Research on Transformer Voiceprint Feature Extraction Oriented to Complex Noise Environment

Shen Xiang

State Grid Shaoxing Power Supply Company, Shaoxing 312000, China. E-mail: xiang.shen@yahoo.com

Xu Fei

State Grid Zhejiang Electric Power Co., Ltd., Hangzhou 310000, China.

Xu Long and Cai Jidong

State Grid Shaoxing Power Supply Company, Shaoxing 312000, China.

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Transformer fault diagnosis based on acoustic characteristics is a new non-contact and non-destructive monitoring method. It has the advantages that the acoustic signal detection is not disturbed by electric and magnetic fields, and the monitoring process does not affect the normal operation of the transformer. Aiming at the difficulty of extracting transformer voiceprint features in complex noise environment, a transformer voiceprint feature extraction method based on Variable Mode Extraction (VME) is proposed. In this method, the center frequency of the Intrinsic Mode Function(IMF) is set according to the generation mechanism of transformer radiated noise, thus the uncertainty of decomposition results caused by random distribution and other frequency search methods is eliminated; Then, taking the frequency-domain energy aggregation of IMF and the minimum center frequency energy of residual signal as the optimization objectives, the cyclic iterative decomposition is used to identify and extract the transformer voiceprint features, so as to reduce the impact of environmental noise and other equipment noise. The analysis results of simulation signals and field signals show that this method can effectively reduce the impact of environmental noise and extract more clear and accurate transformer voiceprint features.

1. INTRODUCTION

As important equipment of the power system, the health of the power transformer will directly affect the stable operation of the whole power system. The acoustic signal of the transformer during operation contains rich information about the vibration and deformation of the equipment structure. At the same time, the fault diagnosis technology based on non-contact measurement has the least impact on the equipment. Therefore, it is of great significance to study the transformer condition monitoring and fault diagnosis based on the voiceprint characteristics.[1–4]

Large power transformers usually work in complex industrial environments. The acoustic signals are vulnerable to the interference and pollution of ambient noise and other equipment acoustic signals. The reflection and scattering of acoustic signals in the transmission process will also affect the accurate extraction of voiceprint features. The above phenomena lead to the slow development of fault diagnosis technology based on voiceprint features.[5–7]

Using advanced signal processing technology to obtain effective features representing the operating state is the premise of transformer fault diagnosis. Scholars have carried out a lot of theoretical and engineering application research. Based on the vibration and noise test platform of the transformer core model, Zhang[9] built the Mel time spectrum convolutional neural network transformer core voiceprint pattern recognition model by taking the Mel time spectrum preprocessing dimension reduction of the sound signal as the input of the depth learning model, and the accuracy of this model for acoustic signal recognition under three different working conditions reached 99.71%. Zhu[10] proposed a feature extraction method of transformer sound frequency spectrum coefficient based on wavelet packet energy spectrum, and then used the feature selection method of Laplacian score and Fisher score to solve the problem of feature redundancy. The analysis results show that wavelet packet energy frequency spectrum coefficient feature can effectively improve the accuracy of fault diagnosis; Wang[11] improved the traditional feature vector extraction algorithm of Mel frequency spectrum coefficient by comprehensively using the weighted processing method and principal component analysis method, and proposed a method for identifying transformer core looseness fault based on the Mel frequency spectrum coefficient and vector quantization algorithm. The proposed method can accurately extract the noise characteristics reflecting the looseness degree of transformer core, and the fault identification result based on vector quantization has a high consistency with the preset working condition. A multi criterion based mathematical approach to identify the health indices of power transformers is proposed by Soni and Mehta,[12–14] compared to the conventional methods, the proposed approach gives more precise result. Abbasi et al.[15–17] put forward a series of fault diagnosis methods for transformer windings, the proposed methods have the necessary capability in providing fault information for a transformer and needs no expertise to detect and classify faults.

The extraction of transformer voiceprint features in the above research is based on the research results of auditory models in the field of speech processing and uses the Mel frequency spectrum coefficient or the improved Mel frequency spectrum coefficient as the transformer voiceprint features. However, the above research does not make full use of prior information such as the generation mechanism of transformer acoustic signals. On the other hand, compared with the low-frequency part of the acoustic signal, the non-linear Mel scale frequency used by the Mel frequency spectrum coefficient has reduced the weight of the high-frequency part. However, the high-frequency part of the transformer's acoustic signal under actual working conditions is an important representation of the transformer's early fault.[18,19]

Aiming at the difficulty of the transformer voiceprint feature extraction in complex noise environment, this paper proposes a method of the transformer voiceprint feature extraction based on variational mode extraction. Variational mode extraction can overcome the uncertainty of decomposition results caused using center frequency search methods such as random distribution in the variational mode decomposition algorithm. The Wiener filtering, IMF cycle iterative extraction and other processes of the variational mode extraction algorithm can eliminate interference components and highlight fault voiceprint features. The effectiveness and practicability of the transformer voiceprint feature extraction method based on variational mode extraction are verified by simulation experiments and engineering applications.

