Abstract: Accurate extraction of abnormal communication signal features in the network is the basis to ensure the completion of network communication. Therefore, a method of feature extraction of abnormal communication signal in network based on nonlinear technology is proposed. In this method, wavelet transform is adopted to decompose the abnormal network communication signals in the high- and low-frequency bands. According to the distribution characteristics of noise and signal in the frequency band, the corresponding parameters are selected for phase space reconstruction and nonlinear dimension reduction of local tangent space mainstream shape recognition algorithm, and the decomposition coefficients of wavelet packet after noise reduction are reconstructed to realize the nonlinear noise reduction of abnormal signal; the denoised abnormal communication signal in network is mapped to the high-dimensional feature space. The principal component is analyzed in accordance with the nonlinear function in the mapped feature space, and the nonlinear function is solved by self-organizing neural network to output the principal component extraction result. According to test results, this method has a significant signal noise reduction effect, results are more than 92% for different abnormal communication signals, and the features of abnormal signals are accurately extracted.

Keywords: nonlinear technology, abnormal network communication, signal feature extraction

Notes to mathematical notation

<table>
<thead>
<tr>
<th>Number</th>
<th>Symbol</th>
<th>Explanatory note</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>$a$</td>
<td>The scale of wavelet signal</td>
</tr>
<tr>
<td>(2)</td>
<td>$b$</td>
<td>The offset of wavelet.</td>
</tr>
<tr>
<td>(3)</td>
<td>$x$</td>
<td>Random variable</td>
</tr>
<tr>
<td>(4)</td>
<td>$f(x)$</td>
<td>Probability density function of random variable $x$</td>
</tr>
<tr>
<td>(5)</td>
<td>$R_x$</td>
<td>The autocorrelation of random process $x$</td>
</tr>
<tr>
<td>(6)</td>
<td>$x_i$</td>
<td>Sample points</td>
</tr>
<tr>
<td>(7)</td>
<td>$k$</td>
<td>Nearest neighbors $X_i$</td>
</tr>
<tr>
<td>(8)</td>
<td>$Q_i$</td>
<td>Orthogonal basis</td>
</tr>
<tr>
<td>(9)</td>
<td>$d$</td>
<td>The dimension of subspaces of low dimensional manifolds</td>
</tr>
<tr>
<td>(10)</td>
<td>$\Omega_i^*$</td>
<td>Moore Penrose generalized inverse of $\Omega_i$</td>
</tr>
<tr>
<td>(11)</td>
<td>$X_i$</td>
<td>Respectively the mean values of $\Omega_i$</td>
</tr>
<tr>
<td>(12)</td>
<td>$T_i$</td>
<td>Respectively the mean values of $t_i$</td>
</tr>
<tr>
<td>(13)</td>
<td>$m$</td>
<td>The embedding dimension</td>
</tr>
<tr>
<td>(14)</td>
<td>$p_{jk}^n$</td>
<td>Wavelet packet decomposition coefficient</td>
</tr>
<tr>
<td>(15)</td>
<td>$n \in [1, N]$</td>
<td>The number of wavelet packet decomposition layers</td>
</tr>
<tr>
<td>(16)</td>
<td>$j \in [0, 2^n - 1]$</td>
<td>The wavelet packet node number</td>
</tr>
<tr>
<td>(17)</td>
<td>$k \in [1, K], K$</td>
<td>The data length in the wavelet packet node</td>
</tr>
<tr>
<td>(18)</td>
<td>$k \in [1, K], K$</td>
<td>The data length in the wavelet packet node</td>
</tr>
<tr>
<td>(19)</td>
<td>$\tau$</td>
<td>Phase space reconstruction delay</td>
</tr>
<tr>
<td>(20)</td>
<td>$m$</td>
<td>Best embedding dimension</td>
</tr>
<tr>
<td>(21)</td>
<td>$P_j = [p_{1j}, \cdots, p_{Kj}]$</td>
<td>Phase space matrix of Wavelet packet decomposition coefficients</td>
</tr>
</tbody>
</table>

* Corresponding author: Baofu Gong, Library, Criminal Investigation Police University of China, Shenyang 110854, China, e-mail: gong_baofu@163.com
1 Introduction

