Research on Transformer Speaker Recognition Feature Extraction Method Based on Variational Mode Extraction (VME)

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Abstract: Transformers are essential electrical equipment in the power system, and their operating state directly determines the safety, stability, and economy of the power grid. In view of the difficulty in extracting transformer voiceprint features in complex noise environments, a transformer voiceprint feature extraction method based on Variational Mode Extraction (VME) is proposed in this paper. Firstly, the central frequency of the inherent mode component is set according to the mechanism of transformer radiation noise generation, to eliminate the uncertainty caused by the random distribution frequency search method on the decomposition results. Then, with the inherent mode component frequency energy aggregation and the residual signal central frequency energy minimum as the optimization objectives, the cyclic iteration is used to complete the recognition and extraction of transformer voiceprint features, reducing the influence of environmental noise and other equipment noise. The analysis results of on-site actual signals show that this method can effectively reduce the influence of environmental noise and extract clearer and more accurate transformer voiceprint features.

1. Introduction

As an important core equipment in the power system, the health condition of power transformers will directly affect the stable operation of the entire power system. The acoustic signals generated during transformer operation contain rich information on equipment structural vibration and deformation. Moreover, fault diagnosis based on non-contact measurement techniques has minimal impact on the device itself. Therefore, research on transformer condition monitoring and fault diagnosis based on acoustic signature analysis is of great significance [1-4].

Obtaining effective features that characterize the operating state of transformers through advanced signal processing techniques is a prerequisite for transformer fault diagnosis. Domestic and foreign scholars have conducted a large number of theoretical and engineering research studies in this area. Zhang Chongyuan [5] and others used a transformer core model vibration and noise testing platform to construct a Mel-frequency spectrogram-convolutional neural network (CNN) transformer core acoustic pattern recognition model by pre-processing the acoustic signal using Mel-frequency spectrogram for dimensionality reduction as the input for deep learning models. The model achieved an accuracy of 99.71% in identifying acoustic signals under three different operating conditions. Zhu Kejia [6] proposed a feature extraction method based on wavelet packet energy spectrum and frequency Cepstral coefficients for transformer sound, and then used feature selection methods based on Laplacian and Fisher scores to solve the problem of feature redundancy. The analysis results show that the wavelet packet energy-frequency Cepstral coefficient feature can effectively improve the accuracy of fault diagnosis. Wang Fenghua [7] and others improved the traditional Mel-frequency Cepstral coefficient feature vector extraction algorithm by combining the weighted processing method and principal component analysis method, and proposed a transformer core loose fault recognition method based on Mel-frequency Cepstral coefficients and vector quantization algorithm. This method can accurately extract noise features that reflect the degree of transformer core loosening, and the fault recognition results based on vector quantization are highly consistent with the pre-set operating conditions. In the above-mentioned studies, the extraction of

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transformer acoustic features draws on the research achievements of auditory models in the field of speech processing, using Mel-frequency Cepstral coefficients or improved Mel-frequency Cepstral coefficients as transformer acoustic features. On the one hand, the above research did not fully utilize prior information on the mechanism of transformer radiation noise generation. On the other hand, compared with the low-frequency part of the acoustic signal, the Mel-frequency cepstral coefficients use non-linear Mel-scale frequencies to reduce the weight of the high-frequency part. However, in actual operating conditions, the high-frequency part of the acoustic signal is an important characterization of early transformer faults [8-9].

2. Variational Mode Decomposition

2.1 Variational Mode Extraction (Vme)

In the VME method, the center frequency of the intrinsic mode function is set based on the device operating mechanism, and the extraction of each intrinsic mode function is completed through iterative cycles [10]. The signal model used in VME is as follows,

$$f(t)=\mu_d(t)+f_r(t) \quad (1)$$

where $f(t)$ is the original signal, $\mu_d(t)$ represents the target intrinsic mode function, and $f_r(t)$ represents the residual signal. The intrinsic mode function $\mu_d(t)$ is a narrowband signal distributed around the center frequency and satisfies the following conditions,