2. VARIATIONAL MODE EXTRACTION THEORY

2.1. Variational Mode Extraction

The center frequency of IMF is set according to the operating mechanism of the equipment for VME, and the extraction of each IMF is completed by a cyclic iteration process.[20] The following signal model is used for VME:

$$f\left(t\right)=\mu_d\left(t\right)+f_r(t); \tag{1}$$

where $f(t)$ is the original signal, $u_d(t)$ represents the target IMF and $f_r(t)$ is the residual signal, t is the time index. The $u_d(t)$ is a narrowband signal distributed near the center frequency, satisfying the following conditions.

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

where ω_d is the center frequency of $u_d(t)$; δ is the Dirac distribution; denotes convolution; J_1 can be regarded as an index of the frequency band width of the target IMF. After the extraction of an intrinsic mode function is completed, the energy of the residual signal near the central frequency of the intrinsic mode function should be close to zero. Therefore, a filter similar to Wiener filter is used and the following penalty function is introduced.

$$J_2=\left\|\beta(t)*f_r\left(t\right)\right\|_2^2; \tag{3}$$

where $\beta(t)$ is the impulse response of the used filter. To ensure the accuracy of IMF extraction and reduce modal mixing, the filter shall have the following frequency response functions:

$$\widehat{\beta}=1/\eta(\omega-\omega_d)^2; \tag{4}$$

where $\widehat{\beta}$ is the filter frequency response function, η is the attenuation coefficient of the amplitude frequency response of the filter. The frequency response function has an infinite gain near the central frequency of the target IMF to ensure the accurate extraction of the IMF, while the frequency response function has a small gain at the frequency band far from the central frequency, reducing the frequency aliasing of the target natural mode function and residual signal near the central frequency. The extraction of target IMF can be converted into the following constraint model:

$$\left\{\begin{array}{c}\min_{\mu_d,\omega_d,f_r}\left\{\alpha J_1+J_2\right\}\\ \mu_d\left(t\right)+f_r\left(t\right)=f(t)\end{array}\right. . \tag{5}$$

Where α is the penalty coefficient for controlling the bandwidth of IMF. To address the constraint model constructed by Equation (5), the constrained variational problem is transformed into the unconstrained variational problem by introducing quadratic penalty term and Lagrangian multipliers, the augmented Lagrangian function is considered as follows:[21–24]

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

where λ refers to Lagrangian multiplier. According to Parseval's equality, Equation (6) can be rewritten as follows:

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

The unconstrained problem of Equation (7) can be solved by the Alternative Direction Method of Multipliers (ADMM).[25] The main idea of ADMM is to update the other variable by fixing two variables. The specific update process is as follows:

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

$$\omega_d^{n+1}=\frac{\int_0^\infty\omega\left|\widehat{\mu}_d^{n+1}\left(\omega\right)\right|^2d\omega}{\int_0^\infty\left|\widehat{\mu}_d^{n+1}\left(\omega\right)\right|^2d\omega}; \tag{9}$$

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

2.2. Transformer Voiceprint Feature Extraction Based on VME

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

Step 1: Obtain the acoustic signal of transformer, set the center frequency of target IMF according to the mechanism analysis of transformer.

Step 2: Analyze possible common faults by using equipment related prior information, to support the setting of parameters such as the number of IMF.

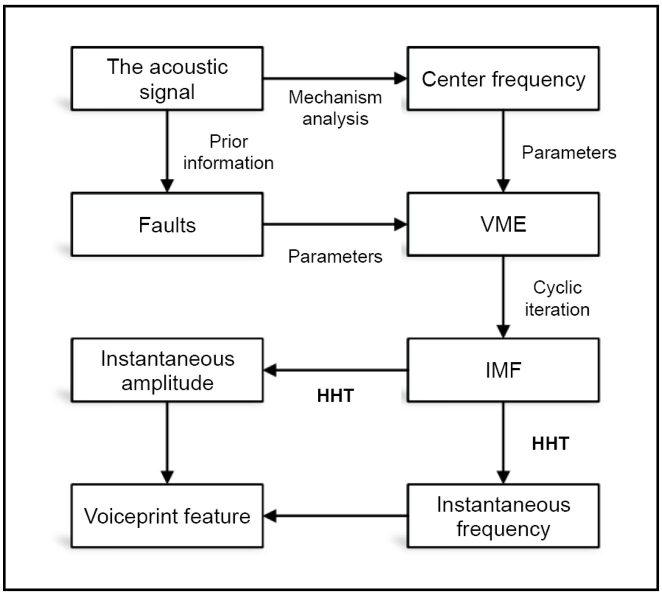


Figure 1. Flow chart of Transformer voiceprint feature extraction.

Step 3: The VME algorithm is used to extract the IMFs of the acoustic signal.

Step 4: Cyclic iteration, extracting several IMFs one by one.

Step 5: Hilbert Huang Transform (HHT) is used to extract instantaneous amplitude and frequency information.

Step 6: Combined with the instantaneous amplitude and frequency of the acoustic signal as voiceprint features, which provides support for transformer condition monitoring, fault diagnosis and other applications.

