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Simulation Study on Fault Diagnosis of Power Electronic Circuits Based on Wavelet Packet Analysis and Support Vector Machine

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With the development of power electronic technology, power electronic equipment is becoming more and more complex, and the fault problems are becoming increasingly prominent. Fault diagnosis of power electronic equipment can find out and solve the fault problems in time and ensure the safe operation of the equipment. In this study, a fault diagnosis method based on wavelet packet analysis and support vector machine was proposed. Firstly, the wavelet packet transform was used to decompose and denoise the signal, and the original fault feature vector was extracted for reconstruction. The improved support vector machine algorithm was used to diagnose the fault based on the new fault feature vector. The three-phase rectifier circuit was taken as an example to make stimulation experiments, and it was found that the method had 95% accuracy, which proved that the method had high accuracy and application value in fault diagnosis of power electronic circuits.

Keywords: Power electronic circuits; wavelet packet transform; support vector machine; feature extraction; fault diagnosis.

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1. Introduction

With the development of technology, power electronic equipment has been widely applied in fields such as military, industry and business [1]. It is a key component in many power and electrical systems, and power electronic circuit has a high possibility of failure [2]. If there is a fault, it will greatly affect the operation of the whole system. Therefore, the fault diagnosis of power electronic equipment is essential to prevent the further deterioration of devices [3, 4]. Wu et al. [5] proposed a method based on hybrid bond graph (HBG) and genetic algorithm (GA) according to the problem of multi-parameter fault diagnosis in electronic circuits, and the effectiveness of the method was verified by simulation experiments. Han et al. [6] proposed a fault diagnosis method based on mixed logic dynamic (MLD) model and fault event identification. Fault event identification was used instead of discrete event identification, and then the feasibility of the method was proved by simulation experiments on three-phase inverter circuit. Cai et al. [7] made comprehensive use of the clustering efficiency of fuzzy c-means (FCM), the continuous dynamic signal processing capability of hidden Markov model (HMM) and the classification ability of support vector machine (SVM) for fault diagnosis of electronic circuits. It was found through experiments that this method has relatively high accuracy. Yan et al. [8] applied the hidden Markov model and high-order spectrum algorithm to fault diagnosis. Simulation experiments were carried out on the main converter of SS8 electric locomotive, and the results showed that the method is better than back propagation (BP) neural network algorithm. In this study, the wavelet packet analysis was used to make fault

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feature extraction of electronic circuits. The new fault feature vector was obtained by decomposing, denoising and reconstructing the signal, and then the fault classification was performed by the support vector machine classifier. The fault classification of samples was made by the stimulation experiments of three-phase rectifier circuit to verify the validity of the method.

2. Notation

The notation used throughout the paper is stated below.

Indexes:

S	the original signal
Y	high-frequency wavelet coefficients
Z	the low-frequency wavelet coefficients
E	the total energy of signal
T’	the normalized fault feature vector

Constants:

$h(k)$	low pass filter coefficient
$g(k)$	high pass filter coefficient
S_{ji}	number of periods of the planning horizon the reconstructed signal of W_j^i
$\{W_j^0, W_j^1, W_j^2, \cdots, W_j^i\}$	he decomposition coefficients of each band of the j-th layer
E_{ji}	the total energy of reconstructed signal

Functions

$\varphi(t)$	the orthogonal wavelet function
$\phi(t)$	the orthogonal scaling function

3. Fault diagnosis of electronic circuits

With the development of science and technology, the functions of power electronic equipment are more perfect, the structure is more complicated, and the fault probability is greatly increased. Once some minor faults occur in the equipment and are not dealt with timely, it is easy to make the fault become more serious, which will not only affect the operation of the equipment and cause economic losses, but also may cause accidents, resulting in casualties and great impact. In addition, due to the complexity of the power electronic equipment, there are many types of faults. The artificial diagnosis not only is too inefficient to diagnose comprehensively, but also consumes too much manpower and material resources.With the development of power electronic technology, diagnosis of equipment faults have been attached more and more importance [9]. Fault diagnosis is based on the fault behavior and hardware of the tested object [10], which can detect the existence and the cause of fault at an early stage, and analyze and handle the fault and prevent further expansion of the fault. In order to ensure efficient operation of power electronic equipment, it is necessary to improve the technology of fault diagnosis.