With the advancement of network technology, a large number of mobile communication network application software are emerging. Mobile communication network provides convenience for people’s life and production in accordance with its own advantages and obtains the favor of more users. However, the following problems also make people worry, for example, network intrusion, service attack, spreading virus, Trojan horse, information theft and other abnormal behaviors seriously affect users’ information security [1]. In this case, one of the difficulties that needs to be solved immediately among the current network problems is the method to accurately identify these abnormal mobile communication network signals, analyze and monitor the communication network operation in real time and accurately [2] and find the potential security threats in the network operation [3], to achieve the purpose of equating appropriate network strategies in time to respond to potential problems, and to ensure safe and efficient network operation and reduce the harm caused to the normal business of the communication network [4] due to various abnormal events. It is of great importance in improving the security of the mobile communication network [5]. Feature extraction of abnormal communication signal in network is the basis of accurate identification of abnormal signal; abnormal communication signal is a serious behavior that deviates from the expected network traffic. The signal has significant nonlinear features, the signal frequency is complex, and the signal-to-noise spatial distribution of each signal component is different, which greatly improves the difficulty of abnormal communication signal features. To ensure the extraction accuracy of abnormal communication signal in network [6], it is necessary to effectively deal with its nonlinear features and complete the processing of the complex frequency of the signal. In the study by Hindarto and Muntasa [7], wavelet transform was used to extract the energy value on each subband of signal wave to complete the feature extraction of abnormal communication signal; Song [8] proposed a method of feature extraction of transmission signals in electronic communication networks on the basis of symmetric algorithm, which performed threshold denoising and data dimensionality reduction to achieve three-layer wavelet packet decomposition of time-domain transmission signals. The adaptive floating threshold was applied as the threshold of wavelet coefficients of quantized signals, which could efficiently remove noise and retain transmission signals that are valuable. Vasudevan proposed an LPboost Convolutional neural network method based on auction optimization to solve the problem that it is difficult to identify abnormal activities in video surveillance. The background was eliminated based on fuzzy multi-level subtraction, and the object was identified using the region descriptor based on the main bow. Then, the extracted content was classified using the clustering method, and the anomaly was classified using the LPboost convolutional neural network based on auction optimization. The research results indicate that the accuracy of this method is significantly higher than several commonly used models [9]. To improve the efficiency and quality of transmission line fault detection and classification, Fahim et al. proposed a spectrogram analysis technique - convolutional neural network framework based on time series imaging to extract the characteristics of transmission line frequency domain correlation, and used discrete wavelet...
transform to denoise the fault voltage and current signals. The experimental results show that this method can achieve high-precision classification and detection of transmission line faults, and this method has certain advantages compared to other models [10]. The aforementioned methods can effectively remove the noise when extracting the features of abnormal communication signals, but there are deficiencies in the processing of nonlinear features in signals. In this article, wavelet packet decomposition is adopted to complete the multiscale detailed analysis of signals in both time domain and frequency domain. After processing the nonlinear features of the abnormal communication signal combined with nonlinear technology, the nonlinear dimension of the signal is reduced several times to complete the feature extraction of the abnormal communication signal.

2 Method of feature extraction of abnormal communication signal in network

2.1 Nonlinear processing of abnormal signals based on wavelet packet decomposition and local tangent space arrangement (LTSA)

Due to nonlinear features of abnormal communication signal in network, to accurately extract the features of abnormal communication signal in network [11], the nonlinear processing of abnormal communication signal in network is completed based on the combination of wavelet packet transform and LTSA mainstream shape recognition algorithm. Among them, wavelet transform is adopted to decompose the communication abnormal signal, and the kernel dimension and information dimension are calculated for the detail signal. The signal is orthogonally decomposed into each frequency band, and the noise reduction of time-domain signal is equivalent to the noise reduction of decomposition coefficients of wavelet packet. According to the distribution characteristics of noise and signal in each subband, the corresponding parameters are selected for phase space reconstruction and nonlinear dimension reduction of LTSA mainstream shape recognition algorithm, and the decomposition coefficients of wavelet packet after noise reduction are reconstructed to finally realize the nonlinear noise reduction of signal.