3. SIMULATION

This section verifies the effectiveness of VME in feature extraction through simulation. The simulation signal contained four sinusoidal signals with different frequencies, representing different frequency components of the acoustic signal during the operation of the transformer. Considering the importance of the time when the acoustic event occurs to the transformer status monitoring, components 2, 3 and 4 were set with different time scales respectively. The waveform of the simulation signal is shown in Figure 2.

VME was used to analyze the simulation signal. The decomposition result is shown in Figure 3. It can be seen from Figure 3 that the first four extracted components clearly corresponded to each frequency component of the simulation signal, and there is no end effect at the two ends of different components. For components 2, 3 and 4 with time scale truncation, their corresponding decomposition results became smoother at the truncation point, and the corresponding time energy distribution has a corresponding relationship with the energy distribution in the residual signal. The above decomposition results show that VME can accurately extract the target frequency components hidden in the signal.

Add noise with different signal-to-noise ratios to the simulation signal, and then calculate the root mean square error of each component extracted with different signal-to-noise ratios. The results are shown in Figure 4. It can be seen from the figure that with the increase of signal to noise ratio, the decomposition error of each frequency component decreased rapidly.

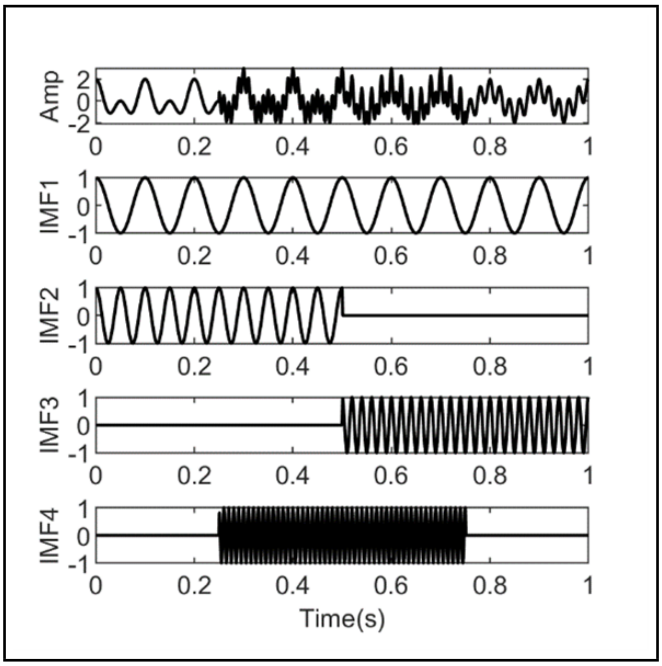


Figure 2. Simulation signal.

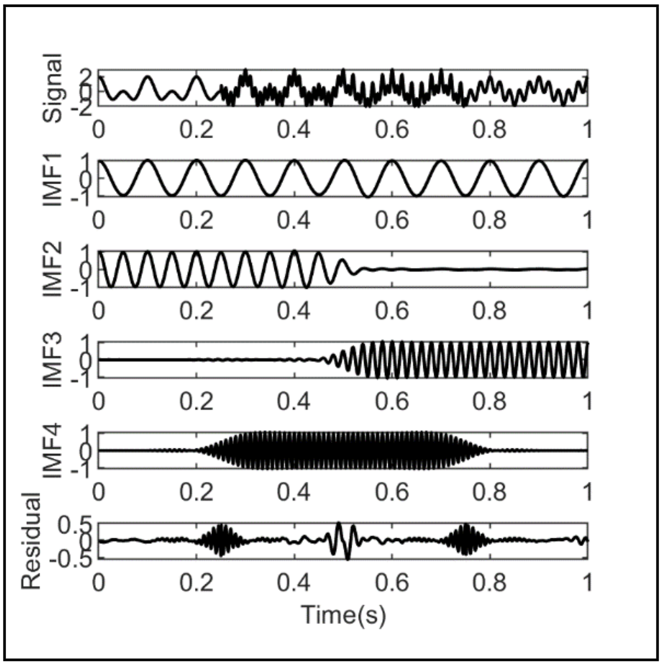


Figure 3. The VME decomposition result of simulation signal.

At the signal to noise ratio of 0 dB, the decomposition error has reached an ideal level; When the signal-to-noise ratio is 10 dB, the reconstruction error of each frequency component was close to 0. Therefore, the signal feature extraction based on VME has good anti-interference performance.