The power electronic circuit is the main part of power electronic equipment, which has characteristics of high fault probability, a large number of fault types and serious consequences. Therefore, the fault diagnosis of power electronic circuits is of great significance to the operation of the equipment.

Circuit faults include faults caused by parameters and structures. Parametric fault, also known as soft fault, refers to the changes in the parameters of capacitors, resistors and other components in the circuit. Although the circuit structure will not be changed, the normal state of the device characteristics will be changed. Structural fault, also known as hard fault, refers to the damage of circuit components, devices, etc., which will change the structure of the circuit, causing extremely fast and great damage. In the actual situation, the proportion of hard fault in the circuit is more than 80% of the total faults, and the damage of switches and power devices is the main ones.

Faults of circuit elements include capacitance, inductance, open circuit of resistance, short circuit, large and small parameter fault, open circuit of switching devices, short circuit, etc. The faults of the circuit components include open circuit, short circuit, relatively large or small parameter fault of the capacitor, the inductor, the resistor, the is too large, the small, the open circuit of the switching device, the short circuit, and the like.

The fault diagnosis of power electronic circuits can be divided into the following three stages:

(1)Sample data signals of electronic circuit system.

(2)Extract feature information from the acquired data and establish fault feature quantities.

(3)Input the feature quantities into the fault decision function and determine the fault type according to the result.

Feature extraction and fault classification are the most important parts in fault diagnosis. The commonly used feature extraction methods include auto-regressive moving average (ARMA) bispectrum analysis [11], wavelet multi-resolution analysis [12], wavelet transform [13] and principle component analysis [14]. The commonly used fault classification methods include neural network [15], hidden Markov model [16] and support vector machine [17]. In this study, the feature extraction method based on wavelet packet transform was used to diagnose faults by using support vector machine.

4. Wavelet packet fault feature extraction

4.1. Wavelet packet transform

Wavelet packet transform is a good signal processing method, which can generate wavelet decomposition, provide more abundant signal analysis and effectively extract fault features [18, 19]. It not only overcomes the problem of low frequency resolution of wavelet changes in the high frequency band, but also improves its time-frequency resolution. The wavelet packet transform is to input the signal into the filter and obtain the high and low frequency information of the signal. The three-layer wavelet packet decomposition is shown in Figure 1.

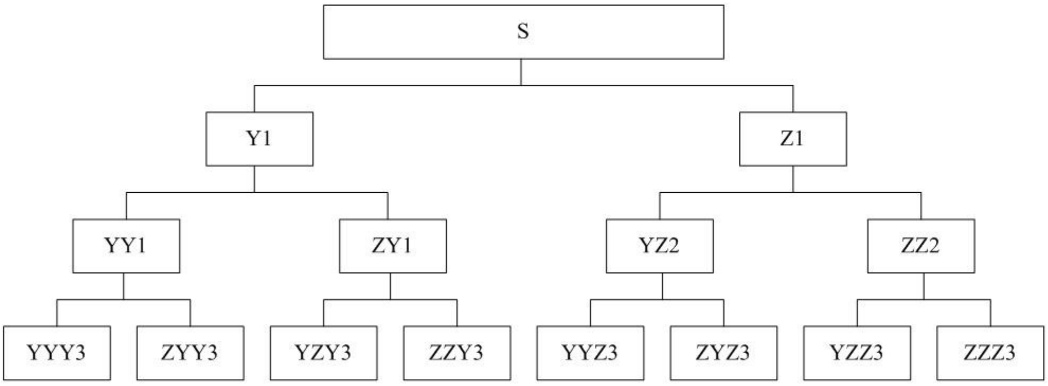


Figure 1. The three-layer wavelet packet decomposition process

where S stands for the original signal, Y stands for high-frequency wavelet coefficients, Z stands for the low-frequency wavelet coefficients, and numbers stands for the decomposition layer numbers. The original signal is decomposed by a layer of wavelet packets to obtain a low frequency component and a high frequency component, and then further decomposed to get the next low frequency component and high frequency component, and so on. Assuming that the orthogonal wavelet function is $\varphi(t)$, and the orthogonal scaling function is $\phi(t)$. These two functions satisfy the two-scale equation:

$$\varphi(t) = \sqrt{2} \sum_{k \in Z} h(k) \varphi(2t - k)$$
$$\phi(t) = \sqrt{2} \sum_{k \in Z} g(k) \phi(2t - k) \quad , \qquad (1)$$

where $h(k)$ stands for low pass filter coefficient and $g(k)$ stands for high pass filter coefficient. Further calculations can get the following equation:

$$\mu_{2n}(t) = \sqrt{2} \sum_{k \in Z} h(k) \mu_n(2t - k)$$
$$\mu_{2n+1}(t) = \sqrt{2} \sum_{k \in z} g(k) \mu_n(2t - k) \quad . \qquad (2)$$

