm were carried out. Compare and analyze the noise reduction effects of each algorithm.

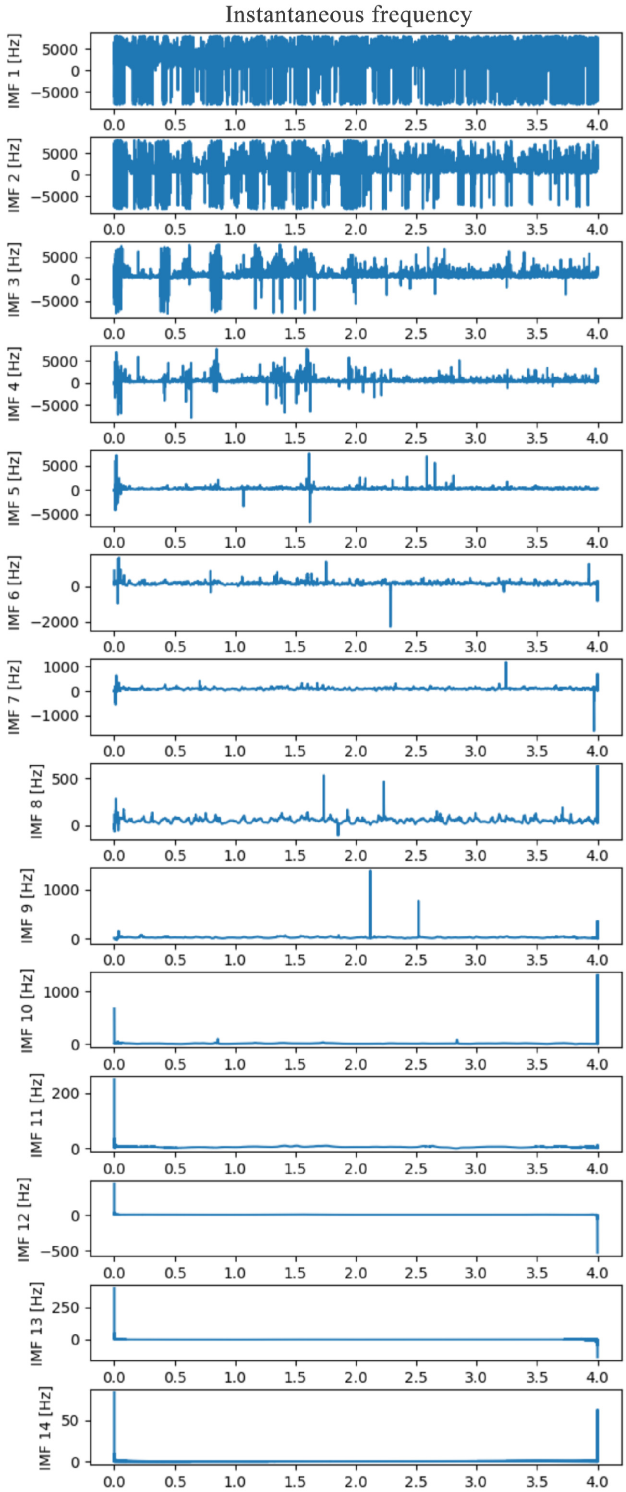

Figure 2. Instantaneous Frequency of IMFs Component in Frequency Domain

In order to verify the effectiveness of the algorithm in this article, this article calculates the signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), root-mean-square error (RMSE) and average Absolute error (Mean Absolute Distance, MAE).

The mathematical expression of SNR is as follows:

$$SNR = 10lg \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N}(\hat{x}(n) - x(n))^2} \tag{11}$$

The mathematical expression of PSNRis as follows:

$$PSNR = 10lg\frac{\sum_{n=1}^{N}(2^n-1)^2(n)}{\sum_{n=1}^{N}E(\hat{x}(n)-x(n))^2} \quad (12)$$

The mathematical expression of RMSEis as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{x}(n)-x(n))^2} \quad (13)$$

The mathematical expression of MAEis as follows:

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|\hat{x}(n)-x(n)| \quad (14)$$

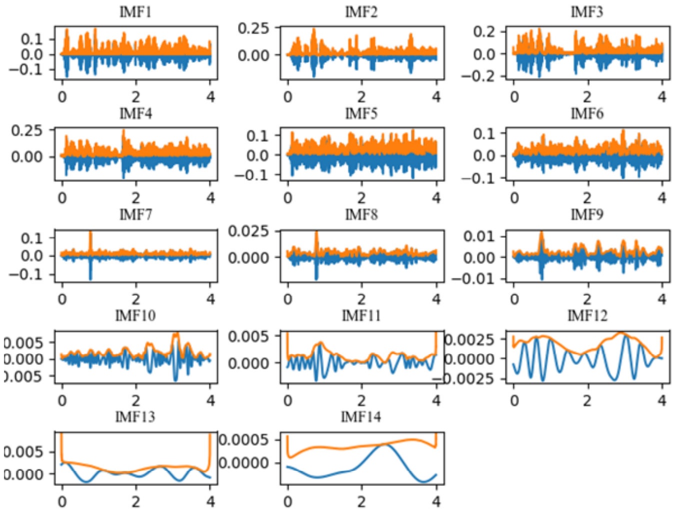

Figure 3. Envelope curve of Instantaneous frequency of IMFs component in time domain

After CEEMDAN decomposition, the results of different algorithms for high and low frequencies are shown in Table 1. As can be seen from the table, the algorithm in this paper is the best in terms of SNR, PSNR, RMSE and MAE index results. Compared with the CEEMDAN+OMLSA algorithm, the algorithm in this paper is better than it, which proves that low-frequency noise is more sensitive to algorithm processing. The MAE in this paper is 0.1 lower, indicating that low frequencies affect the clarity of sound more.