2.1.1 Wavelet packet decomposition

Although the traditional method of feature extraction for abnormal signal in network can be conducted in both time domain and frequency domain and because the abnormal communication signal in network is a nonlinear signal, the traditional time-domain analysis and frequency-domain analysis are global transformation changes, the abnormal signal cannot be analyzed in both time domain and frequency domain at the same time. Wavelet decomposition can transform the abnormal signal locally in time and frequency domain and effectively extract the abnormal information [12]. It can refine and analyze the abnormal signal in multiscale, so it is suitable for nonlinear feature extraction. Wavelet packet analysis can provide a more refined analysis method for signals. Wavelet packet analysis divides the time–frequency plane into more detailed parts, and its resolution for the high-frequency part of the signal is higher than that of the dyadic wavelet. Moreover, it introduces the concept of optimal basis selection based on the wavelet analysis theory. That is, after dividing the frequency band into multiple levels, the optimal basis function is adaptively selected based on the characteristics of the analyzed signal to match it with the signal, to improve the signal analysis ability. Therefore, wavelet packets have the extensive application value, so this study will choose wavelet packet transform as the algorithm for this study. The expression of the basic wavelet is given as follows:

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t - b}{a} \right),
\]

where \(a\) is the scale of wavelet signal and \(b\) is the offset of wavelet.

The basic wavelet transforms the scale and displacement to make the inner product with the original signal, and the result is the wavelet coefficient. This process is called continuous wavelet transform. However, to facilitate the analysis of abnormal signals [13], discrete wavelet transform is adopted in this article, and its expression is expressed as follows [14]:

\[
\psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m}t - n).
\]

After the discrete wavelet decomposition of the original abnormal signal, the characteristic solutions of the abnormal signal can be obtained in high frequency and low frequency. To illustrate the effectiveness of higher order cumulants in nonlinear abnormal signal processing, the concept of characteristic function is first introduced. It lets the probability density function of random variable \(x\) be \(f(x)\), and the first characteristic function equation of random variable is given as follows:

\[
\Phi(\omega) = E[e^{i\omega x}] = \int_{-\infty}^{\infty} e^{i\omega x} f(x) dx = \int_{-\infty}^{\infty} e^{i\omega x} f(x) dx.
\]

The second characteristic function equation of \(x\) is:
\[
\phi(\omega) = \ln \Phi(\omega).
\]  

(4)

For random vector \(x\), its higher-order cumulant can be defined as follows:

\[
C_{v_1,v_2,\ldots,v_k} = (-1)^r \frac{\partial^r \Phi(\omega_1, \omega_2, \ldots, \omega_k)}{\partial \omega_1^{v_1} \partial \omega_2^{v_2} \ldots \partial \omega_k^{v_k}} |_{\omega_1=\omega_2=\ldots=\omega_k=0},
\]

(5)

where \(r = v_1, v_2, \ldots, v_k\); the \(k\)-order cumulant of zero mean stationary random vector \(x = (x_1, x_2, \ldots, x_k)\) is given as follows:

\[
C_{x_1}(\tau_1, \tau_2, \ldots, \tau_{k-1}) = \text{cum}(x(t), x(t - \tau_1) \ldots x(t - \tau_{k-1})).
\]

(6)

Given the random process \(x\), the first- to fourth-order cumulants are calculated by the following method:

\[
\begin{align*}
C_{x}(i) &= E[x(n)] \\
C_{x}(i, j) &= E[x(n)x(n + i)] \\
C_{x}(i, j, k) &= E[x(n)x(n + i)x(n + j)] - R_x(i)R_x(j - k) - R_x(j)R_x(k - j) - R_x(k)R_x(i - j),
\end{align*}
\]

(7)

where \(R_x\) is the autocorrelation of random process \(x\).

It demonstrates that the mean and the mean square difference of the first-order cumulants and the second-order cumulants are the embodiment of the basic information in the signal; the third-order and the fourth-order cumulants of Gaussian random variable \(x\) are always zero. Therefore, when the signal conforms to the Gaussian process, the colored noise can be completely eliminated theoretically, reflecting the nonlinear features of autocorrelation in the abnormal signal. Therefore, this article adopts the second-order cumulants, the third-order cumulants, and the fourth-order cumulants as the method of feature extraction.