The recursive formula of wavelet packet coefficient is:

$$d_{j+1}^{2n} = \sum_k h(k-2t) d_j^n(k)$$
$$d_{j+1}^{2n+1} = \sum_k g(k-2t) d_j^n(k) \quad . \qquad (3)$$

The wavelet packet reconstruction formula is:

$$d_j^n(k) = 2 \left[\sum_\tau h(k - 2\tau) d_{j+1}^{2n+1}(k) + \sum_\tau g(k - 2\tau) d_{j+1}^{2n}(k) \right] \quad . \qquad (4)$$

Flow chart of wavelet packet decomposition is shown in Figure 2.

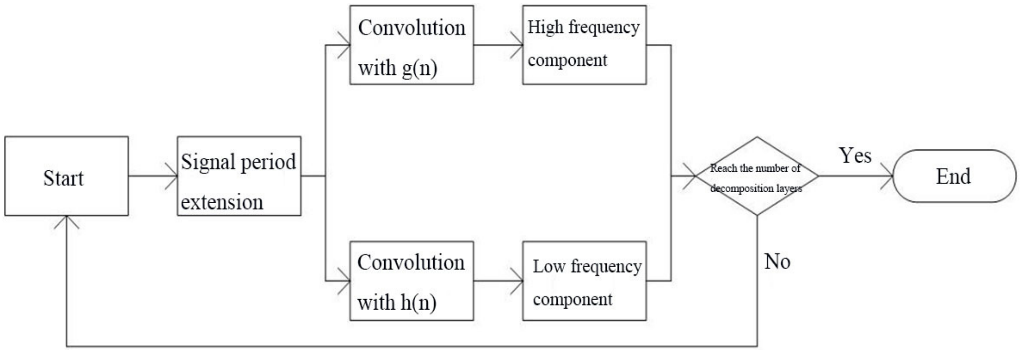


Figure 2. Flow chart of wavelet packet decomposition

4.2. Signal denoising

(1) Wavelet decomposition: decompose a noisy fault signal.

(2) Decomposition coefficient threshold quantization: use the soft threshold denoising method to remove wavelet decomposition coefficients below the threshold.

(3) Wavelet packet reconstruction: reconstruct the signal of wavelet decomposition coefficients which have been decomposed by wavelet packet and quantified by threshold.

4.3. Fault feature extraction

(1)Sampling. Sample the signal $f(t)$, and denoise.

(2)Select the mother wavelet coefficient and set the decomposition layer number as j.

(3)Perform the wavelet packet decomposition of j layers, extract the decomposition coefficients of each band of the j-th layer, one group per band, a total of 2^j groups. $\{W_j^0, W_j^1, W_j^2, \cdots, W_j^i\}$ stands for the decomposition coefficients of each band of the j-th layer, $i = 0,1,2,\cdots,2^j - 1$.

(4)Reconstruction. S_{ji} stands for the reconstructed signal of W_j^i, the signal S is：

$$S = \sum_{i=0}^{2^j-1} S_{ji} ,$$

the total energy of reconstructed signal E_{ji} :

$$E_{ji} = \int | s_{ji}(t) |^2 \ dt = \sum_{k=1}^{n} | X_{ik} |^2 ,$$

$X_{ik} (k = 1,2,\ldots,n)$ is the amplitude of the discrete point S_{ji}.

(5)Establish feature vector: $T = [E_{j0}, E_{j1}, E_{j2}, \cdots, E_{j(2^j-1)}]$.

(6) Normalization. Set the total energy of signal as E, and set the normalized fault feature vector as T’.

$$E = \sqrt{\sum_{k=0}^{2^j-1} | E_{jk} |} , \quad T = \frac{E_{j0}}{E}, \frac{E_{j1}}{E}, \frac{E_{j2}}{E}, \ldots, \frac{E_{j(2^j-1)}}{E} .$$

5. Support vector machine

Support vector machine algorithm is an algorithm based on risk minimization, which can effectively ensure that the obtained extreme value solution is the global optimal solution, and has great application value in fault classification [20]. In this study, an improved support vector machine algorithm was selected for fault diagnosis classification, as shown below.