Table 1. Comparison of test result of different denoising algorithms

Algorithm	SNR	PSNR	RMSE	MAE
Omlsa + Kalman	0.55	1.70	0.06	0.04
CEEMDAN + kalman	0.56	1.69	0.06	0.05
CEEMDAN + omlsa	3.97	2.60	0.02	0.02
high-frequency kalman + low-frequency omlsa	0.73	1.70	0.06	0.04
This article	4.24	2.81	0.016	0.01

In order to further analyze the impact of different algorithms on noise, this article conducts comparisons in the time domain and frequency domain. The time domain comparison is shown in Figure 4. It can be seen from the figure that at the high frequency position, the wave peak after denoising is slenderer than before denoising, and the burrs on the wave peak are flat; at the low frequency position, the flat wave peak is divided into multiple slender peaks, which can better reflect the timbre of deep sounds. The three algorithms of OMLSA + Kalman filter, CEEMDAN + Kalman filter, and CEEMDAN + high-frequency Kalman filter + low-frequency OMLSA have full-frequency distortion, and the CEEMDAN + OMLSA algorithm has low-frequency distortion. The spectrum comparison is shown in Figure 5. It can be seen from the figure that for CEEMDAN+Kalman filtering, CEEMDAN+high-frequency Kalman filtering+low-frequency OMLSA algorithm, the high frequency is higher than the original signal, and the noise increases; the OMLSA+Kalman filtering algorithm has a large amplitude at high frequency Reduce,speech distortion. Compared with the algorithm of this article, the CEEMDAN+OMLSA algorithm has reduced the amplitude of high frequencies by 10%, the troughs between high frequencies are slenderer, and the low frequencies are smoother and more layered. The logarithmic spectrum comparison is shown in Figure 6. It can be seen from the figure that the CEEMDAN+high-frequency Kalman filter+ low-frequency OMLSA algorithm is compared with the algorithm in this paper. Although the amplitude below 128Hz (low frequency) is significantly increased, the sound is more obvious; However, at 128Hz-512Hz (medium frequency), the algorithm in this paper has a flat amplitude, no aggregation, and the denoised signal is stable. The noise amplitude above 1024Hz (high frequency) is significantly reduced, and the noise is significantly reduced.

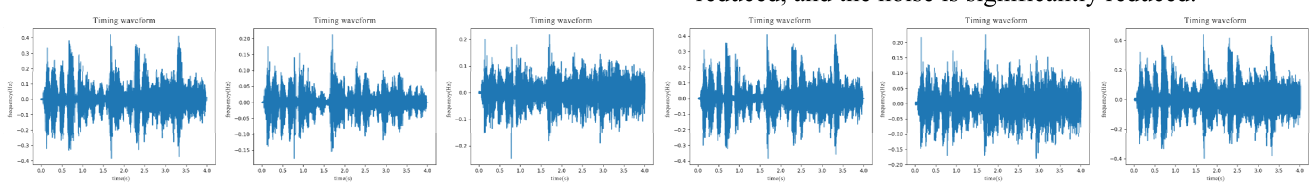

Figure 4. Comparison of sequential waveform of different denoising algorithms

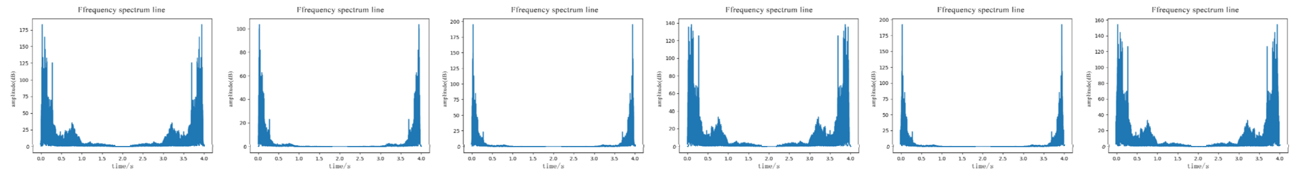

Figure 5. Comparison of frequency spectrum of different denoising algorithms

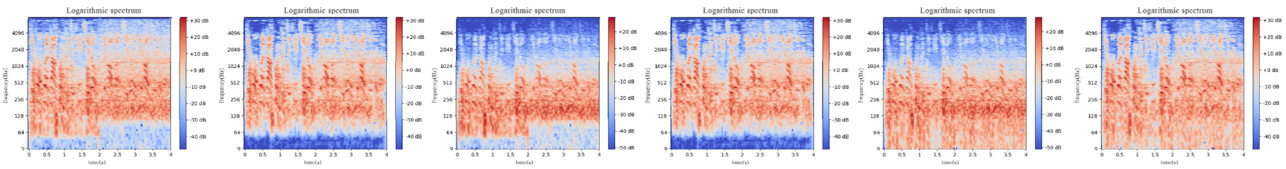

Figure 6. Comparison of logarithmic spectrum of different denoising algorithms

4. Summary

This paper proposes a high and low frequency filtering algorithm based on CEEMDAN for the complex and special environment of equipment trains in fully mechanized mining working faces. The train voice signal of the fully mechanized mining face equipment processed by this algorithm is clearer and smoother than the traditional algorithm. The test results show that the processing results of the proposed algorithm are significantly improved in SNR, PSNR, RMSE and MAE indicators. Therefore, the high and low frequency filtering algorithm based on CEEMDAN proposed in this article has good application value for noise reduction of speech signals acquired in the train environment of fully mechanized mining face equipment, and is beneficial to improving the accuracy of subsequent speech recognition.

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