Application of Probabilistic Neural Network in Bonding Quality
Ultrasonic Detection of Composite Material

Runjing Zhou, Guanzhong Ren, Ze Zhang
College of Electronic Information Engineering, Inner Mongolia University
E-mails: auzhourj@163.com
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Abstract
The bonding quality of composite plate material is detected by ultrasonic waves. Taking ultrasonic
detection signal as the research object, the theory of detection method pulse reflection echo method is
comprehensively analyzed. Surveying the information carried by the echo signal of detection ultrasonic
waves, the signal energy, signal duration and the product of singular wave peak value and quantity are
regarded as characteristic values. According to the Probabilistic Neural Network sorting algorithm,
the composite plate material bonding quality is divided by the qualitative judgment. Experimental
results show that compared with Radial Basis Function Neural Network, the algorithm is very exact for
recognition of bonding quality, and is more suitable for the classification of discrete data.

Keywords: Bonding Quality, Probabilistic Neural Network, Ultrasonic Echo Simulation

1. Introduction
With the wide application of composite material in the field of national defense industry, aviation &
aerospace industry and medical industry as well as the prevention of serious accidents resulting from
bonding quality, the bonding structural safety and quality has become especially important. In the non-
destructive testing of metal and nonmetal bonding technology, the ultrasonic detection has found its
great application for its strong penetrating power, high sensitivity, physical harmlessness and well-
developed technique and so on. Reference[1] proposed that energy of echo signal be used as
characteristic data to distinguish signals, but it is greatly influenced by pressure and surface
smoothness in practical application. Reference[2] put forward BP neural network based on Radio
Frequency signal detection theory, but the accuracy of the results is low. Reference[3] presented that
Radial Basis Function Neural Network (RBFNN) be faster in convergence rate and more exact in
approximation accuracy. However, when the quantity of samples expands, the number of neurons in
hidden layer increases greatly which results in the network has a huge structure, and the performance
declines.

Probabilistic Neural Network (PNN) is becoming popular in recent years. It is one of the
transformation forms of the RBFNN, which has simple structure and rapid training speed, especially
suitable for pattern classification issues.

2. Mathematical model of echo signal
2.1. Theory of pulse reflection echo method
The detection method used to examine the composite plate is pulse reflection echo method, that is,
the ultrasonic waves are transmitted to the examined workpiece in a very short time, then echoes of the
bottom surface or internal defects can be taken to detect the location and size of reflection source. The
theory of pulse reflection echo method is shown as Figure 1. Generally only one probe that can
transmit and receive signals is needed to process the testing.

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2.2. **Physical model of ultrasonic propagation**

When the ultrasonic wave propagates in medium, its amplitude will gradually decreases with the distance increases, which is so-called attenuation. Theoretically, when ultrasonic waves pass through the interface of different media, the propagating behavior is shown in Figure 2, the following events will happen:

1. Ultrasonic signals will be reflected, refracted and scattered, which cause the energy dispersion.
2. In the propagation process, ultrasonic signals will weaken as part of the energy is absorbed.

The attenuation equation is

\[
E = E_0 e^{-\alpha x}
\]  

(1)

Where \( E_0 \) is the energy of ultrasonic signals at \( x = 0 \); \( E \) is the energy that signals arrive at \( x \); \( \alpha \) is the attenuation factor of the medium.

\[R = \frac{Z_2 - Z_1}{Z_1 - Z_2}\]  

(2)

Where \( Z_i = \rho_i C_i \), \( Z_1 \) is the acoustic impedance of incident medium, \( \rho_i \) is the density of incident medium, and \( C_i \) is the propagation velocity of ultrasonic waves in the incident medium; \( Z_2 = \rho_2 C_2 \) is the acoustic impedance of reflecting medium, \( \rho_2 \) is the density of incident medium, and \( C_2 \) is the propagation velocity of ultrasonic waves in the reflecting medium. When ultrasonic signals transmit from solid to gas \( Z_1 \gg Z_2 \) or from gas to solid \( Z_2 \gg Z_1 \), \( R \) approximate equals 1, which is called total reflection.