### 2.1.2 LTSA mainstream shape recognition algorithm

LTSA is a very effective nonlinear dimension reduction method. It is mainly used to describe the local geometry of the manifold by the low-dimensional tangent space in the neighborhood of sample points, and then to globally arrange the low-dimensional tangent space to obtain the low-dimensional global coordinates of sample points. Aiming at the correlation features between nonlinear and non-stationary abnormal signals generated in the process of network communication [15], in accordance with the correlation features between abnormal signal features, the LTSA in the nonlinear manifold learning method can eliminate a large amount of redundant information, reduce the signal noise, and improve the sensitivity of abnormal signal features. It can effectively obtain the internal low-dimensional manifold structure, which is embedded in high-dimensional space and mine the internal essential features of abnormal communication signal in networks. Therefore, on the basis of wavelet decomposition, this article uses LTSA mainstream shape recognition algorithm to further complete the signal denoising.

The signal set \(X = \{x_1 \in R^{d}; i = 1, \ldots, N\}\) is composed of the signal after wavelet decomposition. The main shape recognition using LTSA algorithm mainly includes the following steps:

(1) Construct neighborhood: For each sample point \(x_i\), determine its \(k\) nearest neighbors \(x_i\), and \(X_i = \{x_{i1}, x_{i2}, \ldots, x_{ik}\}\). The number of samples contained in the sample set is \(N\).

(2) Extract local information: Select a set of orthogonal bases \(Q\) in the neighborhood of data sample point \(x_i\), project \(X_i\) onto \(Q\), and mine the main information of signals in the neighborhood [16]. In the solution process, \(Q\) is mainly composed of the eigenvectors consistent with the \(d\) maximum eigenvalues of \((X_iH_k)(X_iH_k)^T\), where \(d\) is the dimension of the low dimensional manifold subspace, the local low dimensional coordinates of \(X_i\) are \(\Omega_i = Q^TX_iH_k\), and \(H_k = I - ee^T/k\) is the centralization matrix.

(3) The local tangent space global arrangement can be converted into a minimization problem’s approximate solution process, and its equation is given as follows [17]:

\[
\arg \min_T \sum_{i=1}^{N} E_i = \arg \min_T \sum_{i=1}^{N} \|T_iH_k - L_i\Omega_i\|,
\]

(8)

where the global low dimensional coordinate of \(X_i\) is \(T_i = [t_{i1}, \ldots, t_{ik}]\). In accordance with the equation, when \(L_i = T_iH_k\Omega_i^+\), the mapping error is the minimum, and \(\Omega_i^+\) is the Moore Penrose generalized inverse of \(\Omega_i\).

(4) Mainstream shape reconstruction: After obtaining the low-dimensional coordinates \(T = [t_1, \ldots, t_N]\) of all signals, the mainstream shape is reconstructed in its high-dimensional space by Eq. (9):

\[
\tilde{X}_i = X_i + QL_i^{-1}t_i - QL_i^{-1}t_i,
\]

(9)

where \(X_i\) and \(t_i\) are, respectively, the mean values of \(X_i\) and \(t_i\); the generalized inverse of \(L_i\) is \(L_i\). Finally, the mainstream shape \(Y \in R^{m \times N}\) in high-dimensional space is obtained; the embedding dimension is expressed in \(m\).

### 2.1.3 Overall process

Based on the above two parts, the overall flow of nonlinear signal processing based on wavelet packet transform and LTSA is obtained. The steps are as follows:

(1) The wavelet packet is used to decompose the one-dimensional time series \(x(t), t = 1, 2, \cdots, T\), and the corresponding wavelet packet decomposition coefficient \(p_{i,k}^n\) is obtained, where \(n \in [1, N]\) is the number of wavelet
2.2 Feature extraction of abnormal communication signals in network

2.2.1 Feature extraction

Principal component analysis (PCA) is an optimal orthogonal transformation based on the statistical features of the target and has the ability to extract the maximum descriptive features in the mode. However, PCA is a linear algorithm, which only considers the second-order statistical features in the data. When there are massive nonlinear relationships in the features of network communication signals, it cannot meet the requirements [18]. Therefore, kernel principal component analysis (KPCA), which is formed by the organic integration of PCA and kernel learning method is not only suitable for dealing with nonlinear problems but also can provide more information. KPCA realizes the selection of important characteristic variables while classifying in accordance with the size of energy entropy. Based on the analysis of network communication signals without assuming the distribution of signals [19], the nonlinear processing and dimensionality reduction of signals are realized by mapping the input space to the high-dimensional feature space.

