X-ray Power Fault Detection Method Based on Feature Spectrum Reconstruction and Convolutional Neural Network

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Abstract. The high frequency of X-ray high-voltage power supply (XHPS) leads to conspicuous parasitic effect of power components. And this will transform the equipment into a time-varying and nonlinear complex system. By applying the combination of convolutional neural network (CNN) and traditional methods, this paper proposes a fault detection method based on 2-D feature spectrum reconstruction and CNN. Firstly, the multi-wavelet transform is utilized to decompose the 1-D high-voltage power signal to obtain the coefficients of each frequency band. Secondly, the inverse Zigzag scan reconstructs the multi-wavelet coefficients into a feature spectrum that satisfies the input form of VGG-16, and then cascades the deep features obtained by VGG-16 with the multi-wavelet features. Finally, the final fault detection result is obtained by the support vector machine (SVM). The simulation results show that the proposed method has better fault detection performance and could provide a workable idea for fault prediction and avoidance.

1. Introduction
The X-ray high-voltage power supply (XHPS) is the primary component of the X-ray system, and its performance determines the life cycle of X-ray application system. As the density of circuit integration and complexity of XHPS keep increasing, minor fault may cause huge economic losses, casualties and even serious social impact. By exploring the physical mechanism of various faults of XHPS and obtaining the fault state physical quantity that is easy for computer processing, it can greatly prevent and reduce the occurrence of power fault. Therefore, it is of great practical significance to study the establishment of the correlation mechanism between XHPS fault and typical physical quantity.

The high frequency of the XHPS causes the conspicuous parasitic effect of the components of power supply. This effect makes the power supply a complex nonlinear and time-varying system. It is difficult to establish an accurate mathematical model to describe the working state of the power supply and it makes fault problems difficult to locate. Wavelet transform has been extensively used in fault diagnosis, separation of fault characteristic frequency and extraction of weak signals. Since there is only one wavelet basis function, the classic wavelet analysis cannot match multiple types of fault features due to different external factors in practical applications. It is also impossible to satisfy the characteristics of orthogonality, symmetry, tight support, and high-order vanishing moment. Having multiple wavelet basis functions, multi-wavelet analysis could better match multiple types of fault features. At the same time, it has many very notable and excellent characteristics in signal processing.

Domestic and foreign researchers have applied multi-wavelets to practical engineering problems. For example, Kaewarsa et al. combined multi-wavelets with neural networks together and applied to the identification and classification of power quality [1]. Yuan et al. constructed an adaptive
multi-wavelets based on the similarity transformation in two scales, and took the maximum kurtosis as the optimization target to obtain the adaptive optimal multi-wavelets, and then extracted the fault components of rotating machinery impact [2]. A fault diagnosis method of commutation failure in the high-voltage direct current (HVDC) system based on wavelet packet decomposition (WPD) and general regression neural network (GRNN) proposed by Liu et al. can recognize commutation failure and direct current (DC) transmission fault, then identify the commutation failure reasons correctly [3]. However, the application of multi-wavelet theory in fault detection has only just begun, and the advantages of multi-wavelets in the field of fault detection have not been fully exploited. It can be seen that the application of multi-wavelet analysis in fault and weak fault detection has significant engineering value.

Convolutional neural networks (CNN) are a common deep learning network architecture. And it not only has the advantages of the traditional neural network, such as better fault tolerance, adaptability and strong self-learning ability, but also possesses the advantages of automatic extraction of features, weight sharing and good combination of the input image and the network structure. Li et al. proposed a cascading architecture based on CNN, and the cascading architecture has very strong discrimination ability, while maintaining high performance, which can distinguish foreground and background accurately [4]. Eren et al. studied the performance of a generic real-time induction bearing fault diagnosis system by employing compact adaptive 1-D CNN classifier [5].

We found that the features of fault and normal signals extracted by CNN are very different and exhibit certain rules. This allows us to improve the traditional fault detection method based on multi-wavelet features by adding deep features extracted by CNN. However, the fault detection task of XHPS is mainly to analyze the typical nonlinear one-dimensional sequence signals collected and obtain the detection results. Therefore, it is not suitable to use the CNN model to directly extract features from one-dimensional sequence signals. Based on this, we propose an XHPS fault detection method based on feature spectrum reconstruction and CNN. Firstly, signal decomposition of GHM (Geronimo-Hardin-Massopust) multi-wavelets is used to obtain the coefficients of each frequency band. Then, the multi-dimensional feature matrix reconstructed by the inverse Zigzag scan method is used as the input of CNN to obtain deep features. Finally, the final test results can be obtained by classifying the cascading feature vectors composed of deep features and multi-wavelet features using support vector machine (SVM).