Suppose the sample set is $T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_{n,} y_n)\}$, and $x_i \in R^d$, $y_i \in \{1,2,\cdots,k\}, i = 1,2,\cdots,n$.

The sample concludes k training subsets Ti. In the $j-th\ (j \in y_i\ )$ classifier of k classifiers, the j-th training sample was taken as a class, category number: $y_i^j = +1$, and the rest j-1 as a class, category number: $y_i^j = -1$. The output function of the j-th classifier is as follows:

$$f^j(x) = sign\left[\sum_{SVs} a_i^j y_i^j K(x_i, x) + b^j\right].$$

The fault classification process is shown as follows:

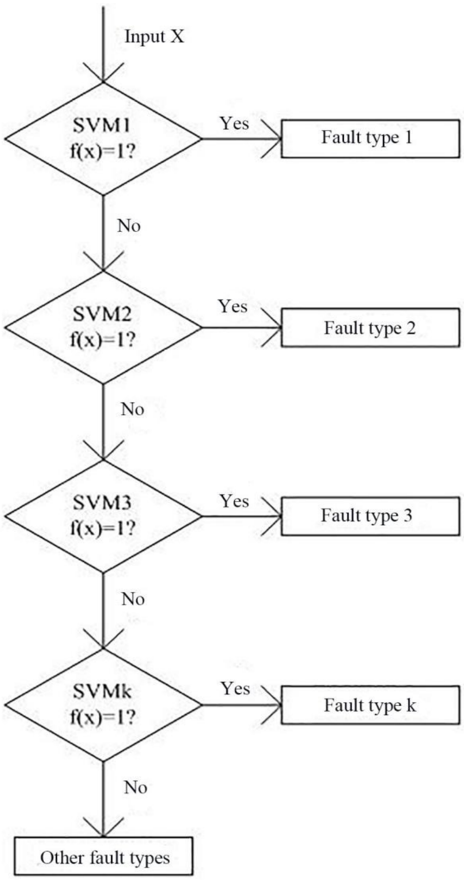


Figure 3. The fault classification process

6. Fault model simulation and analysis

This study took the three-phase bridge rectifier circuit as an example, and its working principle is shown in the Figure 4.

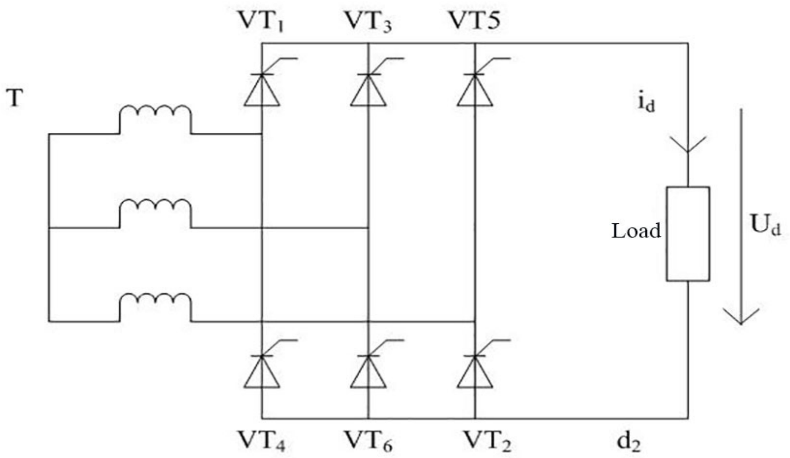


Figure 4. The three-phase bridge rectifier circuit diagram

The DC pulse voltage U_d is easy to be detected, which contains the fault information of the thyristor. This study used U_d as the object to classify the fault and verify the correctness of the diagnostic method.

The fault conditions of the three-phase bridge rectifier circuit only has one thyristor fault and the simultaneous faults of and two thyristors. The kinds of fault conditions can be listed as follows:

(1)Fault -free.

(2)Only one thyristor fault.

