Model-based Intelligent Recognition for Aluminum Plate Seam Defects

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Abstract. In order to study the application of nonlinear ultrasonic in the quantitative identification of defective aluminum plate, different depth cracks are machined on the aluminum alloy plate with a thickness of 10 mm by wire cutting to simulate the defects in the plate. The normal and defective aluminum plates are selected to establish the experimental model, and the continuous wavelet transform (CWT) is used to extract the characteristic parameters of the aluminum plate nonlinear ultrasonic signal. The dimensions of the data are reduced by principal component analysis (PCA), and the principal component with the top three contribution rate are selected as the characteristic value. Finally, the support vector machine (SVM) algorithm is used to analyze the aluminum alloy plate state and classify the defect signal. The experimental results show that the feasibility of nonlinear ultrasonic signal recognition of aluminum plate defects is verified by combining principal component analysis and support vector machine model.

Keywords: Nondestructive testing, CWT, PCA, SVM

1. Introduction

Sheet metal is the key part of mechanical equipment, and its quality directly affects the operation reliability of mechanical equipment [1-2]. It is necessary to detect the possible defects such as pores and cracks in sheet metal. Ultrasonic nondestructive testing is suitable for the detection of internal defects of mechanical equipment due to its advantages of high detection accuracy and harmless to human body and experimental objects [3-4]. At present, the domestic research on this aspect mainly focuses on the recognition of non-linear coefficient of non-linear ultrasonic echo signal of metal plate defects, but the research on feature extraction of non-linear ultrasonic echo signal of defects and the application of the extracted data to the classification and recognition of defects is still relatively few [5]. The quantitative identification of defects is a new research focus in the field of nonlinear ultrasonic testing, and it is also a problem to be solved.

The accuracy of nonlinear ultrasonic testing usually depends on the experience of the operator and the accuracy of the equipment. In this context, digital information technology (such as continuous wavelet transform and principal component analysis) is proposed for nonlinear ultrasonic testing to provide decision-making information. Chen et al. used PCA to reduce the dimension of defect signal, and then used support vector machine to identify the defect signal of pipeline girth welding [6]. F. C.
Cruz et al. used machine learning to identify defects. The obtained nonlinear ultrasonic signal obtained features through continuous wavelet transform, and then reduced the dimension of the obtained feature signal through principal component analysis. The neural network is trained to identify defects intelligently [7].

Support vector machine (SVM) has incomparable natural advantages in the analysis of small sample data, such as strong learning ability and generalization ability. It is widely used in regression estimation, system identification and pattern recognition. Chen et al. used wavelet kernel to fit the point of nonlinear function in high-dimensional feature space, and chose Morlet wavelet support vector machine for gear pattern recognition [8]. S. Sambath et al. combined wavelet decomposition with support vector machine classifier to detect crack defects in steel sheet [9].

In the feature parameter extraction of nonlinear ultrasonic echo signal of plate defects, in order to avoid directly selecting many feature parameters as the eigenvalues of support vector machine, this paper combines principal component analysis and support vector machine to identify and classify defect signals [10]. For the nonlinear ultrasonic signal collected in the experiment, continuous wavelet transform is used to extract the characteristic parameters of the nonlinear ultrasonic signal, PCA is used to reduce the dimension of the data, and the principal component with the top three contribution rate after dimension reduction is selected as the characteristic value, and then SVM is used for intelligent recognition of the defect signal. Finally, the results verify the feasibility of using this method to detect the seam defects of sheet metal.

2. Continuous Wavelet Transform
The basic idea of wavelet transform is that different frequency components in the actual signal have different time-varying characteristics. Generally, the slowly changing signal has the spectrum of lower frequency components; on the contrary, the sharply changing signal has the spectrum of higher frequency components. The function of wavelet transform is to combine the signal with a translation stretching wavelet base which has localization properties in time domain and frequency domain the convolution function is used to decompose the signal into components in different time and frequency bands [11-12].

By introducing the window function \( \psi_{(a,b)}(t) = \frac{1}{\sqrt{\pi a}} \psi \left( \frac{t-b}{a} \right) \), the continuous wavelet transform can be defined as:

\[
W_f(a,b) = \frac{1}{\sqrt{\pi a}} \int f(t) \psi \left( \frac{t-b}{a} \right) dt
\] \hspace{1cm} (2-1)

Where \( a \in R \) and \( a \neq 0 \), \( a \) is the scaling factor, which represents the frequency dependent stretching, and \( b \) is the time translation factor.