The rest of this paper is organized as follows. Section 2 explains our approach in detail. In Section 3, we describe the experimental setup and the obtained results. We present our conclusions and discussions in Section 4.

2. Fault detection of XHPS based on feature spectrum reconstruction and CNN

Figure 1 shows the fault detection model of XHPS designed in this paper. Firstly, GHM multi-wavelet decomposition is used to transform the working signal of XHPS into multi-wavelet domain, and the frequency coefficients of the signal are obtained. Secondly, the multi-wavelet coefficients are reconstructed into multi-dimensional feature spectrum which adapts to the input form of CNN according to the inverse Zigzag scan method. Finally, the learned deep features and the constructed multi-wavelet features are cascaded and normalized, and the final fault detection results are obtained by inputting them into the SVM classifier.

![Figure 1. The structure diagram of fault detection method based on feature spectrum reconstruction and convolutional neural network.](image-url)
2.1. Convolutional neural network

CNN is a deep learning method proposed by imitating the way neurons in the nervous system process visual stimuli [6]. In the CNN structure, following the multiple convolutional layers and pooling layers, one or more fully connected layers are connected to realize classification. Each neuron in the fully connected layer is connected to all neurons in the previous layer, which can integrate local information with class discrimination in the convolutional layer or the pooling layer.

CNN adopts local receptive field, shared weights and spatial domain subsampling. In addition, it has stable characteristics relative to displacement, scaling and distortion. It has unique advantages for dealing with uncertain and nonlinear mapping problems, and can detect patterns and trends that cannot be detected by other classification techniques. Therefore, it is of great research significance to introduce CNN into fault detection of XHPS.

There are many classic CNN models, such as AlexNet, GoogleNet, CaffeNet, VGGNet, etc. VGGNet is proposed by Oxford University and has multiple versions, such as VGG-16, VGG-19, VGG-F, etc. It is the most commonly used deep learning model, showing good performance in image classification and further semantic recognition and image segmentation. The conspicuous characteristics of VGG-16 are simple structure, low parameter and strong generalization ability. Therefore, the paper will complete the XHPS fault detection experiment based on this model.

2.2. Feature spectrum reconstruction

Multi-wavelets refers to the wavelets generated by a series of functions as components [7]. Being an extension of wavelet analysis, multi-wavelet analysis has multi-resolution analysis spaces generated by multiple scale functions and wavelet functions. The multi-scale function \( \Phi(x) = [\phi_1(x), \phi_2(x), ..., \phi_j(x)]^T \) and the multi-wavelet function \( \Psi(x) = [\varphi_1(x), \varphi_2(x), ..., \varphi_j(x)]^T \) in multi-wavelet analysis should satisfy the following two-scale matrix equations, i.e.,

\[
\Phi(x) = \sqrt{2} \sum_k G_k \Phi(2x - k),
\]

\[
\Psi(x) = \sqrt{2} \sum_k H_k \Psi(2x - k),
\]

where \( G_k \) and \( H_k \), with the size of \( r \times r \), are the filtering matrices of the low-pass and high-pass filters, respectively.

The scaling coefficients and wavelet coefficients of multi-wavelets are denoted by \( V_{j,k} \) and \( U_{j,k} \), and the multi-wavelet decomposition and reconstruction equations are shown in equation (3) and equation (4), i.e.,

\[
\begin{align*}
U_{j+1,k} &= \sqrt{2} \sum_n H_n U_{j,n+2k} \\
V_{j+1,k} &= \sqrt{2} \sum_n G_n U_{j,n+2k} \\
U_{j,k} &= \sqrt{2} \sum_k (H_k^T U_{j+1,k+2n} + G_k^T V_{j+1,k+2n}),
\end{align*}
\]

where \( V_{j,k} = (V_{1,k}, ..., V_{r,k})^T \) represents the low frequency component and \( U_{j,k} = (U_{1,k}, ..., U_{r,k})^T \) represents the high frequency component.