The basic idea of KPCA is to map the abnormal communication signal in the network denoised in Section 2.1 to a high-dimensional feature space [20] through a nonlinear mapping and then to carry out linear principal component analysis on the feature space. Assuming that the input abnormal communication signals \( x_k \) in network are mapped to \( \phi(x_k) \), and they have been centralized, that is, the condition of Eq. (11) is satisfied, there is [21]:

\[
\sum_{k=1}^{N} \phi(x_k) = 0,
\]  

(11)
where \( x_i(k = 1, ..., N) \) is \( N \) abnormal communication signal samples of input training network and \( \phi(x_k) \) is the transformed training abnormal communication signal in network sample.

Covariance matrix \( C \) of abnormal communication signal sample of training network after mapping is given as follows:

\[
C = \frac{1}{N} \sum_{k=1}^{N} \phi(x_k)^T \phi(x_k). \tag{12}
\]

The following characteristic equations are solved:

\[
\lambda v = Cv. \tag{13}
\]

In accordance with the reproducing kernel theory, the eigenvector \( v \) must be located in the space composed of \( \phi(x_1), ..., \phi(x_N) \), that is, it can be expressed by the linear combination of \( \phi(x_1), ..., \phi(x_N) \):

\[
v = \sum_{i=1}^{N} a_i \phi(x_i), \tag{14}
\]

where \( a_1, ..., a_i \) is a constant.

Define a \( N \times N \) matrix \( K \):

\[
K_i = \phi(x_i)^T \phi(x_i). \tag{15}
\]

Eq. (15) is also called the kernel matrix. By substituting Eqs. (12), (14), and (15) into Eq. (13), we obtain:

\[
K a = N \lambda a. \tag{16}
\]

In this way, the problem of solving the eigenvector \( v \) of Eq. (13) is transformed into finding the eigenvector \( a \) of eigenequation (15). From Eq. (15), it can be seen that the nuclear matrix \( K \) is a symmetric, semi positive definite square matrix, and its eigenvalue will be nonnegative. By solving the characteristic Eq. (16), a set of nonzero eigenvalues \( \lambda_j \) and the corresponding eigenvector \( a_j(j = 1, ..., N) \) satisfying the normalization condition can be obtained. The condition expression satisfied is given as follows:

\[
\lambda_j(a_j, a_j') = 1. \tag{17}
\]

In accordance with Eq. (14), the projected principal component [22] of the network communication signal in the feature space can be obtained, which is represented by \( v_j(j = 1, ..., N) \).

Let \( x \) be a test sample, then its projection on \( v_j \) is given as follows [23]:

\[
(v_j)^T \phi(x) = \sum_{i=1}^{N} a_j^i \phi(x_i)^T \phi(x) = \sum_{i=1}^{N} a_j^i K(x_i, x). \tag{18}
\]

In accordance with the aforementioned steps, the projection feature vector of the original network communication signal can be obtained. In the aforementioned process, the selection process of principal component \( V \) is the process of feature extraction of abnormal communication signals in network.

KPCA is an extension of PCA. Its coordinates are nonlinear, that is, the nonlinear function representing \( X \) can be expressed by the principal component matrix \( U \), and its equation is given as follows:

\[
U = F(X), \tag{19}
\]

where \( F(\cdot) \) represents a nonlinear function, and its principal component inverse transformation is also nonlinear [24]. The calculation equation of inverse result \( \widehat{X} \) is given as follows:

\[
\widehat{X} = G(U), \tag{20}
\]

where \( G(\cdot) \) is also a nonlinear function. After obtaining the results in accordance with the above equation, important principal variables are selected to represent the most important information contained in the sample data.

In the process of feature extraction, KPCA guarantees the principle of minimum mean square deviation between cost functions \( X \) and \( \widehat{X} \), and it is expressed as follows:

\[
\min_{i=1}^{n} \| (X_i) - (\widehat{X}_i) \|, \tag{21}
\]

where \( X_i \) is the \( i \)th component of \( X \) and \( \widehat{X}_i \) is the \( i \)th component of \( \widehat{X} \).