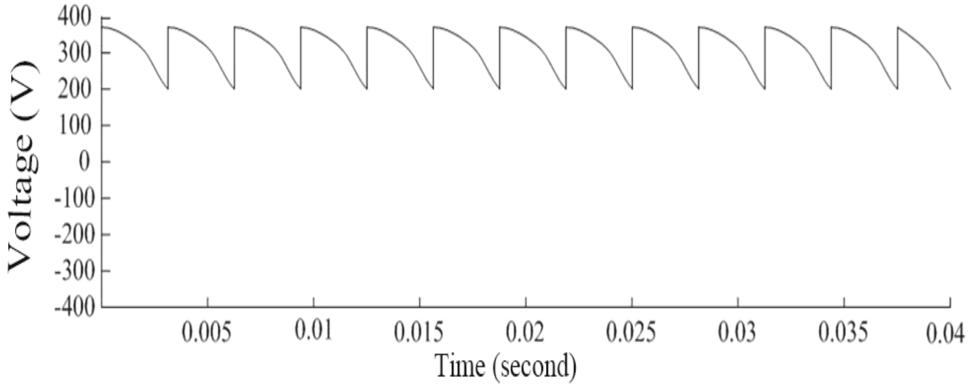
Two thyristors faults can be divided as follows:

(3)The fault thyristors are in the same phase but different groups: VT1 and VT4 fault, VT3 and VT6 fault, or VT5 and VT2 fault.

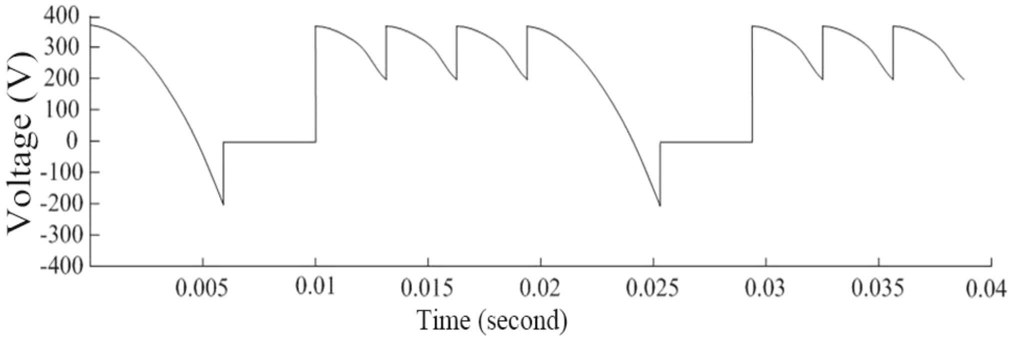
(4)The fault thyristors are in the same group but different phases: VT1 and VT3 fault, VT1 and VT5 fault, VT2 and VT4 fault, VT2 and VT6 fault, VT3 and VT5 fault, or VT4 and VT6 fault.

(5) The fault thyristors are in the different phases and groups: VT1 and VT2 fault, VT1 and VT6 fault, VT2 and VT3 fault, VT3 and VT4 fault, VT4 and VT5 fault, or VT5 and VT6 fault.

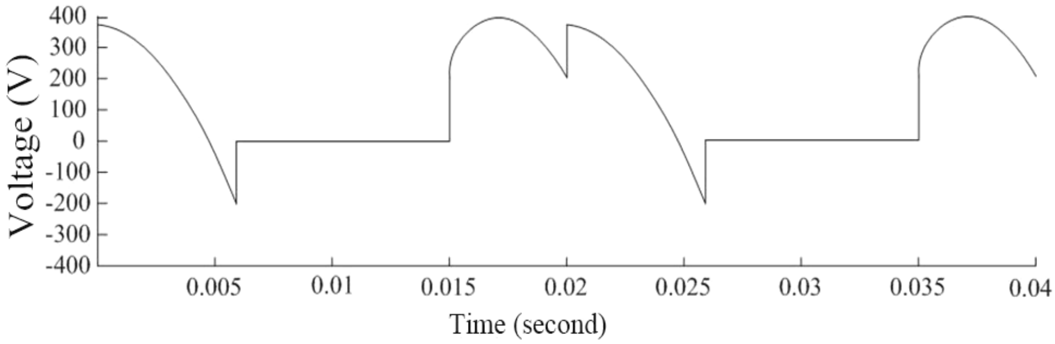
When the triggering angle is 30°, the u_d waveform of the above five types of fault conditions is as shown in the Figure 5.