4. FIELD APPLICATION

4.1. Field Signal Voiceprint Feature Extraction

Two 110 KV transformers were installed in a substation. Microphone sensors were used to collect the acoustic signal of transformer. The sampling frequency was 2048 Hz, and the sampling length was 2048. The data acquisition was conducted

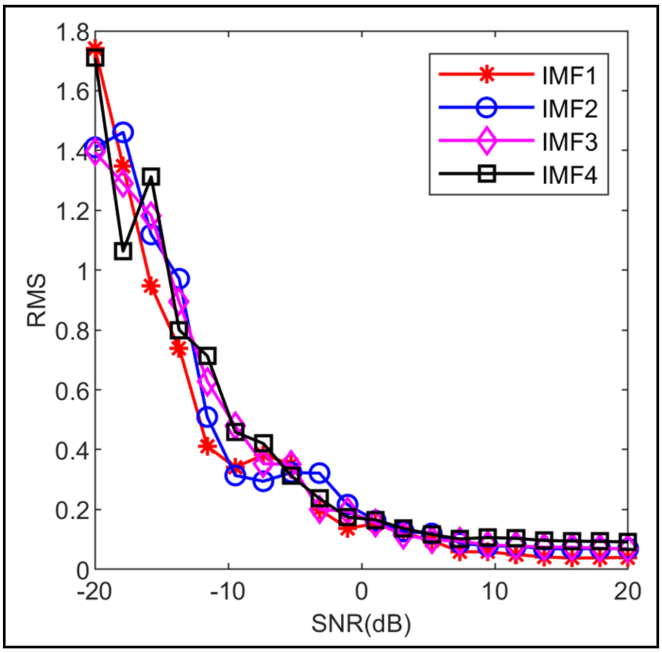


Figure 4. Decomposition error of different signal-to-noise ratio.

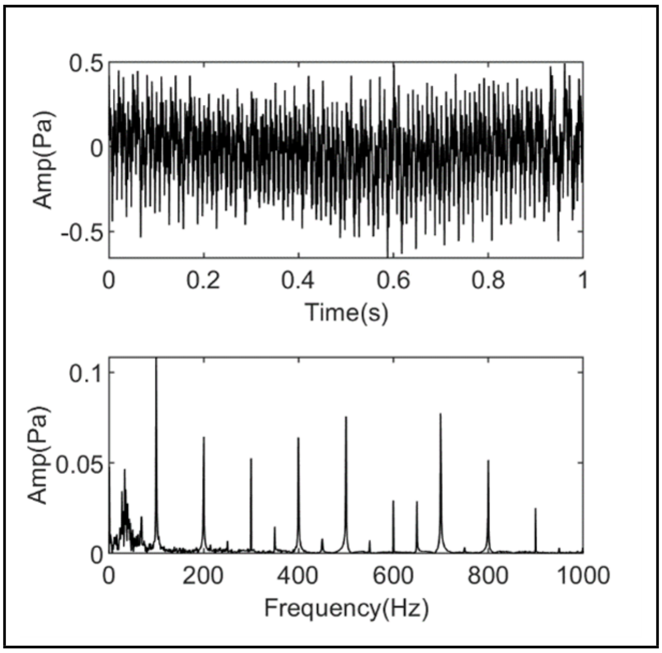


Figure 6. The Waveform and FFT of field acoustic signal of transformer.

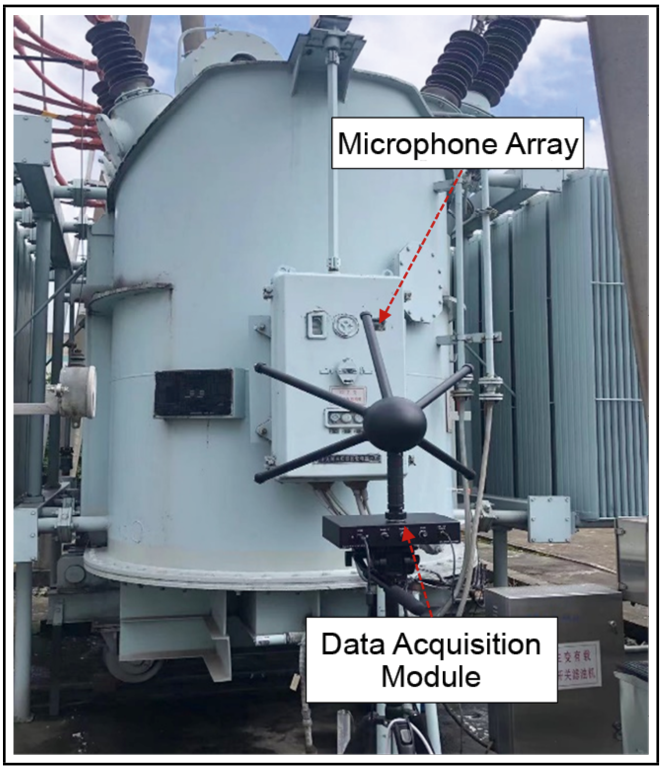


Figure 5. Installation Microphone sensors.

on April 14, July 5, July 23, July 26, and July 28, 2021, respectively. The installation diagram of microphone sensor is shown in Figure 5, and the waveform and spectrum of acoustic signal are shown in Figure 6.