The Fourier transform of window function is as follows

\[
\psi_{(a,b)}(\omega) = \frac{1}{\sqrt{\pi a}} \int_{-\infty}^{\infty} \psi \left( \frac{t-b}{a} \right) e^{-i\omega t} dt = \frac{a}{\sqrt{\pi \omega}} e^{-ia\omega} \psi(\omega a)
\] \hspace{1cm} (2-2)

Let wavelet function and its Fourier transform meet the requirements of window function. It can be proved that for any parameter \((a, b)\), continuous wavelet and its Fourier transform meet the requirements of window function, and their center and window width are:

\[
\begin{align*}
E(\psi(a, b)) &= b + aE(\psi) \\
\Delta(\psi(a, b)) &= |a|\Delta(\psi)
\end{align*}
\] \hspace{1cm} (2-3)

Where \( E(\psi) \) and \( \Delta(\psi) \) are the center and window width of wavelet function, \( E(\Psi) \) and \( \Delta(\Psi) \) are the center and window width of Fourier transform.

Therefore, the time window and frequency window of continuous wavelet \( \psi_{(a,b)}(t) \) are:

\[
\left[ b + aE(\psi) - |a|\Delta(\psi), b + aE(\psi) + |a|\Delta(\psi) \right]
\] \hspace{1cm} (2-4)

It is easy to get that the time-frequency window of continuous wavelet \( \psi_{(a,b)}(t) \) is a variable matrix on the time-frequency plane.

\[
\left[ b + aE(\psi) - |a|\Delta(\psi), b + aE(\psi) + |a|\Delta(\psi) \right] \times \left[ \frac{E(\Psi)}{a}, \frac{\Delta(\Psi)}{|a|} \right]
\] \hspace{1cm} (2-5)

The area of time-frequency window is:
The area of time-frequency window is not related to parameters \((a, b)\), but only to \(\psi(t)\). When \(a > 0\) and \(a\) is small, the time-frequency window width \(|a|\Delta(\psi)\) becomes smaller with \(a\), the time window \([b - |a|\Delta(\psi), b + |a|\Delta(\psi)]\) becomes narrower (here \(\Delta(\psi) = 0\), and the center frequency \(E(\psi)/a\) becomes higher. At this time, the detection of wavelet transform is mainly high-frequency components, and the high-frequency components change rapidly in the time domain. In order to get the information of high-frequency components accurately, the time window at this point is smaller, and wavelet transform has this function. When \(a > 0\) and \(a\) is larger, the time window width \(|a|\Delta(\psi)\) becomes larger with \(a\), the time window \([b - |a|\Delta(\psi), b + |a|\Delta(\psi)]\) becomes wider, and the center frequency \(E(\psi)/a\) becomes lower. At this time, the signal detected by wavelet transform is mainly the low-frequency component. The low-frequency component transforms slowly in time-frequency. In order to get all the information of a low-frequency point, the time window at that point should be larger, and wavelet transform also has such characteristics.

In addition, the wavelet transform \(\psi_{(a,b)}\) of the signal \(f(t)\) adaptively extracts the time-frequency information in the time bands \([b - |a|\Delta(\psi), b + |a|\Delta(\psi)]\) and \([\frac{|\psi(\tau)|}{a} - \frac{\Delta(\psi)}{a}, \frac{|\psi(\tau)|}{a} + \frac{\Delta(\psi)}{a}]\), and localizes the signal in the time and frequency domains. This is the localization ability of wavelet transform, which can realize the localization of time and frequency domain at the same time. Therefore, the time and location of defects can be determined.

3. PCA Dimension Reduction

In order to improve the efficiency and accuracy of plate defect classification, feature parameters need to be obtained more fully. However, the similarity between feature parameters will greatly affect the classification results, but the increase of feature parameters will also increase the complexity of the algorithm. Therefore, to analyze the feature parameters, extract the effective components of the classification algorithm, and classify different defect states, we need to reduce the complexity of the feature parameters, which is of great significance for the defect classification algorithm.