$$J_1=\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*\mu_d(t)\right]e^{-j\omega_d t}\right\|_2^2 \quad (2)$$

where ω_d represents the center frequency of the target intrinsic mode component, δ represents the Dirac distribution function, and * represents the convolution operation. J_1 can be regarded as an indicator of the frequency bandwidth of the target intrinsic mode function $\mu_d(t)$. After the extraction of an intrinsic mode function is completed, the energy of the residual signal $f_r(t)$ around the central frequency of this intrinsic mode function should be close to zero. To achieve this, a penalty function similar to Wiener filtering is introduced, as follows

$$J_2=\|\beta(t)*f_r(t)\|_2^2 \quad (3)$$

where $\beta(t)$ is the impulse response function of the filter used. In order to ensure the accuracy of modal extraction and reduce the modal aliasing between each other, the filter should have the following frequency response function,

$$\hat{\beta}=\frac{1}{\eta(\omega-\omega_d^n)^2} \quad (4)$$

where $\hat{\beta}$ represents the frequency response of the filter, and η is the attenuation coefficient of the amplitude frequency response of the filter. The frequency response has infinite gain around the central frequency of the target IMF to ensure the accurate extraction of the IMF, while the gain of the frequency response in the frequency band far away from the central frequency is relatively small, reducing the frequency mixing between the target IMF and the residual signal in the vicinity of the central frequency. In summary, the extraction of the target IMF can be transformed into the following constrained model:

$$\begin{cases}\min\limits_{\mu_d,\omega_d,f_r}\{\alpha J_1+J_2\}\\ \mu_d(t)+f_r(t)=f(t)\end{cases} \quad (5)$$

where α is the penalty coefficient that controls the bandwidth of the intrinsic modal functions.

For the solution of the constrained model constructed for equation (5), the constrained variational problem is transformed into an unconstrained variational problem by introducing the Lagrange multiplier operator and penalty factor, resulting in an extended Lagrange expression [11-13].

$$\mathcal{L}(\mu_d,\omega_d,\lambda)= \alpha\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*\mu_d(t)\right]e^{-j\omega_d t}\right\|_2^2 +\|\beta(t)*f_r(t)\|_2^2 +\|f(t)-(\mu_d(t)+f_r(t))\|_2^2 +\langle\lambda(t),f(t)-(\mu_d(t)+f_r(t))\rangle \quad (6)$$

where λ is the Lagrange multiplier operator. According to the Parseval's theorem, equation (6) can be transformed into:

$$\mathcal{L}(\mu_d,\omega_d,\lambda)= \alpha\|j(\omega-\omega_d)\left[(1+\operatorname{sgn}(w))\hat{\mu}_d(\omega)\right]\|_2^2 +\left\|\hat{\beta}(\omega)\hat{f}_r(\omega)\right\|_2^2 +\left\|\hat{f}(\omega)-\left(\hat{\mu}_d(\omega)+\hat{f}_r(\omega)\right)\right\|_2^2 +\left\langle\hat{\lambda}(\omega),\hat{f}(\omega)-\left(\hat{\mu}_d(\omega)+\hat{f}_r(\omega)\right)\right\rangle \quad (7)$$

The unconstrained problem in equation (7) can be solved using the Alternating Direction Method of Multipliers (ADMM) [14]. The main idea of ADMM is to update one variable while fixing the other two variables, and the specific updating process is as follows:

$$\hat{\mu}_d^{n+1}(\omega)= \frac{\hat{f}_r(\omega)+\alpha^2(\omega-\omega_d^{n+1})^4\hat{\mu}_d^{n+1}(\omega)+\frac{\hat{\lambda}(\omega)}{2}}{[1+\alpha^2(\omega-\omega_d^{n+1})^4][1+2\alpha(\omega-\omega_d^n)^2]} \quad (8)$$

$$\omega_d^{n+1}=\frac{\int_0^\infty \omega|\hat{\mu}_d^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{\mu}_d^{n+1}(\omega)|^2 d\omega} \quad (9)$$

$$\hat{\lambda}^{n+1}=\hat{\lambda}^n+\tau\left[\frac{\hat{f}(\omega)-\hat{\mu}_d^{n+1}(\omega)}{1+\alpha^2(\omega-\omega_d^{n+1})^4}\right] \quad (10)$$