The widely used multi-wavelets include GHM, CL, and SA4. Among them, the GHM multi-wavelets [8] constructed by Geronimo et al. using the difference function have features, e.g., symmetry, orthogonality, tight support and second-order vanishing moment. Figure 2 shows the decomposition process of GHM multi-wavelets with 3 layers. Differing from wavelet analysis, multi-wavelets need to pre-filter and post-filter the original signal before signal decomposition and reconstruction. \( S_1 \) and \( S_2 \) are the signal sequences obtained after pre-filtering the original...
one-dimensional signals. In this paper, repeat-row pre-filtering method is adopted to obtain low-frequency parts (i.e., L1 and L2 in Figure 2) and high-frequency parts (i.e., H1 and H2 in Figure 2) through multi-wavelet decomposition at the first layer. In such a way, L1 and L2 are decomposed into low-frequency parts (LL1 and LL2), high-frequency parts (LH1 and LH2). The signal decomposition is iteratively executed three times and we could get different coefficients of three layers. Since GHM multi-wavelets has multiple wavelet dimensions \( r = 2 \), that is, it has two basis functions, so the low frequency and high frequency have two band components respectively after each decomposition. Compared with the classical wavelet analysis, multi-wavelets has multi-wavelet basis functions, which can be decomposed to get more frequency band components and hence better matching ability with fault signals. 

![Figure 2. 3-layer decomposition process of GHM multi-wavelets.](image)

Being an outstanding technology in image processing problem, this paper introduces CNN into XHPS fault detection. The premise of using CNN in this method is to reconstruct a feature spectrum that satisfies the input form of CNN. Zigzag scan is a method of scanning matrix, which can transform a \( n \times n \) dimensional matrix into a one-dimensional sequence of length \( n^2 \) by "Z"-shaped scanning. Zigzag scan is widely used in the field of image and video coding [9]. For example, in CA VLC coding, after transformation and quantification of sub-blocks, the non-zero coefficients are mainly concentrated in the low frequency part (upper left), while the high frequency part is concentrated in the lower right. Using Zigzag scan, the non-zero coefficients can be arranged centrally on the left side of one-dimensional sequence, which can greatly improve the coding efficiency. Therefore, a method of feature spectrum reconstruction based on inverse Zigzag scan is proposed, and its structure block diagram is shown in Figure 3.

![Figure 3. The process of feature spectrum reconstruction.](image)

When the length of the input signal is \( L \) (the integer power of 2), GHM multi-wavelet decomposition can be used to obtain two coefficient vectors of length \( L \). And the low frequency is mainly distributed on the left side, while the high frequency is concentrated on the right side. The two row coefficient vector obtained by the decomposition is sequentially subjected to inverse Zigzag scan to reconstruct a two-channel feature spectrum. In this paper, \( L = 2048 \) is selected, and the reconstructed feature spectrum is set to \( 45 \times 46 \) by the end-filling 0, and normalized to the range \([0, 255] \). In order to make the reconstructed feature spectrum satisfy the input requirements of VGG-16, we take the mean of the first two channels of the feature spectrum as the third channel to obtain the three-channel feature spectrum.

The final results of feature spectrum reconstruction are shown in Figure 4. Figure 4 (a) is the result of feature spectrum reconstruction when the power supply is working under normal state, and Figure 4 (b) is the result of feature spectrum reconstruction when the power supply fails. And we can see that the feature spectrum reconstructed from the waveforms of the two states are clearly different, which makes fault more distinguished. The energy distribution of the feature spectrum of the normal waveform is more balanced, while that of the fault waveform reconstruction is unbalanced, showing texture features.
2.3. Fault detection

After the GMH multi-wavelet decomposition is used to obtain the coefficients of each frequency band, the wavelet features such as maximum value, minimum value, energy and information entropy are extracted. And then the deep features learned by the CNN model are cascaded and uniformly normalized into the specified interval. After obtaining the feature representation of the input signal, it is necessary to establish a classifier to complete the classification task and detect whether it is a fault signal. Common classifiers include KNN, Decision Tree, Boosting and SVM, etc., in which SVM is a common supervised binary model with solid theoretical basis of statistical learning, perfect mathematical form, intuitive geometric interpretation and good generalization ability [10].

The main purpose of SVM is to construct a classification hyperplane to distinguish different types of samples and ensure that the interval is maximized. The objective function and constraints are given as

\[
\begin{align*}
\min_{\omega, b, \xi} & \quad \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{N} \xi_i, \\
\text{s.t.} & \quad y_i (\omega x_i + b) \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0, \quad i = 1, 2, ..., N
\end{align*}
\]

(5)

where \( C \) is the penalty factor, and \( \xi_i \) is the relaxation variable introduced in the case of linear inseparability.

Lagrange multiplier \( \alpha_i(i = 1, ..., N) \) is introduced, and the Lagrange function of the original problem is described as

\[
L(\omega, b, \xi, \alpha, \mu) = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{N} \xi_i - \sum_{i=1}^{N} \alpha_i (y_i (\omega \cdot x_i + b) - 1 + \xi_i) - \sum_{i=1}^{N} \mu_i \xi_i,
\]

(6)

where \( \alpha_i \geq 0, \mu_i \geq 0 \).