Principal component analysis (PCA) can effectively reduce the complexity of defect feature parameters, and it is easy to implement the algorithm, so it plays an important role in feature dimension reduction. Principal component analysis (PCA) is a nonlinear dimension reduction method, which can not only keep the effective information of defects completely, but also simplify the complex information of defects. Therefore, the principal component analysis method is selected to reduce the complexity of defect signal characteristic parameters.

In order to better implement the feature parameter dimension reduction algorithm, it is necessary to analyze the data and algorithm involved in principal component analysis.

3.1. Data

Suppose that the representation of data is a set of \(m\) vectors

\[
\hat{X} = \{\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_m\}
\]

Each element of vector \(\hat{x}_i\) contains \(n\) features, such as \(\hat{x}_i = \{x_{i,1}, x_{i,2}, \ldots, x_{i,n}\}\). It is necessary to analyze the application direction of feature vector and make feature dimension reduction scheme. In the process of defect detection, each element in the vector set represents the reference basis for defect classification.

Each feature parameter is grouped to generate the corresponding feature vector. For the feature set \(\hat{X}\), the feature vector \(k\) is expressed as \(C_{x,k} = [x_{1,k}, x_{2,k}, \ldots, x_{m,k}]^T\). \(k\) is the dimension of feature parameter, and \(x\) in its subscript is used to distinguish it from the feature principal component analysis.

The vector \(C_{x,k}\) represents each element in the vector set. It is represented by column vectors and grouped as follows:

\[
C_{x,k} = [c_{x,1}, c_{x,2}, \ldots, c_{x,n}]
\]

After the principal component analysis of vector \(C_{x,k}\), we can get the principal component which is more sensitive to defects, so we use covariance to study the change of data statistically, and then keep
the defect data which has obvious change. Based on the above principle, the work of grouping eigenvectors is completed.

3.2. Covariance
Calculating the covariance of eigenvectors can indicate the degree of correlation between eigenvectors. For the eigenvector composed of two elements, the vector is expressed in the form of \( \mathbf{x}_i = [\mathbf{x}_{i1}, \mathbf{x}_{i2}] \), the covariance is as follows

\[
\sigma_{x,1,2} = E[(\mathbf{x}_{i1} - \mu_{x,1})(\mathbf{x}_{i2} - \mu_{x,2})]
\]  

(3-3)

In order to reduce the dimension of aluminum alloy plate defects, we need to carry out the product algorithm between the feature elements. \( E \) is to calculate the expected value of the feature elements. For the mean \( E[\mathbf{c}_{x,k}] \), we can get the product of the mean \( E[\mathbf{c}_{x,k}] \) and the unit vector, so as to get the vector \( \mathbf{x} \). Each element in the vector represents the mean value of the feature, so the calculation process of covariance first requires the mean value of the difference between each eigenvalue and its corresponding eigenvalue, and then multiplies the elements and calculates the mean value of the product.

\[
\sigma_{x,1,2} = \frac{1}{m}((\mathbf{x}_{i1} - \mu_{x,1})(\mathbf{x}_{i2} - \mu_{x,2}))
\]  

(3-4)

In the process of covariance calculation, each column vector represents a group of defect features. For the case that each row vector represents defect features, the formula is transformed into the form of the latter factor device. For the above two cases, the covariance is calculated, and the symmetric relationship \( \sigma_{x,1,2} = \sigma_{x,2,1} \) is obtained.

Covariance can be used to judge the correlation between feature parameters. Different feature parameters will have many aspects of correlation, and covariance only studies the feature parameters which are linearly correlated.

3.3. Covariance matrix
For the extracted feature parameters, when it presents a multi-dimensional form, one group of feature parameters of each covariance is defined, and the covariance is combined in the form of matrix, namely covariance matrix. The specific definition is as follows

\[
\Sigma_x = \begin{pmatrix}
\sigma_{x,1,1} & \cdots & \sigma_{x,1,n} \\
\vdots & \ddots & \vdots \\
\sigma_{x,n,1} & \cdots & \sigma_{x,n,n}
\end{pmatrix}
\]  

(3-5)

The form of covariance matrix can be changed as follows

\[
\Sigma_x = \frac{1}{m}((\mathbf{c}_x - \mu_x)(\mathbf{c}_x - \mu_x))
\]  

(3-6)

Since the covariance has a symmetric relationship, the elements in the diagonal position of the covariance matrix are the variances of the defect features, so the matrix contains defect information. PCA is used to express the covariance in the form of diagonal matrix. In other words, this method transforms the defect information to reduce the correlation between the defect feature parameters, so as to be better applied to the defect classification.