2.2 The Voiceprint Feature Extraction of Transformers Based on Vme

Based on the VME algorithm principle and practical application requirements mentioned above, Figure 1 shows the flowchart of the transformer voiceprint feature extraction method based on VME. The specific steps are as follows:

1)Obtain the running sound signal of the transformer and set the central frequency parameter according to the working mechanism of the transformer;

2)Analyze possible common fault modes and support the setting of parameters such as the number of decomposition based on device-related prior information;

3)Use the VME algorithm to extract the intrinsic modal components in the sound signal;

4)Iterate in a loop to extract several set intrinsic modal components one by one;

5)Use the Hilbert-Huang Transform (HHT) to extract the instantaneous amplitude and instantaneous frequency information of the sound signal;

6)Combine the instantaneous amplitude and instantaneous frequency of the sound signal as voiceprint features, providing support for applications such as transformer state warning and fault diagnosis.

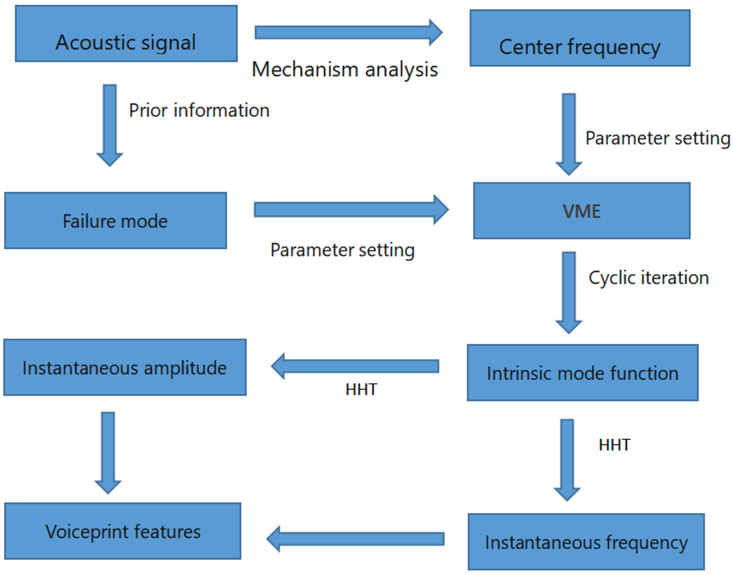


Fig.1 Fault Diagnosis Process

3. Application

A certain substation is equipped with two 110KV transformers, and microphone sensors are used to collect the radiation sound of the transformer during operation. The sampling frequency is 2048Hz, the sampling length is 2048, and the data acquisition work was carried out on April 14th, July 5th, July 23rd, July 26th, and July 28th in 2021. The on-site installation schematic diagram of the microphone sensor is shown in Figure 2, and the waveform and spectrum of the sound signal are shown in Figure 3.