SVM uses sequential minimal optimization (SMO) algorithm for learning, which is characterized by constantly decomposing the original quadratic programming problem into sub-problems. The solution is then solved analytically until all variables satisfy the KKT (Karush-Kuhn-Tucher) conditions. In this way, the optimal solution of the original quadratic programming problem can be obtained through a heuristic method. When dealing with nonlinear problems, the basic idea of SVM classifier is to transform it into linear problems by kernel function, and then find the optimal hyperplane to realize the classification of samples. The fault detection of XHPS in this paper is a nonlinear classification problem.

3. Experimental results and analysis

3.1 Experimental environment

Due to the particularity of XHPS, it is extremely difficult to obtain massive observation data.
Therefore, this paper multiplexes the VGG-16 network trained by ImageNet and sends the reconstructed feature spectrum into the trained VGG-16 network to dig its deep features.

We designed three groups of experiments to compare with the fault detection methods proposed in this paper, which are wavelet analysis feature + SVM (WA_SVM), multi-wavelet feature + SVM (GHM_SVM) and CNN feature + SVM (CNN_SVM). And these experiments compare and verify at different decomposition scales. Among them, scalar wavelet is chosen as DB5 wavelet in Daubechies wavelet series [11], which is widely used in fault detection. The selected performance evaluation indicators include precision and recall rate. The proposed method is verified under the conditions that PC specifications are CPU pentium-i7 3.6GHz and RAM 16G. In addition, the simulation software is MATLAB R2017a and the deep learning framework is Pytorch.

3.2. Experimental analysis
The paper takes the resonance current of X-ray high-voltage power switch tube as the research object. Silicon carbide (SiC) switching device is prone to failure due to temperature, high and low voltage impact and electromagnetic interference. Two typical waveforms are shown in Figure 5. The first behavior fault state waveform and the second behavior corresponding to the output waveform of the normal working state. A total of 800 samples (including 300 positive samples and 500 negative samples) are collected in this paper. Specifically, 150 positive samples and 150 negative samples constitute the training set, and 150 positive samples and 350 negative samples constitute the test set.

![Figure 5. Comparison of fault samples with normal samples.](image)

The feature spectrum reconstruction results of positive and negative samples ($45 \times 46 \times 3$) are shown in Figure 6. Figure 6 (a) is the result of the feature spectrum reconstruction of the normal sample, and Figure 6 (b) is the result of the feature spectrum reconstruction of the fault sample. It can be seen that the energy distribution of the feature spectrum reconstructed by fault samples is very unbalanced, showing texture features. And then VGG-16 model was used to extract the deep features of the feature spectrum reconstructed by inverse Zigzag scan method. In this paper, the third depth layer feature of VGG-16 model is selected as the deep feature cascaded with multi-wavelet features.

The detection performance of different methods is shown in table 1, and the decomposition scale is 4 and 6 respectively. It can be seen from the data in the table 1 that the proposed method in this paper has higher precision and recall rate than other methods. This is mainly due to the following three points: (1) more frequency band components are obtained after GHM multi-wavelet decomposition, and the matching ability with fault signals is stronger; (2) sending feature spectrum to VGG-16 model can further dig out potential fault information; (3) the effective combination of traditional multi-wavelet features and deep features improves the discriminating ability of SVM classifier.
Table 1. Performance comparison of fault detection of high-voltage power switch tube by different methods.

| Scale | 4         | 4         | 6         | 6         |
|-------|-----------|-----------|-----------|-----------|
|        | Precision | Recall rate | Precision | Recall rate |
| WA_SVM | 0.78      | 0.56      | 0.81      | 0.76      |
| GHM_SVM | 0.91      | 0.92      | 0.90      | 0.92      |
| CNN_SVM | 0.97      | 0.96      | 0.95      | 0.93      |
| Ours   | 0.97      | 0.96      | 0.97      | 0.95      |

4. Conclusion
In this paper, CNN is introduced into the state analysis of XHPS. Aiming at the common fault problems, a fault detection method based on feature spectrum reconstruction and CNN is proposed on the basis of GHM multi-wavelet method. The deep features extracted by CNN are more discriminative and robust than the hand-crafted features. Then, we cascade the deep features with the traditional multi-wavelet features, and get the final detection results by SVM classifier. Experiments show that the proposed method achieves better detection performance and has higher practical value in engineering. As a future work, we will test this method on a larger data set, and adjust the model to get better performance.

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