3.4. Data transformation
Principal component analysis maps every feature in vector set \( X \) to a single feature in vector set \( Y \) through a nonlinear transformation \( W \), which makes the features in vector set \( Y \) linearly independent, that is, the covariance between different features is 0. The definition is as follows:

\[
\mathbf{c}_Y = \mathbf{c}_X W^T
\]  

(3-7)

The results are as follows:

\[
\mathbf{c}_Y = W \mathbf{c}_X^T
\]  

(3-8)

In order to obtain the covariance of the features in vector set \( Y \) from the features in vector set \( X \), the above two formulas are transformed as follows:

\[
\Sigma_Y = \frac{1}{m}[(W \mathbf{c}_X - E[W \mathbf{c}_X^T])(\mathbf{c}_Y W^T - E[\mathbf{c}_Y^T W^T])] \]

(3-9)

The matrix \( W \) is factorized as follows:

\[
\Sigma_Y = \frac{1}{m}[W(\mathbf{c}_X - \mu_x)^T(\mathbf{c}_X - \mu_x)W^T]
\]  

(3-10)
It can adjust the matrix $W$ so that $\Sigma_Y$ is a diagonal matrix, that is, the features in $Y$ are linearly independent.

### 3.5. Inverse transformation

The defect characteristic parameters in the set $X$ are changed, and the mapping process is completed to obtain the matrix $Y$ containing characteristic elements. This process is called inverse transformation. The covariance matrix of the transformed matrix $Y$ is in the form of diagonal matrix, and the inverse transformation is equivalent to performing transpose, as follows:

$$ W^{-1} = W^T $$

The results are as follows:

$$ \Sigma_Y = W^{-1} \Sigma_X (W^T)^{-1} $$

Because of the symmetry of covariance matrix $\Sigma_X = (\Sigma_X)^T$, and there are:

$$ W^{-1} \Sigma_X (W^T)^{-1} = W^{-1} \Sigma_Y (W^T)^{-1} $$

The results are as follows:

$$ W^{-1} = (W^{-1})^T \text{ and } (W^T)^{-1} = ((W^T)^{-1})^T $$

The mapping relation $c^T_Y = WC^T_X$ can be expressed as:

$$ W^{-1} c^T_Y = W^{-1} WC^T_X $$

The results are as follows:

$$ W^{-1} c^T_Y = c^T_Y $$

### 3.6. Eigenvalue

Because the inverse transformation is equivalent to performing transpose, formula (23) can be expressed as follows:

$$ \Sigma_X W^T = W^T \Sigma_Y $$

Expand the left and right sides of the equation to get:

$$ \Sigma_X W^T = \Sigma_X \begin{bmatrix} W_{1,1} \\ \vdots \\ W_{n,1} \\ \vdots \\ W_{1,n} \\ \vdots \\ W_{n,n} \end{bmatrix} + \cdots + \begin{bmatrix} W_{1,1} \\ \vdots \\ W_{n,1} \\ \vdots \\ W_{1,n} \\ \vdots \\ W_{n,n} \end{bmatrix} $$

By calculating the above formula and combining formula (3-17), the matrix $W$ is obtained as follows:

$$ \Sigma_x W_i = \lambda_i W_i $$

Where $W_i$ matrix is the i-th row of $W$, which is the eigenvector of the matrix, and $\lambda_i$ is the eigenvalue of the matrix.

### 3.7. The solution of eigenvalue

Let $I$ be the identity matrix, then $\lambda_i W_i = \lambda_i IW_i$, then from formula (3-19) can see that:

$$ (\lambda_i - \Sigma_x )W_i = 0 $$

When the eigenvector is 0, the solution is very simple; when the rank of determinant is solved, another set of solutions is as follows:

$$ \det(\lambda_i - \Sigma_x ) = 0 $$

The above formula is the characteristic equation. The eigenvalue $\lambda_i$ can be obtained by formula (3-21), so as to further obtain the eigenvector $W_i$, the column vectors of the transformation matrix $W$ are eigenvectors.

