Optimization Research on Abnormal Diagnosis of Transformer Voiceprint Recognition based on Improved Wasserstein GAN

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Abstract. Transformer is an important infrastructure equipment of power system, and fault monitoring is of great significance to its operation and maintenance, which has received wide attention and much research. However, the existing methods at home and abroad are based on model analysis for detection and diagnosis techniques, and their application is limited by the maturity and applicability of expert knowledge. In recent years, deep learning artificial intelligence has made important breakthroughs, however, the relevant research is still mainly focused on the field of speech, and intelligent diagnostic techniques on machine voice patterns have just begun. Therefore, this article adopts an unsupervised learning anomaly detection method based on WGAN-GP to diagnose the electrical and mechanical anomalies of transformer equipment. The experimental results show that the method can effectively identify transformer anomalies and provide an idea for artificial intelligence-based machine voice pattern recognition.

1. Introduction

The transformer is an important power equipment in the power system, and its operation status is of great significance for the safe and stable operation of the power grid. With the increasing scale of the power system and the accumulation of the operating life of large transformers, efficient and accurate fault diagnosis of transformers is becoming increasingly important. The current transformer fault diagnosis methods mainly include oil chromatography detection, vibration detection, partial discharge detection, etc., can achieve more accurate fault diagnosis and fault location. The disadvantage is that the need for transformer power outages, in order to carry out off-line mode of fault diagnosis, this regular outage maintenance costs are very high, and affect the normal operation of power transformers and power grids.

Transformer and other equipment in operation, the core, winding and other structures can vibrate and produce sound. In fact, the sound of a transformer contains a great deal of information about the state of the equipment, and long ago, experienced instructors were able to identify the state of a transformer's operation by its operating sounds. The method of using transformer sound for transformer condition has the advantage of online monitoring, non-stop power, and is unaffected by electromagnetic coupling. With the rapid development of artificial intelligence and acoustic signal recognition technology, the sound signal of transformer gradually receives attention. However, at present, the application of artificial intelligence and acoustic signal recognition is mostly concentrated in voice recognition, and the research
on transformer fault diagnosis has just started. A part of scholars have noticed the transformer sound signal's usefulness. Liangliang Pan[1] et al. use hierarchical thresholds for noise cancellation of acoustic signals to give an algorithm for wavelet packet extraction of feature vectors of measured acoustic signals of electrical equipment. Jinsong Fu[2] uses time-frequency analysis and interval energy extraction to extract feature information reflecting the real state of the equipment from the transformer audible acoustic signals. Hua Dongsheng[3] introduces a feature extraction method based on the amplitude-frequency characteristics of transformer acoustic data, and then applies a support vector machine(SVM) algorithm to classify the acoustic signals, so as to achieve the purpose of detecting the state of substation electrical transformers. However, the above research results are only applicable to a single small transformer model in the laboratory and not in a large transformer in field operation, so the general applicability of the method needs to be verified.

This paper first summarizes the sound patterns of transformers to derive a set of expert knowledge, and then provides noise cancellation for various types of noise that may occur during field acquisition of transformer sound signals. In order to detect anomalies from transformer vibration signals, this paper proposes to do signal pre-processing with S-transformation and use the WGAN-GP network for anomaly detection.

2. Transformer Operating State Sound Law Analysis

The power transformer is the core device in the power system, which undertakes the core task of electrical energy conversion and transmission, and is one of the most important devices in the power grid. The sound emitted by the transformer has long been considered to be a form of noise pollution[4], but in fact, when in the field, some experienced maintenance masters can determine the operating status of the transformer by its sound. The source of vibration is relatively single when the transformer is operating steadily, and the timbre of the noise produced by each transformer is relatively certain. Transformer noise and transformer failure there is a certain connection, after the operation and maintenance personnel of the field to figure out the summary, to come up with a set of expert knowledge. See Table 1 for the specific classification.[5]

| Serial number | Anomaly | Possible causes of anomalies | Inspection method or site |
|---------------|---------|------------------------------|---------------------------|
| 1             | Continuous high-frequency screeching | overexcitation harmonic current direct current system anomaly | Operating voltage harmonic analysis DC polarization Neutral point current |
| 2             | Abnormally large and distinctive murmur (“guttural” sound) | Loose iron core structure Mechanical vibrations at the joints direct current | Listen to the source of the sound Listen to the source of the sound DC polarization Casing connection part Oil tank flange connection bolts |
| 3             | "Squeak" or "pop." | Discharge due to poor contact | Temperature and hydrocarbons Gas in gas relay |
| 4             | "Hissing" | Corona discharge on casing surface or conductor corners | Infrared temperature measurement, ultraviolet light measurement |
| 5             | The boiling sound of “feeding.” | Local overheating or nitrogen filling of fire extinguishing apparatus with nitrogen into the body | Temperature and hydrocarbons Gas in gas relay |
| 6             | “Whoa!” | overloaded | Listen to the source of the sound Load current |

