The Study on the Intelligent Defect Recognition Methods in the Ultrasonic Non-Destructive Test of Welds

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Abstract: For a long time, intelligent and qualitative defect recognition problem in the ultrasonic non-destructive tests of welds has been a difficult problem that needs to be solved urgently but cannot be solved properly. This paper introduces a method that uses wavelet packet transform technology to perform the noise reduction and characteristic value extraction of defect echo signals. And then based on the distance and pattern recognition method by artificial neural network, use both the classification separability criterion to perform automatic recognition and classification for them. On this basis, we have developed the intelligent defect recognition system for ultrasonic flaw detection of welds based on the MATLAB software. It can achieve automatic collection, processing as well as intelligent recognition and classification of defect echo signals. The testing results show that both the characteristic value extraction method and qualitative defect recognition method that are used in this paper are very effective.

Keyword: Ultrasonic Testing; Intelligent Defect Recognition; Wavelet Packet Transform; Feature Extraction; Neural Network

1 Introduction

Ultrasonic testing is a non-destructive test method that is widely used now. However, qualitative defect recognition problem in the ultrasonic flaw detection hasn‘t been solved completely. Its main causes are as follows: ultrasonic defect echo signal is a typical transient signal, the frequency spectrum from traditional Fourier analysis method can not reflect feature information such as mutation position of its time domain and appropriate frequency simultaneously, and feature extraction and selection of defect echo signals is the premise of defect classification. Accordingly, the advantages and disadvantages of feature extraction method affect directly on the correctness and reliability of defect classification.

The wavelet transform has the features of higher time-frequency resolution and multi-resolution analysis. It is applicable to the analysis and processing of transient signals. In this paper, the defect echo signals measured actually are decomposed into the different scales using wavelet packet decomposition method. By statistical analysis for the energies on these scales, select characteristic energy on the typical frequency band to compose characteristic vectors that reflect the essential features. We perform the separability measure analysis for them by using classification separability criterion based on the distance, the ultrasonic testing for defect recognition and classification of welds by using the neural network classifier, and the related testing studies and verifications.

2. Feature extraction of ultrasonic echo signals by wavelet packet transform

After performing wavelet packet decomposition, smoothing and detailed signals in these scale spaces can provide time-frequency local area information of original signals, especially composing information of the signals in the different frequency bands. On the other hand, the property of echo signals can be described by its wavelet packet factor. The more wavelet packet factor is, the more information the energy of the signal will carry. The wavelet packet transform has a “concentration” capacity which can concentrate the energy of signals into minority factors within the wavelet packet transform. The values of these factors are greater than that of other wavelet packet factors. If the signal energies on the different decomposition scales have been evaluated, select the energies on the decomposition scales that have larger wavelet packet factor, and sort them in the order of the scales, then the characteristic vectors can be formed for subsequent recognition. These are basic principles of multi-scale space energy feature based on the wavelet packet decomposition extraction signal [4]. As described above, wavelet packet library contains several wavelet packet basis and each group of wavelet packet basis forms a different orthogonal basis of the space, therefore, for target echo signals, the decomposition can be performed by using different wavelet packet basis, thus there is the problem of optimal basis selection. In all wavelet packet basis, the decomposition results of optimal basis can reflect time-frequency features of the signal at most and also reflect the self-adaptability of wavelet packet algorithm for signal feature. This paper hereby selects the wavelet packet basis constructed by the Daubechies118 wavelet as optimal basis for the decomposition [2] [5]. Individual energy feature extraction process is shown in the figure 1. Where, the purpose of time-frequency preconditioning process is mainly for the energy normalization processing of echo signals. Partial scale spaces mainly refer to the spaces having larger wavelet factors (i.e., the space with relatively concentrated energy).

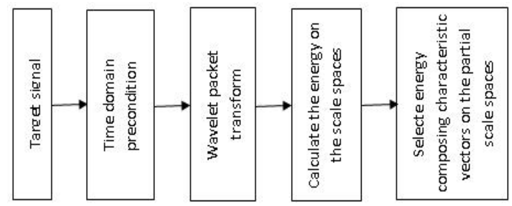

Figure 1 Energy feature extraction method of multi-scale space based on the wavelet packet transform

3. Feature extraction and evaluation of echo signals for ultrasonic testing

Using the above method, we have performed the energy feature extraction of multi-scale spaces for ultrasonic defect echo signals by Model CTS222 ultrasonic defectoscope. Select the Daubechies18 wavelet packet as optimal basis, and perform the wavelet packet decomposition on the five spaces for these signals. Its decomposition binary tree is shown in Figure 2.