2.2.2 Determination of nonlinear function

To ensure the best feature extraction, the two nonlinear functions of \( F(\cdot) \) and \( G(\cdot) \) should be determined. This article is completed based on self-organizing neural network. Figure 2 shows the network structure.

Self-organizing neural network is a five-layer forward network composed of two self-organizing neural networks, which consists of one input layer, one output layer, and three hidden layers. The input layer and output layer are \( n \) neurons, and the hidden layer in the middle is also called bottleneck layer. It is not only the output of the front self-organizing neural network but also the input of the back self-organizing neural network. The extracted main metadata can be used for the subsequent signal analysis [25].

The nonlinear transformation function \( f_1 \) is used for mapping the input vector \( X \) to the first hidden layer. The mapping result is \( h_{1}^{(X)} \), and the column vector length is \( l \), then:

\[
h_{1}^{(X)} = f_1((W^{(X)}X + b^{(X)})), \tag{22}
\]

where \( W^{(X)} \) and \( b^{(X)} \) are the weight matrix and bias vector of the hidden layer, respectively. The weight matrix of the hidden layer is trained by the network, and the bias vector is usually chosen as a constant.
where the weight matrix of $l \times n$ is $W^{(X)}$; the offset parameter vector of $l$ is $b^{(X)}$, where $i = 1, 2, ..., l$. The transformation function $f_2$ is adopted to map $h^{(X)}$ to the bottleneck layer to obtain the main element vector $U$ with only one element $\mu$, which is expressed as follows:

$$\mu = f_2(\omega^{(X)} h^{(X)} + b^{(X)}).$$

(23)

Generally, $f_1$ uses hyperbolic tangent function and $f_2$ selects the identity function. The mapping relationship between $f_1$ and $f_2$ constitutes $F(\cdot)$, so as to realize the dimensionality reduction extraction process of nonlinear principal component $U$.

After extracting the nonlinear principal component $U$, the nonlinear transformation function $f_3$ is selected to map $U$ to the third hidden layer. The mapping result is $h^{(U)}$, and its equation is given as follows:

$$h_i^{(U)} = f_3((W^{(U)} U + b^{(U)})_i),$$

(24)

where $i = 1, 2, ..., l$.

The nonlinear transformation function $f_4$ is adopted to map $h^{(U)}$ to the output layer to obtain the vector with $n$ elements. The equations are given as follows:

$$\widehat{X} = [\widehat{x}_1, \widehat{x}_2, ..., \widehat{x}_n]^T,$$

(25)

$$\widehat{X} = f_4((W^{(U)} h^{(U)} + b^{(U)}_i)).$$

(26)

When selecting the nonlinear transformation function, $f_1$ and $f_2$ select the same nonlinear function; $f_2$ and $f_4$ select the same nonlinear function [26], and the mapping relationship between $f_3$ and $f_4$ constitutes $G(\cdot)$, so as to realize the mapping process from $U$ to $X$.

### 3 Experimental analysis

To verify the performance and effect of the proposed method, a 500 megabit fiber-optic network server system in a laboratory is used as an example, and the communication state is simulated by MATLAB software. The parameter settings of the experimental environment are shown in Table 1.

<table>
<thead>
<tr>
<th>Number</th>
<th>Project</th>
<th>Size</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>Memory</td>
<td>1,024</td>
<td>GB</td>
</tr>
<tr>
<td>#2</td>
<td>Operating system</td>
<td>Windows XP</td>
<td>/</td>
</tr>
<tr>
<td>#3</td>
<td>Programming tools</td>
<td>Python, C++</td>
<td>/</td>
</tr>
</tbody>
</table>

The minimum value of the cost function of Eq. (19) is obtained by finding the optimal $W^{(X)}$, $\omega^{(X)}$, $B^{(X)}$, $W^{(U)}$, and $B^{(U)}$, so as to minimize the variance between the output $\widehat{X}$ and the original $X$ achieved by the neural network. When $f_2$ and $f_4$ select identity functions, we obtain [27]:

$$\mu = \omega^{(X)} \cdot h^{(X)} + b^{(X)},$$

(27)

$$\widehat{X} = (W^{(U)} \cdot h^{(U)} + b^{(U)}).$$

(28)

Based on the aforementioned steps, the feature extraction of abnormal communication signal in network is completed.