### 3.8. The contribution rate $V$ of each eigenvalue is calculated as shown in formula (3-22).

$$ V_i = \frac{\lambda_i}{\sum \lambda_i} \times 100\% $$

The larger the calculated value of $V_i$, the stronger the covering ability of the relevant principal components for the original characteristic parameters. The contribution rate $V_i$ of different eigenvalue conditions is calculated, and the values are sorted from large to small, and the corresponding principal components are obtained. Then, according to the cumulative contribution rate, the final retained principal component is selected. The cumulative contribution rate $P(m)$ is as follows:
The cumulative contribution rate is calculated by equation (3-23). When the cumulative value is greater than 85%, these principal components are used as the new characteristic parameter matrix.

4. Support vector machine
Support vector machine (SVM) is a kind of machine learning, which adopts the principle of structural risk minimization, and based on the statistical theory, finds the optimal result between the complexity of the model and the learning ability according to the limited sample information.

Support vector machine can intelligently recognize and classify two different kinds of samples. The classification problem can be divided into linear separable in the sample space or non separable in the sample space. When the sample space is linearly separable, different samples can be divided by introducing a partition hyperplane. The optimal partition hyperplane means that in many partition planes, the distance between two different samples closest to the partition plane is the largest, and the partition hyperplane is the optimal. In the case that the sample space is not separable, it is impossible to find a partition hyperplane in the sample space to divide different samples. At this time, it is necessary to map the samples to a higher latitude space through nonlinear mapping, and find the optimal partition hyperplane in the higher latitude mapping space, so as to solve the problem of linear inseparability in the original space.

Two kinds of training samples are given

\[(x_i, y_i), i = 1, 2, \ldots, n, x \in R^d, y \in \{1, 0\}\]  

(4-1)

Where \(n\) is the number of training samples, \(d\) is the dimension of samples, and \(y\) is the class label.

The linear equation of classification is as follows

\[\omega \cdot x + b = 0\]  

(4-2)

Where \(\omega\) is the weight coefficient vector of classification surface and \(b\) is the threshold value of classification.

If all training samples can be correctly separated by a hyperplane, and the distance between the nearest heterogeneous samples is the largest, then the hyperplane is the optimal hyperplane, and the nearest heterogeneous sample is called support vector, which has a one-to-one correspondence with the hyperplane.

For the problem of linear separability, the normalization of the vectors in the training set is satisfied.

\[y_i(\omega \cdot x_i + b) \geq 1, i = 1, 2, \ldots, n\]  

(4-3)

The distance between the support vector and the hyperplane is \(1/||\omega||\), so the distance between the support vector machines is \(2/||\omega||\), so the problem of constructing the optimal hyperplane is transformed into the problem of finding the minimum value of \(||\omega||\).

If the linearity is not separable, add a non negative relaxation variable \(\xi_i \geq 0\) in equation (4-3), which is expressed as follows:

\[y_i(\omega \cdot x_i + b) \geq 1 - \xi_i, i = 1, 2, \ldots, n\]  

(4-4)

Change the minimization objective function to:

\[\frac{1}{2}||\omega||^2 + C(\sum_{i=1}^n \xi_i)\]  

(4-5)

when the optimal classification surface is determined, the minimum wrong samples and the maximum classification interval are considered. \(C > 0\) is considered to be certain, which controls the punishment degree of wrong samples.

The optimal classification surface problem is transformed into a simple dual problem by Lagrange operator.

\[
\begin{cases}
\min Q(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\
\sum_{i=1}^n y_i \alpha_i = 0 \\
C \geq \alpha_i \geq 0, i = 1, 2, \ldots, n
\end{cases}
\]

(4-6)

The classification decision function is obtained as

\[sgn(\sum_{i=1}^n \alpha_i y_i (x_i \cdot x) + b)\]  

(4-7)
For nonlinear classification, SVM uses an appropriate inner product kernel function $K(x_i, x_j)$ to map the data samples to a high-dimensional space to find the optimal classification surface, and realizes the linear classification after nonlinear transformation without increasing the computational complexity.

$$Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i=1}^{n} a_i a_j y_i y_j K(x_i, x_j)$$

Choosing different inner product kernel functions will form different SVM models. In this paper, radial basis function (RBF) is chosen.

$$K(x, y) = \begin{cases} \exp \left( -\frac{\|x-y\|^2}{\sigma^2} \right) \\ 0 \end{cases}$$

The parameters of SVM kernel function need to be set artificially. Cross validation method is used to determine the best kernel parameter $\gamma$ and penalty factor $c$.