Harmonics in the power grid system will seriously saturate the transformer core and further endanger the transformer. When harmonic current flows into the transformer, it will increase the copper loss and iron loss of the transformer, and the skin effect will become more serious with the increase of harmonic frequency. Therefore, higher harmonics are more likely to cause transformer heating than lower harmonics, and harmonic current will also cause transformer shell, silicon steel sheet and some fasteners to heat, Local overheating of the transformer will be caused, and the corresponding radiation noise will also become larger. Based on the above phenomena and considering that the transformer works in an open and complex industrial environment, the collected acoustic signals included field environmental noise, transformer operation acoustic signals, and various reflected and scattered acoustic signals. To reduce the complexity of VME decomposition and improve the decomposition efficiency, according to the working mechanism of the transformer, the transformer body acoustic signal consisting of core noise and winding noise was mainly 100 HZ and its harmonics. Therefore, the center frequency of VME decomposition was set as the power fundamental frequency and its harmonic frequency. The first nine components of the decomposition result are shown in Figure 7. It can be seen from the figure that the odd components 1, 3, 5 and 7 corresponded to 100 HZ and its harmonics in the acoustic signal of the transformer, and the even components 2, 4, 6 and 8 corresponded to 150 HZ, 250 HZ, 350 HZ and other frequency components in the acoustic signal of the transformer, also these components exhibited certain frequency modulation and amplitude modulation phenomena.

The Hilbert transform was performed on VME decomposition results of transformer acoustic signal to obtain HHT time-frequency spectrogram as shown in Figure 8. It can be seen from the figure that the time-frequency characteristics such as the instantaneous amplitude and frequency of the main components of the transformer acoustic signal were clearly visible. The 100 HZ and its harmonics amplitude and frequency in the transformer acoustic signal were relatively stable, while the amplitude and frequency of the 150 HZ, 250 HZ, 350 HZ and other frequency components fluctuated regularly. As an effective voiceprint feature, It can provide effective information support for the monitoring of transformer operation status.

Figure 9 shows the HHT time- frequency spectrogram of the transformer acoustic signal based on traditional empirical

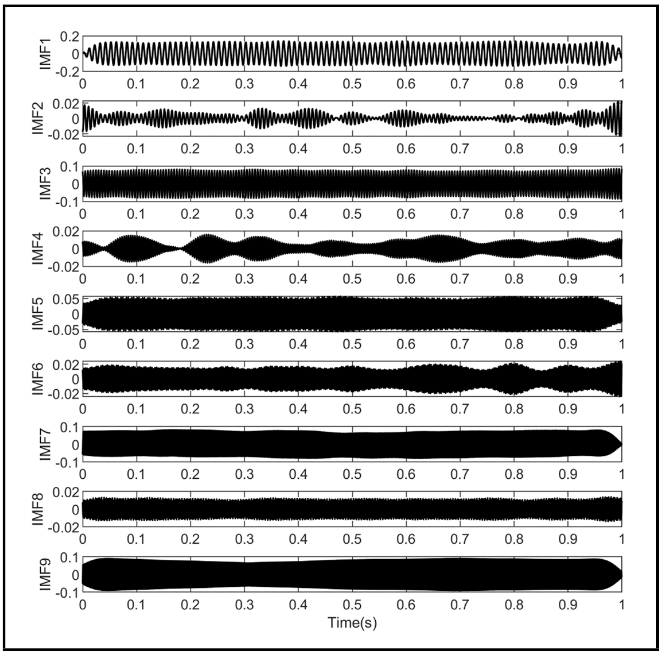


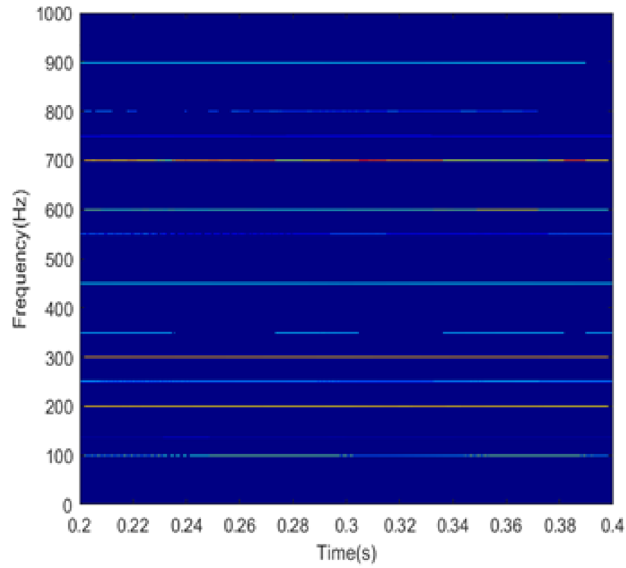
Figure 7. The VME decomposition result of filed acoustic signal.

mode decomposition. It can be seen from the diagram that due to the complexity of the acoustic signal, it was difficult for traditional empirical mode decomposition to accurately extract the IMFs in the signal due to mode mixing and other reasons, which leads to the HHT time-frequency spectrogram showing energy divergence and spectrum ambiguity, indicating the effectiveness of VME based on prior information in processing field acoustic signal of transformer.