2.3. **Mathematic model of ultrasonic echoes**

Echo signal has a cosine form of decay index, which can be expressed as:
In this formula, parameter $A$ is a constant which reflects the bonding quality. The bigger $A$ is, the more energy returns and the worse the bonding quality is; and the smaller $A$ is, the better the bonding quality is. Parameter $\alpha$ is a constant which reflects the attenuation speed of echo signal energy in the plate, for the same plate it is the same.

The total echo signal is the superposition of multiple echo, and the intervals $t_d$ of every two echoes is the same, so the total echo signal is as follows:

$$h(t) = \sum_{i=1}^{k} Ae^{-\alpha t} \exp[-i\omega(t - (i - 1)t_d)] \cos[\omega(t - (i - 1)t_d)]$$

Where $k$ is the number of superimposed echo during a period of observation time.

The simulation parameters of echo signal is set up according to the above formula: the thickness of the plate in the assumption is 3mm, the velocity of ultrasonic signal is 5000m/s, then

$$t_d = \frac{2 \times 3mm}{5 \times 10^{-2} \times 10^{-3} \text{mm/s}} = 1200\text{ns}$$

Considering the observation time of echo is about 10us, then the superposition number of the echo in the observation time is 8 ($k=8$); attenuation factor of the plate is set up as 13 ($\alpha=13$); assuming that central frequency of echo signal is 2.5MHz, then $\omega=15.7(T-1)$. Taking $A=0, 0.3, 0.5, 0.7$, the echo signal is simulated respectively, results are showed in Figure 3 – Figure 6.
3. Probabilistic neural network

PNN is evolved from Bayesian criterion of multivariate pattern classification. Figure 7 shows the construction of PNN that can divide the input samples into two categories. It is a four-layer forward network, including: input layer, pattern layer, accumulation layer and output layer.

Samples are delivered to every node of pattern layer; the function of nodes in pattern layer is to weight sum of the input, then after an operation of a nonlinear operator, pass to the accumulation layer, as is shown in Figure 8.
Here the nonlinear operator is
\[ g(z_j) = \exp\left(\frac{(z_j - 1)}{\sigma^2}\right) \]  

If \( X \) and \( W_j \) are standardized to unit length, equation (6) is equivalent to
\[ g(z_j) = \exp\left[-\frac{(W_j - X)^T(W_j - X)}{2\sigma^2}\right] \]

The accumulation layer is just to sum up the inputs from pattern layer which are corresponding to the same kinds in training samples, namely:
\[ f_s(x) = \sum_{j=1}^{s} g(z_j) \]  

The output layer also known as decision layer, its node is shown in Figure 9. It generates a binary output, in which weight c equals to minus prior probabilities ratio of the two types and divided by the number ratio of the two types of training samples.

PNN shown as Figure 7 is equivalent to Bayes pattern classification method when the multivariable probability density function is Gauss core(following formula).
\[ f_i(X) = \frac{1}{(2\pi)^{v/2} \sigma^v} \sum_{j=1}^{s} \exp\left[-\frac{(X - X_{Aj})^T(X - X_{Aj})}{2\sigma^2}\right] \]  

Where \( X \) is the input sample vector; \( s \) is the variable number of sample vectors; \( X_{Aj} \) is the \( j \)th training sample vector which belongs to type A, it is used as weight in PNN; \( m \) denotes the number of training sample vector that belongs to type A; \( \sigma \) is the smoothing coefficient.

This is a common PNN, does not need to learn, and the so-called training is just to take the training samples of every type as the weight of input layer and pattern layer, and each type has the same smoothing coefficient. When a set of samples are inputted, they are classified by the network output value.