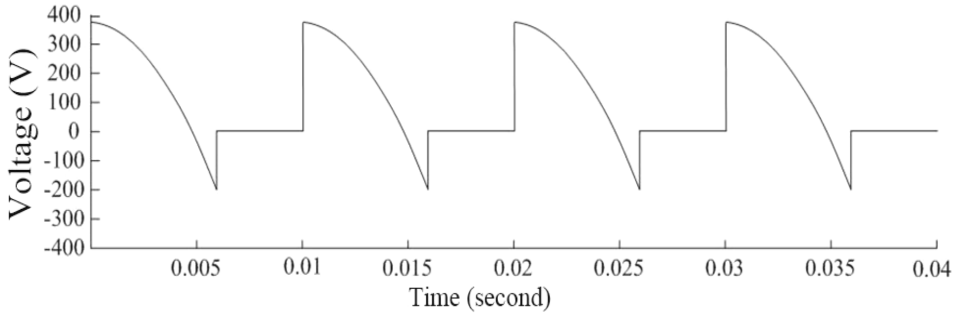
(1) No fault (original signal)



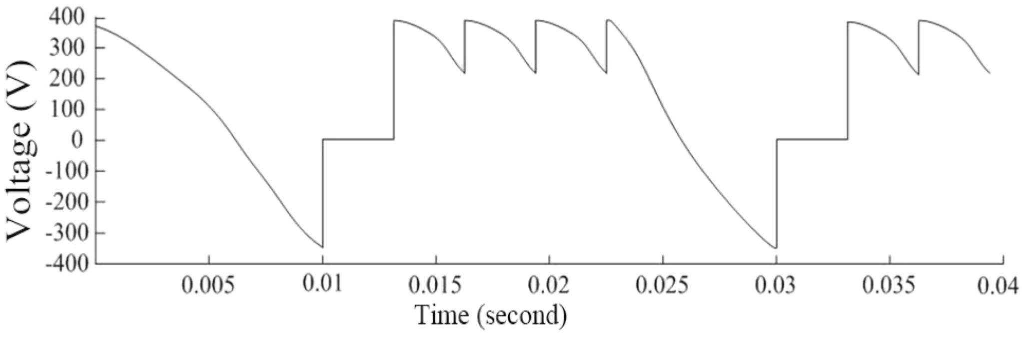
(2) One thyristor has fault



(3) Fault thyristors have the same phase but are in different groups



(4) Fault thyristors are in the same group but have different phases



(5) Fault thyristors are in different groups and have different phases

Figure 5. The u_d waveform of five types of fault conditions

7. Experimental procedures and results

7.1. Fault diagnosis process of power electronic circuits

Combined with feature extraction and support vector machine classification, the fault diagnosis process of this study is shown in the Figure 6.

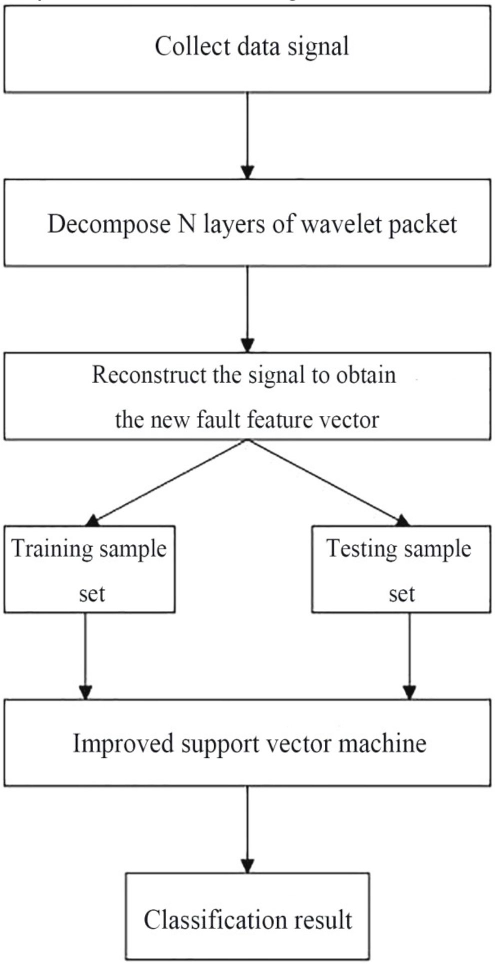


Figure 6. The fault diagnosis process

7.2. Fault feature vector

In higher wavelet packet decomposition layer, the number of frequency bands and the dimension of feature vector was larger, which will increase the difficulty of fault classification. Therefore the number of wavelet packet decomposition layer was set as 3.