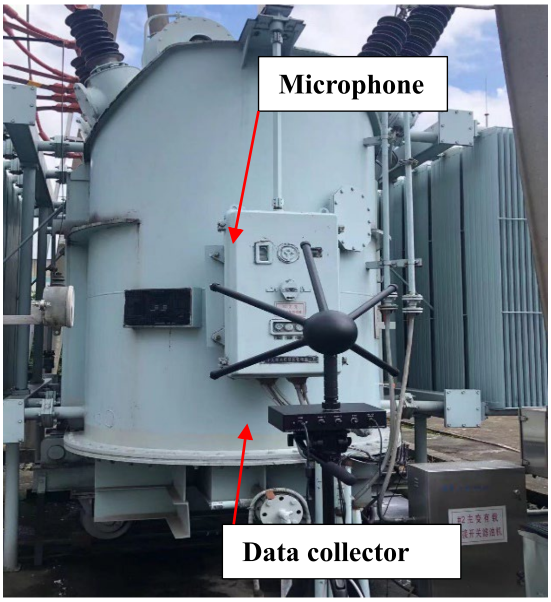


Fig.2 The on-Site Installation of the Microphone

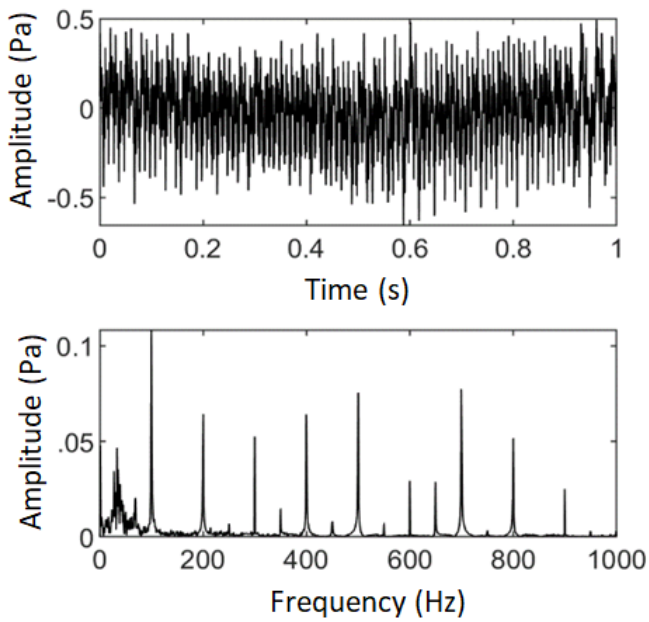


Fig.3 Waveform and Spectrum of Transformer Sound

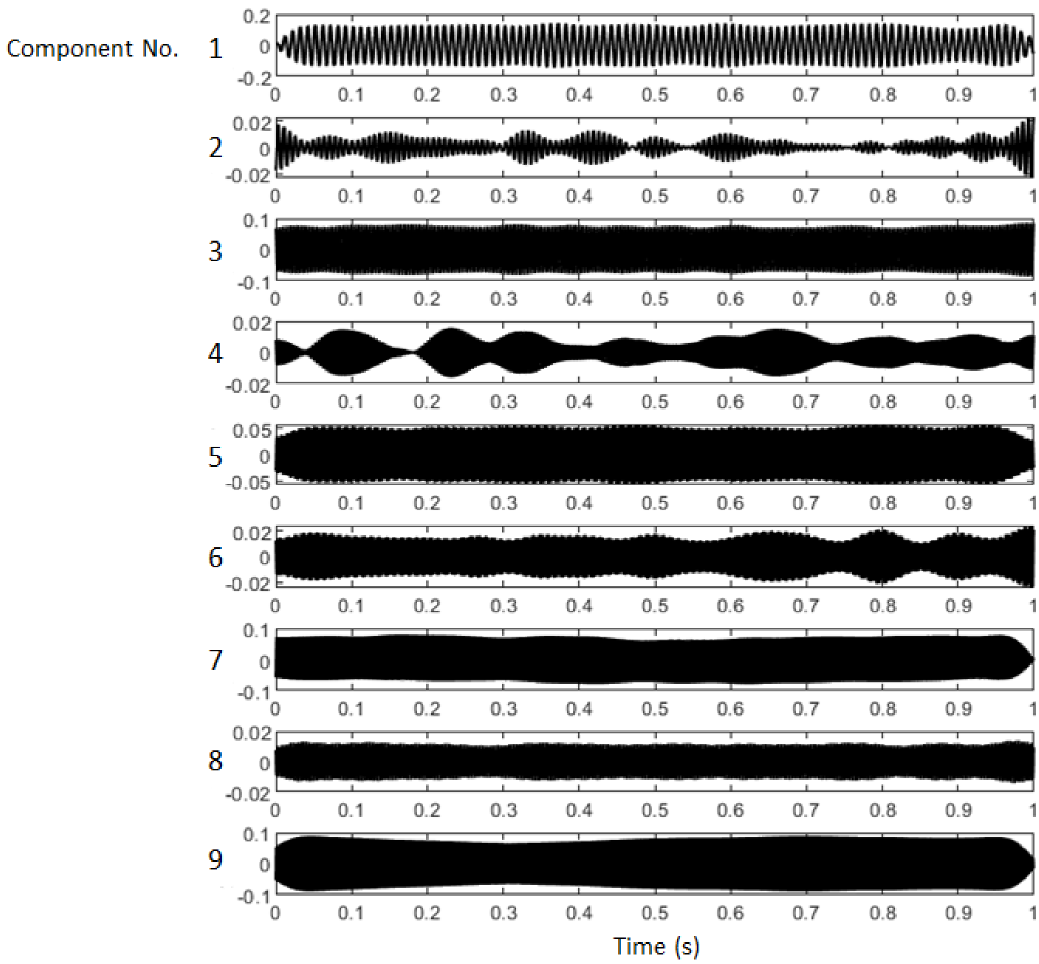
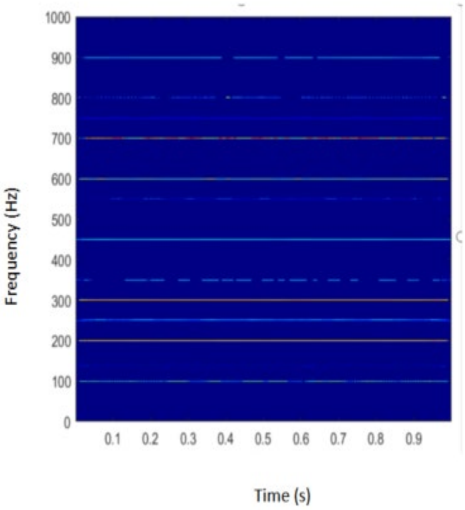