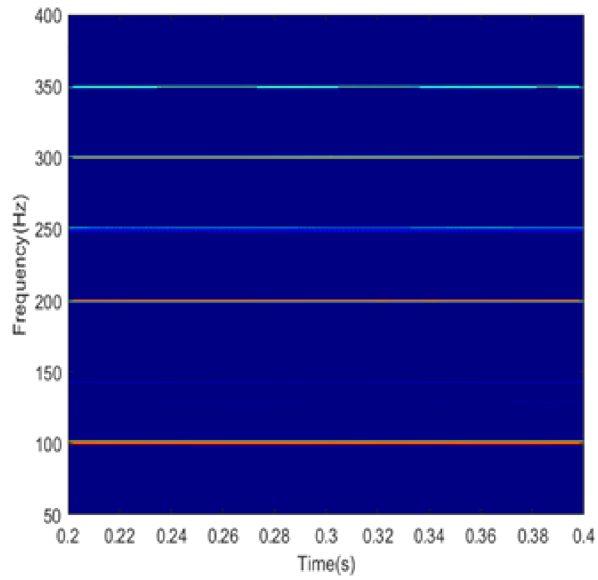
4.2. Analysis of Field Signal Interference Components

There are two factors that affect the extration accuracy of the transformer's early weak voiceprint features: the first part is the background noise in the harmonic environment of the power grid and other interference signals from outside the equipment, and the second part is the noise generated by the non fault components inside the transformer. For the noise from the non fault components inside the transformer, because the acoustic signal generated by the internal components of the transformer is usually linear superposition, based on high-order statistics and information theory, the blind source separation algorithm[26,27] can be used to effectively extract the target signal. This paper focuses on the influence of external background noise and other interference signals on the accuracy of voiceprint feature extraction. The Wiener filtering of the VME algorithm and the iterative process of IMF extration can eliminate interference components and highlight fault voiceprint features, improving the accuracy of equipment status monitoring and fault diagnosis.

The VME was used to extract the main voiceprint features of the transformer acoustic signal, and the residual signal was taken as the interference part of the acoustic signal. Through the component analysis of the interference signal, it can lay a foundation for further accurate extraction and application of the voiceprint features. The short-time Fourier transform time-frequency spectrogram of the interference signal is shown in Figure 10. It can be seen from the figure that the interference



(a) HHT spectrogram



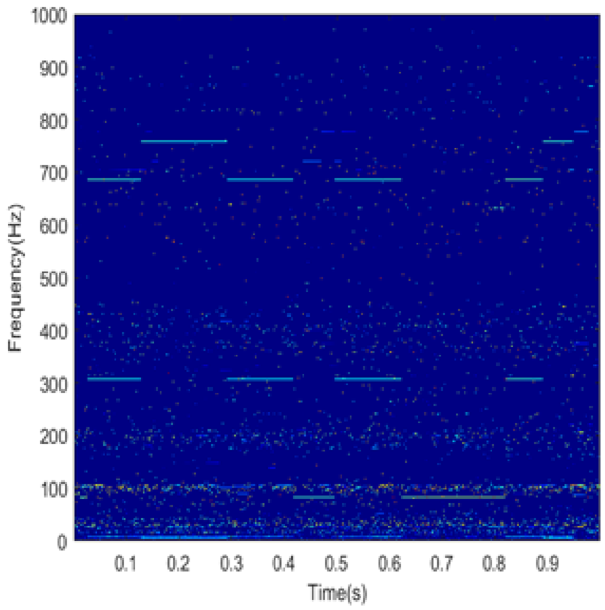
(b) HHT spectrogram (50∼250 Hz)

Figure 8. HHT time-frequency spectrogram based on VME decomposition.

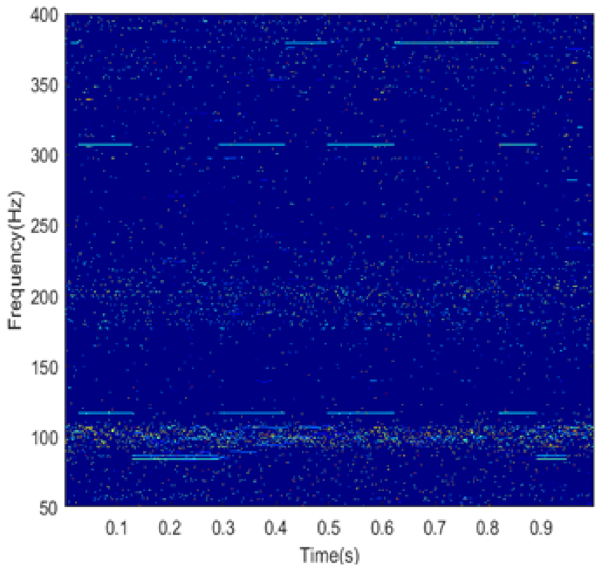
noise was mainly distributed in the low frequency band below 100 Hz, and the intensity of the interference signal gradually decreases with the increase of the frequency. The above phenomenon was consistent with the empirical rule that the environmental noise was mainly distributed in the low frequency band, which further illustrates the effectiveness of the transformer voiceprint feature extraction algorithm based on VME.

4.3. Transformer Condition Monitoring Based on One-shot Learning and Voiceprint Feature

In this section, the one-shot learning method based on siamese network was applied to the monitoring of transformer operation condition. Various factors, such as the changeable operating conditions and the complex working environment, made it difficult to apply the traditional deep learning method to the monitoring of transformer condition.