Taking the trigger angle of 30° as an example, the five types, a total of 15 fault signals, which obtained from sampling, were decomposed into three layers of wavelet packets, feature vector was extracted using the formula mentioned in section 3, and the signal energy was calculated. Taking VT2 fault, VT3 and VT5 fault, VT2 and VT5 fault as an example, the comparison between the energy of each frequency band and the normal operation of the thyristor is shown in the Figure 7.

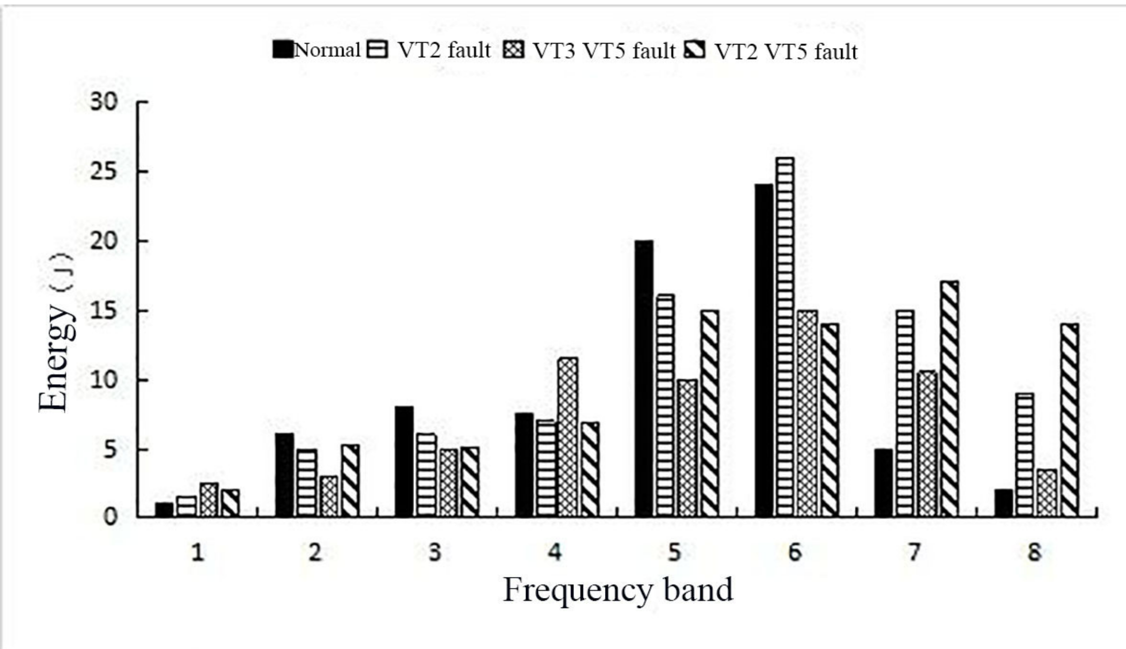


Figure 7. The comparison of different fault conditions and the normal condition

It could be found from the above results that the energy distribution under different fault conditions was quite different, and has abundant fault information, which was convenient for the next fault classification.

5% of the noise was added to the simulation circuit to simulate the actual circuit operating noise. For each fault mode, the trigger angle of the thyristor was changed every 30 degrees from 0°to 90°, and 20 sets of data for each angle were collected. There were 80 sets of data for each fault mode, of which 50 were used as training sample sets and 30 were used as testing sample sets. There were 1100 sets of training samples and 660 sets of testing samples. The collected data was calculated to obtain the fault feature vector.

7.3. Classifier establishment

There are significant differences in signal energy under different fault conditions. The vector machine was trained according to the obtained fault feature vector, and twenty-two classifiers were built through the training sample set. The results are shown in Table 1.