5. Experimental device and echo signal acquisition

5.1 experimental device

The detection system used in this experiment was RAM-5000-SNAP high-energy ultrasonic detection system developed by American ritec company. The detection system mainly has six modules: RAM-5000-SNAP platform module, impedance matching module, attenuator module, low-pass filter module, active amplifier module and band-pass filter module. The schematic diagram of the experimental device composed of six modules, computer, DSOX2020A oscilloscope, transmitting probe, sample and receiving probe is shown in Fig.5-1. The excitation signal (electrical signal) generated by the ultrasonic nonlinear detection system is transmitted to the transmitting probe through impedance matching, attenuator and low-pass filter. After the transmitting probe converts the electrical signal into vibration signal, it is transmitted into the test piece and propagated to the receiving probe. In the process of signal propagation in the metal plate, there will be reflection, refraction and other phenomena, resulting in waveform distortion and secondary and higher harmonics. Due to the weak high-order harmonic signal, it is easy to be covered by the noise and fundamental signal attached to the system. The receiving probe converts the vibration signal into an electrical signal, and then the electrical signal needs to be processed by a band-pass filter and a signal amplifier, and then the signal is transmitted to the receiving terminal 1. Because the passband filter will filter out the low frequency signal, the received echo signal is mainly the second harmonic signal. Fig.5-2 shows the user software display interface. In the process of non-linear ultrasonic testing, DSOX2020A oscilloscope connected to RAM-5000-SNAP platform can detect the time domain signal of echo signal in real time.
In this experiment, ipsilateral ultrasonic excitation receiving method was used. The ultrasonic signal excited by the excitation probe propagates along the direction of the specimen and was received by the receiving probe. The angle adjustable probe was used to excite the ultrasonic wave. As shown in Fig.5-1, according to the actual measurement, when the angle of transmitting probe and receiving probe was adjusted to 50°, the display of echo signal on the oscilloscope was the best. In this experiment, 2.5 MHz sine pulse train was selected as the center frequency of the excitation signal, and Hanning window was used to adjust the excitation signal. After windowing, the energy of the excitation signal can be more concentrated, the side lobe can be obviously suppressed and the energy leakage can be reduced, so that the effect of the received signal was better. In order to ensure that the frequency component of the response signal was more pure, the number of the pulse train should be as many as possible, and then ensure that the received signal can not overlap, so the excitation signal of 15 cycles was selected. Therefore, the excitation signal finally selected in this experiment was 15 cycles single frequency sine pulse train modulated by Hanning window. Fig. 5-3 shows the time domain waveform of the excitation signal.

5.2 Test specimen
The material of the test piece was 6061 aluminum alloy, and the size was 250mm × 100mm × 10mm. In the middle of the test piece along the width direction, the wire cutting method was used to process artificial cracks with depth of 0mm, 1mm, 5mm and width of 0.1mm. The relationship between the nonlinear ultrasonic echo signal and the defect state of sheet metal was studied.

5.3 Echo signal acquisition
The consistency of measurement conditions should be maintained when collecting echo signals of different defect states. The non-linear ultrasonic experiments were carried out on the plates of 0mm, 1mm, 5mm. The time-domain waveform of echo signal was collected by DSOX2020A.
oscilloscope. The center frequency of transmitting probe was 2.25 MHz, and that of receiving probe was 5 MHz. Because this experiment uses the excitation signal of the pulse train, the echo signal was also the form of the pulse train, and the main information of the defect was also concentrated in the echo pulse train, and the extracted echo signal mainly collects the pulse train of the echo signal. The echo signals collected by the three groups of experiments are shown in the green box of fig.5-4.