(a) HHT spectrogram



(b) HHT spectrogram (50∼250 Hz)

Figure 9. HHT time-frequency spectrogram based on EMD decomposition.

The siamese network based one-shot learning method is a commonly used metric based machine learning method, so this paper only describes the network parameters, which were composed of four one dimension convolution layer, four max pooling layers and one full connection layer, and each convolution layer is followed by a max pooling layer. The last max pool layer is followed by a flatten layer and a dropout layer, then followed by a full connection layer. The details of the model are as follows: the first layer of convolution layer uses the wide core convolution with the kernel Size of 64×1 to extract features, and the number of convolution cores was 16. The second, third and fourth layers of convolution layers used the narrow core convolution with the kernel size of 3×1 to obtain more detailed fault features, and the number of corresponding convolution cores are 32, 64 and 64. The activation function of the convolution layer used the Relu function. The four max pool layer adopts a pool window of 2×1 size, and the corresponding number of convolution cores were 16, 32, 64, and 64 respectively. The Dropout layer probability was set to 0.2 to alleviate the over fitting problem. The number of neurons in the full connection layer was 100, and the activation function was sigmoid function.

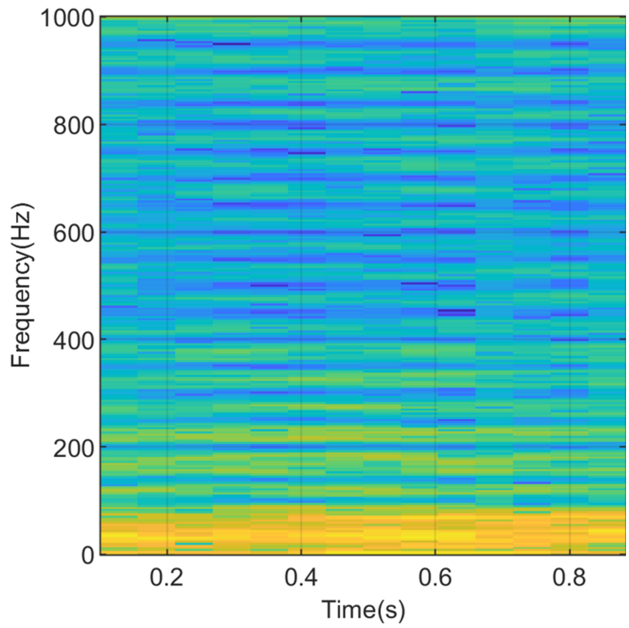


Figure 10. Analysis of field signal interference components.

The dataset included 105 samples collected from April 14 to July 28, 2021. The VME based voiceprint feature extraction method is used to process the original acoustic signal to eliminate the impact of external noise and interference, and then the processed signal was input into the one-shot learning network. The training set, verification set, and test set accounted for 60%, 20%, and 20% of the total dataset respectively. Since the transformer has been in a stable and normal working state in the above data acquisition stage, the purpose of the experiment was to verify whether the trained model can give accurate monitoring results when the background noise of each data was different. The test results show that the success rate of the model classification reaches 100%, which further illustrates the effectiveness of transformer voiceprint feature extraction based on VME.

5. CONCLUSIONS

VME based on prior information is proposed to decompose the acoustic signal of transformer, and then HHT transform is used to extract voice print features such as instantaneous frequency and instantaneous amplitude. The frequency structure and composition of the acoustic signal radiated by the transformer are complex, and the voice print feature extraction method based on VME has good noise resistance. Using prior information such as transformer acoustic signal generation mechanism to determine the parameters such as the center frequency of VME decomposition can reduce the complexity of decomposition on the one hand, and extract voice print features more efficiently and accurately on the other hand. The instantaneous amplitude and frequency of transformer voiceprint features extracted based on VME algorithm show obvious regularity, which can provide effective information support for applications such as transformer state discrimination.