Fig.4 Vme Decomposition Results.

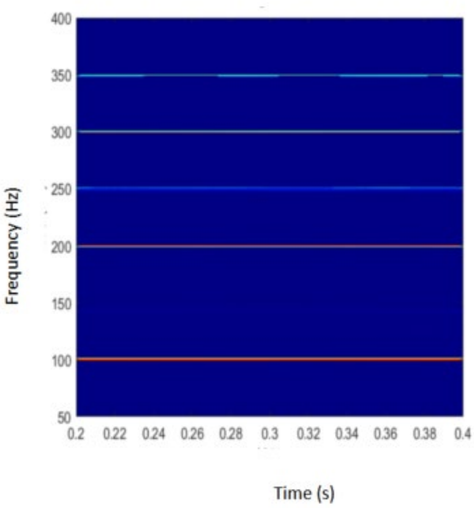
Harmonics in the power grid system can cause severe saturation of the transformer core, leading to further harm to the transformer: when harmonic currents flow into the transformer, they increase the copper loss and iron loss of the transformer, and skin effect becomes more severe with the increase of harmonic frequency. Therefore, high-order harmonics are more likely to cause heating of the transformer, and harmonic currents can also cause heating of the transformer casing, silicon steel sheets, and some fasteners, resulting in local overheating of the transformer, and the corresponding radiated noise will also increase. Based on the above phenomena and considering that the transformer works in an open and complex industrial environment, the collected sound signal includes environmental noise, transformer operating sound signal, and various reflected and scattered sound signals. In order to reduce the complexity of VME decomposition and improve the decomposition efficiency, according to the working mechanism of the transformer, it can be known that the transformer's inherent noise consisting of iron core noise and winding noise is mainly centered at 100 Hz and its harmonics. Therefore, the center frequency of VME decomposition is set as the power supply fundamental frequency and its harmonics, and the first nine components of the decomposition results are shown in Figure 4. From the figure, it can be seen that odd components such as the 1st, 3rd, 5th, and 7th correspond to 100 Hz and its harmonics in the transformer sound signal, and even components such as the 2nd, 4th, 6th, and 8th correspond to frequency components of 150 Hz, 250 Hz, 350 Hz, etc., and these components show certain frequency and amplitude modulation phenomena.