Fig 5-4. Echo signals of three groups of experiments

6. Experimental Results and Analysis

6.1 Continuous wavelet transform results
The difference between the defect states of plates in different states exists objectively. The three groups of echo signals shown in Fig.5-4 are difficult to distinguish them directly from the waveform. In order to highlight the characteristics of defects in various states, continuous wavelet transform is applied to the echo signal based on the characteristics that the nonlinear ultrasonic echo signal is unstable and time-varying. It can be seen from the expression of wavelet transform that wavelet transform uses the function of wavelet function and signal function to detect and analyze the characteristics of signal function. The result of wavelet transform is not only related to the characteristics of signal function, but also related to the selection of basic wavelet function. The basic wavelet should be selected according to the characteristics of signal function, so that the wavelet transform can depict the characteristics of signal, aluminum alloy plate The non-linear ultrasonic echo of wood crack defect is an unstable time-varying signal. The selected base wavelet should be able to obtain outstanding time-frequency resolution of continuous wavelet transform time-frequency map of signal echo. The time-frequency analysis ability of Cmor wavelet is excellent. The time-domain and frequency-domain forms of wavelet have some properties of Gaussian function. Many decompositions can be carried out in the frequency domain, and the analysis signal can be decomposed adaptively. Therefore, in this paper, Cmor wavelet is used as the base wavelet to perform continuous wavelet transform on three groups of experimental signals, and the time-frequency of wavelet coefficients is obtained as shown in Fig.6-1.
It can be seen from Fig. 6-1 that the time-frequency diagrams of the wavelet coefficients of the three groups of experiments show the energy time-frequency distribution of the reflected echoes of different defects, and the wavelet coefficients of the reflected echoes of different defects are obviously different. Continuous wavelet transform (CWT) can provide abundant information of defect echo in different states, and the time-frequency image of wavelet transform can better extract the feature of defect signal.

6.2 PCA results
After feature extraction of the three groups of experimental signals, principal component analysis is used to process them. It is found that the first four principal components contain more than 85% of the effective information. The contribution rate and cumulative contribution rate of each principal component of the three groups of experiments are shown in Fig. 6-2. Therefore, the top three principal components are selected as the eigenvalues.

6.3 Support vector machine results
The experimental data extracted in this paper are non defect data and defect data. The defect data has two states: 1 mm defect signal and 5 mm defect signal. A total of three groups of signals are collected. In each experiment, 200 data sets were selected, among which 140 data of various states were selected as the training set of SVM, and 60 data of each group were selected as the test set. Through cross validation, the optimal kernel parameter $g$ and penalty factor $c$ are determined as $g = 42.2243$.
and Best \( c = 2 \) respectively. The feature values are extracted from the test sets of the three groups of experiments and used as the input of the trained SVM model. The recognition results of the three groups of experimental signals are shown in Fig. 6-3.

![Recognition results of defects in different states](image.png)

**Fig 6-3.** Recognition results of defects in different states

It can be seen from the results that the recognition accuracy of non-defect is 95.625% and 93.75% respectively for 1mm defect and 5mm defect. There is no fitting in the training process, and the defect signal and non-defect signal can be almost recognized, achieving good results. Similarly, this method can be used to identify 1 mm defect and 5 mm defect, and the recognition accuracy of the test set reaches 99.375%, which can well identify defects of different depths.

**7. Conclusion**

An intelligent recognition method based on PCA and SVM was proposed, and experiments were carried out to verify whether the method can effectively distinguish and recognize the plates with different defects. For the nonlinear ultrasonic echo signal, continuous wavelet transform had obvious physical significance. The time-frequency diagram of wavelet coefficients can describe the three-dimensional information of the signal in time-frequency-wavelet coefficients. It can more fully display the effective information of the defect echo and extract the characteristic parameters. Principal component analysis was used to reduce the dimension of the extracted characteristic parameters, which can effectively reduce the characteristic parameters it made the subsequent processing more efficient and accurate. Finally, it was verified that the defects in different states can be identified effectively. In addition, the method can also effectively distinguish the crack defects with different depth. Therefore, it was effective and reliable to apply this method to the detection of aluminum alloy seam defects. This method can also provide a reference for other sheet metal defect detection research.

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