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REFERENCES

1. Peng, L.I., Jiangang,B. I., Hao, Y. U., and Yuan, X. U. Technology and Application of Intelligent Sensing and State Sensing for Transformation Equipment, *HIGH VOLTAGE ENGINEERING*, **46**(9), 3097–3113, (2020).
2. Yunpeng, L., Bowen, W., Huan, L. I., et al. Transient Acoustics Characteristics of Large Transformer Windings Under Multiple Short-circuit Impulse Combined With Fiber-carrying Winding Deformation Measurement, *Proceedings of the CSEE*, **42**(1), 434–446, (2022).
3. Fenglei, T. Genyuan, Z., Haihua, Z., et al. Transformer Anomaly Discrimination Method of Sound-Based Online Monitoring, *Hubei Electric Power*, **45**(5), 26–31, (2021).
4. Zhixin, Z., Zongluo, Z., Ying, Z., et al. A Fast Fault Diagnosis Method of Distribution Transformer Based on Parallel BP Neural Network, *ZHEJIANG ELECTRIC POWER*, **12**, 82–88, (2021).
5. Jianping, Z., and Xing, P. Cause Analysis of Abnormal Noise and Vibration of 500kV Transformer, *Zhejiang Electric Power*, 03, 6–10, (2006).
6. Yuwei, S., Lingen, L., Jingde, C. et al. Mechanical Fault Diagnosis of Circuit Breaker Based on Sound Characteristics and Improved Sparse Representation Classification, *POWER SYSTEM TECHNOLOGY*, **46**(3), 1214–1222, (2022).
7. Wenbo, L., Weikang, J., Siwei, P., et al. Mechanical fault diagnosis method based on texture features of near-field acoustic holography, *Journal of Vibration Engineering*, **26**(4), 617–623, (2013).
8. Jing, C. Research on fault diagnosis method of traction transformer based on sound signal analysis, *Electrical Application*, **39**(2), 25–29, (2020).
9. Zhongyuan, Z., Shihao, L., Haotian, Y., et al. Pattern Recognition of Acoustic Signals of Transformer Core Based on Mel-spectrum and CNN, *HIGH VOLTAGE ENGINEERING*, **46**(2), 413–422, (2020).
10. Kejia, Z. Research on transformer voiceprint feature extraction in high noise environment, North China Electric Power University, 2021.
11. Fenghua, W., Shaojing, W., Song, C., et al. Voiceprint Recogni -tion Model of Power Transformers Based on Improved MFCC and VQ, *Proceedings of the CSEE*, **37**(5), 1535–1542, (2017).
12. Soni, R., and Mehta, B. Review on Asset Management of Power Transformer by Diagnosing Incipient Faults and Faults Identification Using Various Testing Methodologies, *Engineering Failure Analysis*, **128**(2), 105634, (2021).
13. Soni, R., and Mehta, B. Evaluation of Power Transformer Health Analysis by Internal Fault Criticalities to Prevent Premature Failure Using Statistical Data Analytics Approach, *Engineering Failure Analysis*, **136**, 106213, (2022).
14. Soni, R., and Mehta, B. A review on transformer condition monitoring with critical investigation of mineral oil and alternate dielectric fluids, *Electric Power Systems Research*, **214**(5), 108954, (2022).
15. Abbasi A. R, and Gandhi, C. P. A Novel Hyperbolic Fuzzy Entropy Measure for Discrimination and Taxonomy of Transformer Winding Faults, *IEEE Transactions on Instrumentation and Measurement*, **71**, 1–8, (2022).
16. Abbasi A. R, and Mahmoudi, M. R. Application of statistical control charts to discriminate transformer winding defects, *Electric Power Systems Research*, **191**, 106890, (2021).
17. Abbasi A. R, Mahmoudi, M. R, and Arefi, M. M. Transformer Winding Faults Detection Based on Time Series Analysis, *IEEE Transactions on Instrumentation and Measurement*, **70**, 1–10, (2021).
18. Yong, X., Jun, P., Bo, Z. et al. Online monitoring method for partial discharge of transformer based on ultrasonic wave and high-frequency pulse current, *Sichuan Electric Power Technology*, **34**(6), 53–55+84, (2011).
19. Hengxin, M., Jie, Y., and Xiaocen, H. Detection and research on high-frequency components of large transformers during near fault, *Shanxi Electric Power*, **1**, 23–24+34, (2004).
20. Nazari, M., Sakhaei, S. M. Variational Mode Extraction: a New Efficient Method to Derive Respiratory Signals from ECG, *IEEE Journal of Biomedical & Health Informatics*, **22**(4), 1059–1067, (2018).
21. Cheng, Q., Liu, C., and Shen J. A new Lagrange multiplier approach for gradient flows. *Computer Methods in Applied Mechanics and Engineering*, **367**, 113070, (2020).
22. Karl, V., Neitzel, I., and Wachsmuth, D. A Lagrange multiplier method for semilin -ear elliptic state constrained optimal control problems, *Computational Optimization and Applications*, **77**, 831–869, (2020).
23. Ying, Y., Xiaochun, Y., and Yongsheng, L. Solving Engineering Optimization Problem by Augmented Lagrange Particle Swarm Optimization, *Journal of Mechanical Engineering*, **45**(12), 167–172, (2009).
24. Abdollah, K. F, Abbasi, S., Abbasi, A., et al . Optimal probabilistic reconfiguration of smart distribution grids considering penetration of plug-in hybrid electric vehicles, *J. Intell. Fuzzy Syst*, **29**(5), 1847–1855, (2015).
25. Shi, W., Ling, Q., Yuan, K., et al. On the Linear Convergence of the ADMM in Decentralized Consensus Optimization, *IEEE Transactions on Signal Processing*, **62**(7), 1750–1761, (2014).
26. Chen, L., Wu, S. F., Xu, Y., Lyman, W. D., and Kapur, G. Calculating blood pressure based on measured heart sounds, *Journal of Computational Acoustics*, **25**(3), 1750014, (2017).
27. Chen, L., Wu, S. F., Xu, Y., Lyman, W. D., and Kapur, G. Blind separation of heart sounds, *Journal of theoretical and computational acoustics*, **26**(1), 1750035, (2018).