The VME decomposition results of the transformer sound signal were subjected to Hilbert transform to obtain the HHT time-frequency diagram shown in Figure 5. It can be seen from the figure that the time-frequency characteristics such as instantaneous amplitude and instantaneous frequency of the main components of the transformer sound signal are clearly visible. The amplitude and frequency of 100Hz and its harmonics in the transformer sound signal are relatively stable, while the amplitude and frequency of frequency components such as 150Hz, 250Hz, and 350Hz show regular fluctuations. The above changes in instantaneous amplitude and instantaneous frequency can be used as effective acoustic features to provide information support for identifying the operating status of the transformer.

Figure 6 shows the HHT time-frequency diagram of the transformer sound signal based on the traditional empirical mode decomposition. It can be seen from the figure that due to the complexity of the sound signal, the traditional empirical mode decomposition is difficult to accurately extract the intrinsic mode functions in the signal due to mode mixing, resulting in energy divergence and spectral blur in the HHT time-frequency diagram. This demonstrates the effectiveness of the VME based on prior information in processing actual field signals.

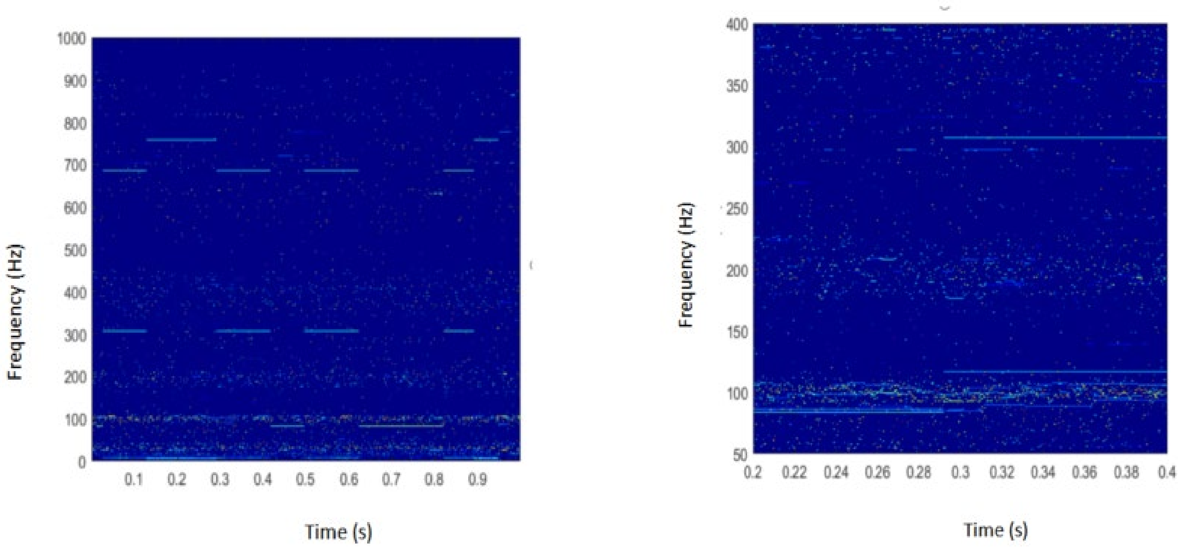


(a)HHT time-frequency plot



(b)HHT time-frequency plot (50~250Hz)

Fig.5 Hht Time-Frequency Representation Based on Vme Decomposition



(a)HHT time-frequency plot (b)HHT time-frequency plot (50~250Hz)

Fig.6 Traditional Hht Time-Frequency Graph

4. Conclusions

Using VME based on prior information to decompose the transformer operating sound signal and then extracting voiceprint features such as instantaneous frequency and amplitude through HHT transformation, the results show that:

1) The frequency structure and composition of the radiation sound signal during transformer operation are complex, and the voiceprint feature extraction method based on VME has good noise resistance;

2) By using prior information such as the mechanism of transformer noise generation to determine the center frequency and other parameters of VME decomposition, on the one hand, the complexity of the decomposition can be reduced, and on the other hand, voiceprint features can be extracted more efficiently and accurately.

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