Table 1. Common transformer body sound anomaly analysis.
3. Sound Signal Denoising Based on Wavelet Threshold Algorithm

At present, when the transformer collects the sound signal, it is very likely to collect redundant, even will have an impact on the result judgment of the noise signal, for example, outdoor substation will collect the sound of wind, the sound of birds, indoor substation may collect the sound of inspectors walking footsteps, so before carrying out the transformer sound pattern recognition, be sure to carry out the transformer sound signal denoising. In addition, are likely to collect the sound of the transformer itself fan discharge. So, for the transformer sound signal, the interference is more complex, the interference signal is also different, in the transformer sound signal denoising, not only to remove the noise signal, but also to make the transformer itself, the sound signal is not affected.

According to reference [6], the possible interference signals in the transformer operating environment are classified according to the noise signal characteristics, as shown in Table 2.

Table 2. Common transformer body sound anomaly analysis.

| Type of noise     | noise interference band/Hz |
|-------------------|----------------------------|
| Instantaneous     | 4000-8000                  |
| Birdsong          | 4000-8000                  |
| Siren             | 1000-8000                  |
| On-load tap-change operation sound | 0-20000                |
| Tone of voice     | 150-5000                   |
| Footsteps         | 1000-11000                 |
| Continuous        |                            |
| Corona discharge  | 5000-20000                 |
| Sound wind turbine | 0-1000                    |

For the transformer itself sound signal, its sound frequency band is 0-4000Hz. The commonly used sound denoising methods include short-time Fourier transform, wavelet algorithm, wavelet packet algorithm and some blind source separation algorithms such as Fast Independent Component Analysis (Fast ICA) algorithm. In this paper, the wavelet transform algorithm based on hierarchical thresholding will be used for the denoising of transformer sound signals. The wavelet transform can well overcome the shortcomings of Fourier transform and is more suitable for analysing short-time high-frequency components as well as low-frequency component signals of longer duration, and the method is based on wavelet transform to optimize the traditional thresholds.

3.1. Denoising Principle Based on Wavelet Transform

The Fourier transform and the short-time Fourier transform are the most basic methods for time-frequency analysis of acoustic signals. They are simple in principle, but due to the disadvantages of the fixed window size in time-frequency conversion, the lack of window adaptability, and the unsuitability to analyse multiscale signals and mutational processes, the time domain and frequency domain are heavily localized.

A one-dimensional signal containing noise can be represented as.

\[ s(n) = f(n) + \sigma e(n) \]  

where \( f(n) \) is the original signal, \( e(n) \) is the noise signal, \( \sigma \) is the noise intensity.

For the original signal \( s(n) \), noise cancellation is to reduce the noise signal in the original signal to zero, so that the effective sound signal of the transformer to recover out, that is, to get the original signal \( f(n) \). Using wavelet transform analysis, the original signal can be decomposed into a series of approximate components and detail components, the signal noise is mainly concentrated in the detail components of the signal, using a certain threshold to deal with the detail components, and then after the wavelet reconstruction amount can be obtained smooth signal, the process model is shown in Figure 1.
In general, the signal denoising process can be divided into the following three steps.

1. Wavelet decomposition: a wavelet is selected and the signal is decomposed into N layers of wavelets.
2. Threshold quantization of wavelet decomposition coefficients: choose a threshold for each layer of coefficients obtained from the decomposition. A soft threshold quantization process is applied to the detailed coefficients.
3. Wavelet reconstruction: determine the threshold value according to the high frequency coefficient of the wavelet decomposition layer and the low frequency coefficient of the underlying layer, so as to carry out threshold quantization processing to achieve wavelet reconstruction.

Among them, the second step has always been the focus of research, has always been how to select the appropriate wavelet threshold is the focus of research, if the threshold selection is too small, then the noise cannot be effectively filtered, if the threshold selection is too large, then it will lead to the choking phenomenon, will also affect the accuracy of the subsequent analysis of the signal.

### 3.2. Wavelet Threshold Denoising

Currently, there are several commonly used thresholding methods: universal thresholding (Shtwolog criterion), Stein unbiased likelihood estimation (Rigsure criterion), extreme thresholding (Minimax criterion), heuristic thresholding (Heursure criterion), and so on [7]. The thresholding method based on Stein’s unbiased likelihood estimation principle first predicts the likelihood estimate of the threshold and then minimizes the likelihood function to obtain the threshold. The extreme value threshold is first determined as an intermediate fixed threshold, which produces a minimum mean square error [8].