![Figure 2: Structure based on self-organizing neural network.](image)

![Figure 3: Time-domain waveform of simulation signal.](image)
interference, and signal tampering under the condition of 5 dB noise of the communication signal system are shown in Figures 3 and 4.

The proposed method is adopted to decompose the above simulation signals by wavelet packet. However, to ensure the decomposition results, the optimal values of the reconstruction time delay and the optimal embedding dimension in the decomposition process of this method should be determined. Taking the decomposed noise results as the measurement standard, the noise values in the decomposed signals under different parameter values are tested. The results are shown in Figure 5.

In accordance with the test results in Figure 5, the noise value fluctuates obviously under different reconstruction time delays, and the noise result is the lowest when the values are 4 and 5; when the optimal embedding dimension is 10, the noise value is the minimum. Combined with the reconstruction time delay results of 4 and 5, the minimum value is selected as the final result. Therefore, the optimal values of reconstruction time delay and optimal embedding dimension are 4 and 10, respectively, which are used in subsequent experiments.

To test the noise reduction effect of the proposed method, the proposed method is adopted for noise reduction of simulation signals. Figures 6 and 7 show the results. The ideal maximum signal spectrum is 0.105.

According to the test results in Figures 6 and 7, after noise reduction by the proposed method, the noise intensity in the signal is low, and there is only a small amount of noise components. It can be seen from the signal spectrum that the amplitude of the simulated signal after noise reduction is 0.1022, and the difference between the ideal signals is very small. The results clearly indicate that the proposed method has a good noise reduction effect.

To test the abnormal communication signals in network feature extraction performance of the proposed method, the resolution and sensitivity of the proposed method to three abnormal communication signals in both time domain and
frequency domain are tested with the resolution and sensitivity as the test standard. Table 2 shows the results.

According to the test results shown in Table 2, under different frequencies, the resolution and sensitivity of the proposed method to the time domain and frequency domain of the three abnormal communication signals are more than 92%, and the increase of frequency has a little impact on the resolution and sensitivity of the proposed method, indicating that the text method has good performance in extracting the features of abnormal communication signals in networks and has high resolution and sensitivity.

To test the feature extraction effect of the proposed method, the cumulative contribution rate of the eigenvalues of three network abnormal signals under different signal feature quantities is tested, so as to measure the extraction effect of this method. Table 3 shows the results. Among them, the number of signal features whose cumulative contribution rate is more than 90% is the principal component of the eigenvector of the abnormal signal.

According to the test results shown in Table 3, when there are five eigenvalues, the cumulative contribution rate of the eigenvalues of the three network abnormal signals reaches more than 90%, and when the number reaches 7, the cumulative contribution rate of eigenvalues of the abnormal signal networks reaches 100%. According to the results, the method proposed has good effect of feature extraction and can complete the characterization of most information of abnormal signal when the number of features is 5, that is, the feature extraction of abnormal signal can be completed at this time.

### 4 Discussion

The research object of nonlinear technology theory is nonlinear phenomenon. It is a kind of phenomenon that reflects the motion essence of nonlinear system, which cannot be explained by the theory of linear system. The main nonlinear phenomena include the frequency of dependence on amplitude, multivalued response and jumping resonance, subharmonic oscillation, asynchronous suppression, frequency capture, self-excited oscillation, bifurcation, and chaos. Abnormal communication signal in network is a typical nonlinear problem. By extracting the features of the signal, we can judge the operational state of the network and ensure the operational safety of the network. In this article, when extracting the features of abnormal communication signal in networks, nonlinear technology is adopted in the two steps of signal denoising and feature extraction, which are LTSA and KPCA, respectively. The combination of the two

### Table 2: Test results of resolution and sensitivity in both time domain and frequency domain, of three abnormal communication signals