Table 1 Classifier and fault condition

Classifier	Fault number	Fault component
SVM1	Fault type 1	Fault-free
SVM2	Fault type 2	VT1
SVM3	Fault type 3	VT2
SVM4	Fault type 4	VT3
SVM5	Fault type 5	VT4
SVM6	Fault type 6	VT5
SVM7	Fault type 7	VT6
SVM8	Fault type 8	VT1 and VT4
SVM9	Fault type 9	VT3 and VT6
SVM10	Fault type 10	VT5 and VT2
SVM11	Fault type 11	VT1 and VT3

SVM12	Fault type 12	VT1 and VT5
SVM13	Fault type 13	VT3 and VT5
SVM14	Fault type 14	VT4 and VT6
SVM15	Fault type 15	VT4 and VT2
SVM16	Fault type 16	VT2 and VT6
SVM17	Fault type 17	VT1 andVT6
SVM18	Fault type 18	VT1 and VT2
SVM19	Fault type 19	VT3 and VT4
SVM20	Fault type 20	VT3 and VT2
SVM21	Fault type 21	VT5 and VT4
SVM22	Fault type 22	VT5 and VT6

The 660 testing samples were collected for fault classification, and 20 groups were randomly selected. The classification results are shown in Table 2.

Table 2 Classification results

Testing sample	Actual fault	Testing results
X1	Fault type 2	Fault type 2
X2	Fault type 3	Fault type 3
X3	Fault type 2	Fault type 2
X4	Fault type 5	Fault type 5
X5	Fault type 11	Fault type 11
X6	Fault type 12	Fault type 12
X7	Fault type 8	Fault type 8
X8	Fault type 9	Fault type 9
X9	Fault type 14	Fault type 17
X10	Fault type 9	Fault type 9
X11	Fault type 20	Fault type 20
X12	Fault type 17	Fault type 17
X13	Fault type 4	Fault type 4
X14	Fault type 7	Fault type 7
X15	Fault type 1	Fault type 1
X16	Fault type 20	Fault type 20
X17	Fault type 12	Fault type 12
X18	Fault type 16	Fault type 16
X19	Fault type 5	Fault type 5
X20	Fault type 9	Fault type 9

The experimental results showed that the accuracy of the testing sample classification was 95% and the accuracy was high when the support vector machine classifier was used for fault diagnosis.

8. Discussion and conclusion

Fault diagnosis of power electronic circuits is of great significance to efficient operation of power electronic equipment [21]. The possibility of power electronic equipment fault is large, the causes of fault are numerous, and the fault types are very complex. Manual troubleshooting is a time-consuming and labor-consuming method with low accuracy. Therefore, the study on fault diagnosis of electronic circuits has received extensive attention. Hou et al. [22] applied the sparse decomposition theory to fault feature extraction, and then used the support vector machine for fault diagnosis and classification, and found that the method had high accuracy. Wang et al. [23] set up the module time-frequency matrix of Wigner-Ville distribution for fault signal, made fault diagnosis through the calculation of its similarity, and verified the validity of the method through simulation experiment. Xie et al. [24] used the particle swarm optimization algorithm to provide a database. Through the iterative operation of particle swarm optimization, they judged whether the electronic circuit was malfunctioning and obtained satisfactory results.

As a signal analysis method, wavelet packet transform had good application in fault diagnosis of electronic circuits. Hui et al. [25] combined wavelet packet decomposition with PCA, got fault feature vector through interval combination method, and then used neural network for identification, which improved the accuracy of fault diagnosis. Support vector machine [26], the same as HMM and BP neural network, is a relatively good classification algorithm. The SVM showed better performance in small sample classification, the classification of the nonlinear and multidimensional classification. In order to have better fault classification, this study improved a SVM classification algorithm to reduce the amount of calculation and improve the test efficiency, and has better effectiveness in dealing with a large number of samples.

In this study, wavelet packet analysis and support vector machine based fault diagnosis method was used. Firstly, fault feature extraction was carried out by using wavelet packet transform. New fault feature vector was obtained by denoising and reconstructing the signal. Then, the improved support vector machine was used for fault classification. It was found that the accuracy of fault classification by using this method was 95%, which proved the validity of this method. The study of the fault classification method still had many shortcomings because of the limited study ability. For example, experimental environment had a big difference with the actual environment and may be bigger in the actual operation, which can interfere the classification. As the simulation experiment results had certain error, it is necessary to validate the real circuit to better prove the result of the experiment. Further study should be carried out to improve the effectiveness of the fault diagnosis of electronic circuits.

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