At present, the commonly used threshold function of the following two kinds of processing: hard threshold function (hard shrinkage), soft threshold function (soft shrinkage) [9]. The 2 functions are:

**Hard threshold function:**

$$\eta(x, \lambda) = \begin{cases} 
  x & |x| \geq \lambda \\
  0 & |x| < \lambda 
\end{cases} \quad (2)$$

**Soft threshold function:**

$$\eta(x, \lambda) = \begin{cases} 
  x - \lambda & x \geq \lambda \\
  0 & |x| < \lambda \\
  x + \lambda & x \leq -\lambda 
\end{cases} \quad (3)$$

where $x$ is the wavelet coefficient, $\lambda$ is the threshold value: $\lambda = \sigma \sqrt{2 \log(N)}$, $\sigma$ is the standard deviation of the noise signal, $N$ is the signal length. In practice, the noise signal $\sigma$ is unknown and usually needs to be estimated.

### 3.3. Analysis of Noise Cancellation Algorithms Based on Hierarchical Thresholds

By comprehensively analysing the nonlinear wavelet transform threshold algorithm, a hierarchical threshold noise cancellation method can be obtained, which can preserve the useful signal at the lower scale level and eliminate the noise signal at the largest scale level for the noise in the transformer sound signal that spans a large scale and is divided into transient noise and continuous noise, and the calculation is shown as follows [10].
\[ T_0 = \log_2(1 + 2\sqrt{N}) - \frac{J}{Z} A \]  

(4)

where \( N \) is the preset power of noise, \( J \) is the magnitude of the scale taken, \( A \) is the maximum extreme point amplitude. Each level of scale magnitude is considered to exist independently of each other, and a best-matched threshold can be set for noise reduction, with signal reconstructions based on the modal maximum points preserved at each level of scale after noise reduction.

4. Unsupervised Learning Anomaly Detection Method Based on WGAN-GP

4.1. WGAN-GP Framework

In recent years, unsupervised learning has been used for anomaly detection\[^{11-13}\]. At the same time, more and more deep learning techniques are being adopted in the field of power transformer fault detection\[^{14-15}\]. In this paper, an unsupervised learning method based on WGAN-GP is used to do anomaly detection on the transformer sound signal. Firstly, the sound signal is collected from the transformer at a sampling frequency of 1260 Hz, and the length of each frame is 64. then the discrete S-transform is used to extract the sound feature image of size 33 \times 64 from the signal, and the feature image is used as the raw input data of the discriminator.

The input data of the generator is a Gaussian noise matrix of size 32 \times 32, and its output data is a falsified 33 \times 64 generated image. Finally, the generated images and sound feature images output from the generator are sent to the discriminator for classification and recognition, and the training results are obtained after the dynamic game and iterative update of the generator and the discriminator.

Its overall framework is shown in the following Figure 2.

![Figure 2. General framework of the WGAN-GP-based transformer sound signal anomaly detection method.](image)

4.2. Feature Extraction and Network Structure

4.2.1. S-transform-based feature extraction. The S-transform is a lossless and reversible signal transformation algorithm that is an effective tool for video analysis\[^{16}\]. In this paper, the acquired sound signal is framed and processed by the discrete S-transform, and the complex matrix \( \hat{S} \) is calculated as follows

\[
\begin{align*}
\hat{S}(kT, \frac{n}{NT}) &= \sum_{n=0}^{N-1} H \left( \frac{m+n}{NT} \right) e^{\frac{2\pi i m^2}{NT}} e^{\frac{-2\pi i nk}{NT}}, n = 1, 2, \ldots, N - 1 \\
\hat{S}(kT, 0) &= \frac{1}{N} \sum_{n=0}^{N-1} h \left( \frac{m}{NT} \right), n = 0
\end{align*}
\]

(5)
where, $H(\cdot)$ denoting the discrete Fourier transform, then

$$H \left( \frac{m + n}{NT} \right) = \frac{1}{N} \sum_{k=0}^{N-1} h(kT) \exp \left[ -j \frac{2\pi (m + n)k}{N} \right]$$

(6)

where, $k = 0, 1, \cdots, N - 1$;

The elements of the complex matrix $\hat{S}$ are modelled and the repetitions are removed to obtain the feature image $x$.

4.2.2. Generator and discriminator network architecture and implementation. Take full advantage of what code-decode networks can do [17-18]. The image is reconstructed by extracting features through the encoding network and decoding network. Among them, the generator architecture design is shown in Figure 3.