<table>
<thead>
<tr>
<th>Test content Frequency (f/Hz)</th>
<th>Time domain features</th>
<th>Frequency domain features</th>
<th>Time domain features</th>
<th>Frequency domain features</th>
<th>Time domain features</th>
<th>Frequency domain features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resolution/%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>95.23</td>
<td>94.25</td>
<td>93.58</td>
<td>92.26</td>
<td>93.38</td>
<td>95.24</td>
</tr>
<tr>
<td>300</td>
<td>95.59</td>
<td>95.57</td>
<td>94.22</td>
<td>94.56</td>
<td>94.47</td>
<td>94.84</td>
</tr>
<tr>
<td>500</td>
<td>97.01</td>
<td>95.62</td>
<td>94.37</td>
<td>94.67</td>
<td>96.12</td>
<td>93.97</td>
</tr>
<tr>
<td>700</td>
<td>94.98</td>
<td>93.76</td>
<td>95.26</td>
<td>92.98</td>
<td>95.53</td>
<td>94.33</td>
</tr>
<tr>
<td>900</td>
<td>96.59</td>
<td>94.11</td>
<td>97.54</td>
<td>93.37</td>
<td>94.76</td>
<td>93.88</td>
</tr>
<tr>
<td>Sensitivity/%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>93.66</td>
<td>92.98</td>
<td>96.63</td>
<td>93.64</td>
<td>94.38</td>
<td>92.96</td>
</tr>
<tr>
<td>300</td>
<td>95.36</td>
<td>95.02</td>
<td>95.46</td>
<td>95.34</td>
<td>93.82</td>
<td>95.15</td>
</tr>
<tr>
<td>500</td>
<td>92.49</td>
<td>96.13</td>
<td>92.28</td>
<td>95.22</td>
<td>94.25</td>
<td>94.47</td>
</tr>
<tr>
<td>700</td>
<td>95.47</td>
<td>93.67</td>
<td>96.01</td>
<td>94.67</td>
<td>93.94</td>
<td>95.06</td>
</tr>
<tr>
<td>900</td>
<td>94.65</td>
<td>94.33</td>
<td>94.41</td>
<td>95.27</td>
<td>95.22</td>
<td>94.62</td>
</tr>
</tbody>
</table>

### Table 3: Test results of eigenvalue cumulative contribution rate of three network abnormal signals (%)

<table>
<thead>
<tr>
<th>Characteristic quantity/unit</th>
<th>Malicious attacks</th>
<th>Communication interference</th>
<th>Signal is tampered with</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42.4</td>
<td>46.2</td>
<td>43.7</td>
</tr>
<tr>
<td>2</td>
<td>50.6</td>
<td>51.8</td>
<td>55.2</td>
</tr>
<tr>
<td>3</td>
<td>71.7</td>
<td>73.2</td>
<td>74.3</td>
</tr>
<tr>
<td>4</td>
<td>84.5</td>
<td>85.6</td>
<td>82.5</td>
</tr>
<tr>
<td>5</td>
<td>94.6</td>
<td>95.2</td>
<td>94.4</td>
</tr>
<tr>
<td>6</td>
<td>98.2</td>
<td>97.8</td>
<td>96.8</td>
</tr>
<tr>
<td>7</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>
nonlinear technologies first reduces the signal noise and then extracts the features. The combination of the two methods can deal with the nonlinear problems in the signal to the greatest extent.

5 Conclusion

With the fast growth of information and communication technology, the communication network has become an indispensable information medium in people’s daily lives. However, the open communication network and its bearer protocol not only bring convenience to people but also cause great hidden dangers to network security. To ensure safe and efficient network operation, reduce the harm caused by different abnormal events to the normal communication network business, and build a credible communication network environment, the communication network operation should be analyzed and monitored in real time and accurately, and the security hidden dangers existing in the network operation should be found to and deal with potential problems. Among them, the feature extraction of abnormal signal is the basis for the analyzing and monitoring the operating state of communication network. Based on this, a method of feature extraction of abnormal communication signals in network is proposed based on nonlinear technology. After the nonlinear processing of abnormal signal is completed by wavelet packet decomposition and LTSA, the feature extraction of abnormal signal is completed by KPCA, which is formed by the fusion of PCA and kernel learning method. According to the test results, this method can significantly reduce the noise in the signal, has good abnormal signal sensitivity and resolution, and can accurately extract the principal components of abnormal signals under the two parameters of optimal reconstruction time delay and optimal embedding dimension.

Funding information: The author states no funding involved.

Author contributions: The author has accepted responsibility for the entire content of this manuscript and approved its submission.

Conflict of interest: The author states no conflict of interest.

Data availability statement: Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

References