In order to improve the classification ability of PNN, reference[5] proposed the improved PNN, in which each pattern type has different smoothing coefficient, and the training process is to make sure
every smoothing coefficient using training samples by optimization method. The common PNN is used to identify the bonding quality in this article.

4. Selection and calculation of characteristic value

4.1. Echo signal energy (ESE)

Difference of bonding quality will lead to the difference of the number and amplitude of echo. Therefore, different bonding quality has different echo energy. As the echo signals are converted to digital signals by the filter circuit and A/D sampling circuit, the energy equation is:

\[ E = \sum_{i=1}^{N} S_i^2 \]  (10)

4.2. Product of singular wave peak value and the quantity (PSWQ)

It can be seen from the simulation of echo signal that if the bonding quality has a problem, strange waves will appear in the echo signal. The worse the bonding quality is, the higher the first singular wave peak value is, and the more the singular wave appears. Therefore, choosing the product of the first singular wave peak value and the quantity in echo signal as a characteristic value can effectively reflect whether the bonding quality is good or bad.

4.3. Duration of signal (DS)

The attenuation of ultrasonic in transmission process is approximate as exponentially decaying of frequency. As the location and size of the bonding defect is different, the decay rate of echo signal is different. The time that from the pulse waveform beginning to the last time it passing through 5% of the peak is selected as a characteristic value. According to the duration of signal, the level of debonding can be judged out.

5. Experiment

The pulse reflection echo method is used to detect 18 metal and nonmetal composite compound plates that the bonding quality is known. The thickness of metal material is 1-10mm and the thickness of nonmetal material is 2-3mm. There are 4 types to be recognized, 6 of the 1st type 100% bonding, 4 of the 2nd type 70% bonding, 5 of the 3rd type 30% bonding, 3 of the 4th type non-bonding. So the 3 characteristic values can be got from 18 ultrasonic echo signals (Table 1). Then 20 unknown bonding quality compound plates which are of the same kind are detected. The data are shown in Table 2.

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Table 2. Characteristic Values (T=Type)

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<td>2072.59</td>
<td>25.51</td>
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5.1. Identification result of RBFNN

RBFNN is trained by the data in Table 1, the number of the neurons in hidden layer is added automatically, until satisfies the error request.

When the number of neurons in hidden layer is added to 28, the error of training samples is almost 0(less than $8 \times 10^{-3}$). The samples to be measured are classified by this network. Results are shown in Table 3.

Table 3. Result of RBFNN (T=Type)

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It can be seen that the errors of 27th, 30th, 35th of the samples are large, more than 0.3, and class recognition is misjudged; the errors of 21st, 24th are between 0.2 and 0.3; and the errors of 20th, 36th and 38th are between 0.1 and 0.2; others are below 0.1. This is because that the discrete samples are different from the continuous functions, RBFNN can not approach perfectly, and the output of the RBFNN is linear, which does not consider the probability of a sample belonging to a type.

5.2. Identification result of PNN

Likewise, PNN is trained by the data in Table 1, after training the network is used to classify the samples in Table 2. The identification results are shown in Table 4. The experiment indicates that the results generated by this method accord with the bonding quality that are confirmed, achieves the purpose of identification.

Table 4. Result of PNN (T=Type)

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The comparison of two algorithms is shown in Table 5.
Table 5. Comparison of two algorithms

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<th>Iterative times</th>
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<tr>
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<td>100%</td>
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</table>

6. Conclusion

The advantages of PNN are that complicated tasks can be completed by employing the linear algorithm instead of nonlinear algorithm, meanwhile the high precision feature is also well achieved. Compared with RBFNN, a lot of feedback calculation will be avoided while the high recognition rate is obtained. The PNN algorithm is simple and just needs a short training time, furthermore it is not easy to converge to a local minimum point. However, the recognition rate has great influence by contact degree of probe and plate, it is needed to keep on improving in this aspect.

7. References