The generator network consists of four inverse convolutional layers, each followed by a Rectifier Linear Unit (ReLU), and the activation function of the output layer uses Sigmoid. 3×3, 3×3, 4×4, and 3×3 convolutional kernels are used in each layer, with step sizes of 1, 1, (1,2), and 1, respectively, and the padding is all 1.

The decoding network consists of 4 convolutional layers and the network structure is inter-inverted with the generator network.

Loss function construction. In this paper, the objective function during training using the GAN network is:

$$\min_G \max_D \mathbb{E}_{x \sim P_x} [D(x)] - \mathbb{E}_{z \sim P_z} [D(G(z))].$$

(7)

where $\tilde{x} = G(z), z \sim p(z)$.

During training, the potential feature $z$ is first passed through the generative network $G$ to obtain the generated sample $\tilde{x} = G(z)$. Then, it is input to the discriminator together with the normal sample after pre-processing to get $x$. In order for the discriminator to distinguish the normal sample from the generated sample and to improve the training effect, the optimizing objective function $L_{\text{con}}$ of the discriminator is as follows:

$$L_{\text{con}} = \mathbb{E}_{x \sim P_X} [D(x)] - \mathbb{E}_{z \sim P_z} [D(G(z))] + \lambda \mathbb{E}_{x \sim P_X} \left[ \left\| \nabla_x D(x) \right\|_2 - 1 \right]^2$$

(8)

where $\tilde{x} = \epsilon x + (1 - \epsilon) \tilde{x}, \epsilon \sim U [0,1]$.

5. Experimental Results and Analysis

5.1. Sound Signal de-noising Experiment based on Hierarchical Thresholds

This experiment selects a section of field collected transformer sound signal (110kV transformer in Hunan Province) and uses the wavelet noise cancellation principle based on hierarchical thresholding to verify the feasibility of this method. The comparison between Figure 4 and Figure 5 clearly shows that this method is very effective in noise cancellation. Figure 5 shows a flatter sound signal compared to Figure 4, with less fluctuation in both amplitude and phase.
5.2. Transformer Fault Diagnosis Experiment based on WGAN-GP

In this experiment, the selected learning rate is 0.001, the batch is 512 and the epoch is 2000. All deep learning methods in this experiment were implemented using Pytorch-GPU 1.6.0 and python 3.8, using a laptop computer with an Intel(R) Core (TM) i7-8750H CPU and NVIDIA GeForce GTX 1050 Ti discrete graphics card as the computational resource. Memory is 8 GB for the 64-bit Windows operating system.

The training data were obtained from two normal 110kV power transformers, two normal 220kV power transformers and one DC bias magnetic operation power transformer. Seven sound sensors were installed on each transformer. Firstly, the sound signal is noise-cancelled. Then, a total of 9128 sets of training data and 25228 sets of test data were collected.

Figure 6 is normal data, and Figure 7 is abnormal data.
Figure 6. Normal data.

Figure 7. Abnormal data.

Figure 8 is a characteristic image of normal data, and Figure 9 is the abnormal one.

Figure 8. Characteristic image of normal data.

Figure 9. Characteristic image of abnormal data.

The average output of the network is taken as the health, and the test results are shown in Table 3.
Table 3. Test results

| Normal transformer | DC polarization |
|--------------------|----------------|
| healthiness        | 0.63           |
|                    | 0.002          |

From the experimental results, using WGAN-GP as the network architecture for anomaly detection, it is possible to use only normal data in the training phase and still detect anomalous signals.

6. Conclusion

(1) Transformer sound signal noise cancellation using wavelet transform method based on hierarchical thresholds can effectively eliminate all kinds of interference noise, which can make subsequent fault diagnosis more accurate.

(2) Good data representation is the basis for anomaly detection of signals. In this paper, we propose to process the vibration signal of power transformer by S-transformation, which effectively extracts the key features in the signal and facilitates the training of neural network.

(3) It has been experimentally verified that unsupervised learning is effective in the field of detection of abnormal vibration signals of power transformers with high accuracy. However, the models obtained by training different signal transformers cannot be migrated and used, which requires further research. There are two possible approaches, either to increase the amount of data collection and the resources used for model training; or to adopt the idea of meta-learning or migration learning, focusing on the common characteristics of the models used by different models of transformers, in order to reduce the cost of training.

In this paper, we study the accurate identification method of transformer noise and its connection with transformer operating state, which provides an important basis for transformer condition assessment and substation noise analysis and control. It provides an important basis for transformer condition assessment and substation noise analysis and control. It provides early warning for transformer faults and prevents huge economic losses caused by transformer faults.

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