In the actual flaw detection, wide frequency band pulse wave is usually used, therefore the frequency spectrum distribution of defect echo is wider, and there is defect information on the scales after performing wavelet packet decomposition. For this reason, select the frequency band energies distributed on the different scales (expressed in the x_0 to x_9 in the figure 3) to compose the vectors.

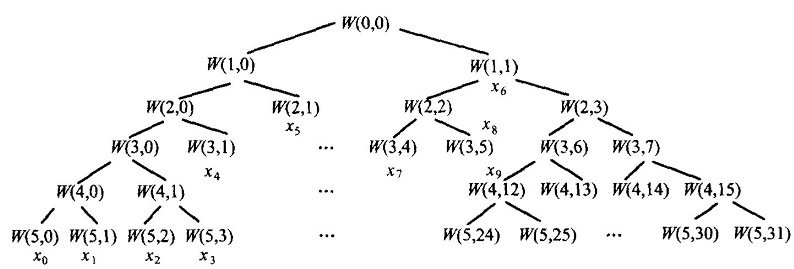

Figure 2 Binary tree and frequency band energy selection for wavelet packet decomposition of ultrasonic testing signals

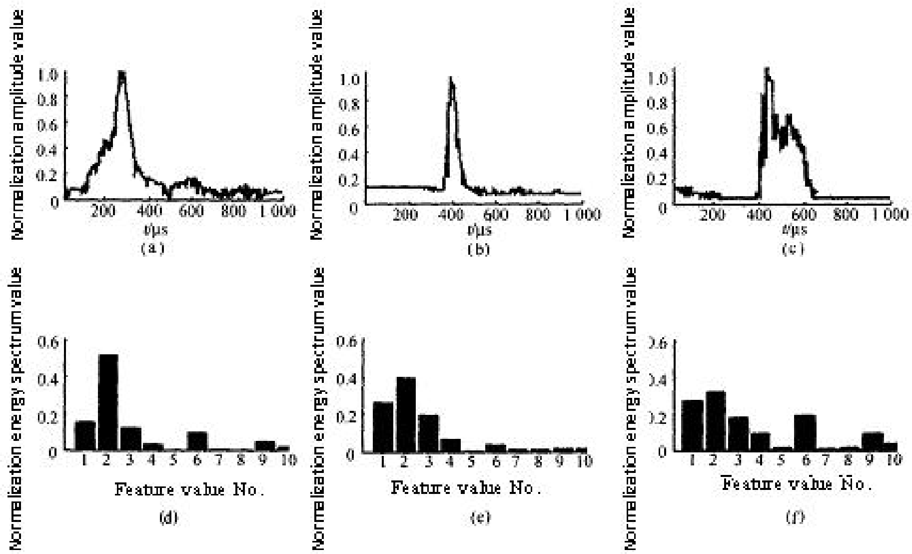

Figure 3 Characteristic energy spectrums for wavelet packet decomposition extraction and defect waveform of adding wire, cracks and porosity

(x_0 , x_1 , ···, x_9), as characteristic value of this signal.

Figure 3 shows actually measured echo signals of adding wire, cracks and porosity in the welds as well as the extracted characteristic energy spectrum histograms after performing their wavelet packet decomposition, where Figure 3a, 3b and 3c are respectively original waveforms of adding wire, crack and porosity defects; Figure 3d, 3e and 3f are respectively the extracted energy spectrums after performing wavelet packet decomposition. From the figures, we can see that after performing wavelet packet decomposition, energy distributions for defect echo signals with different properties have different frequency bands, and distribution difference on the selected frequency band is obvious. Therefore, they can be regarded as characteristic values of different types of defects, and are used as the basis of subsequent defect classification.

Feature extraction of ultrasonic defect echo signals is the premise and key of qualitative defect recognition. The choice of effective characteristic values plays key role for improving accuracy rate of the recognition. There are many methods for feature extraction. A quantitative criterion is required for determining which method has the best classification result. Common classification separability criterions include classification separability criterion based on the distance, separability criterion based on the entropy function, etc [6]. In this paper, we select the classification separability measure method based on the distances within the classification and between the classifications [7], and use this method to perform the separability measure calculation of above multi-scale energy feature based on the Daubechies18 wavelet packet decomposition extraction. The samples under the test consist of three defects of adding wire, cracks and porosity (20 samples for each defect). The sampling frequency of the signals is 20 MHz, and recording length of sampling is 1024 sampling points. The results show that for the extracted characteristic vectors, data quantity isn’t only compressed greatly (at this time, the length of data is only 10), but also the separability measure mean of three types of defects reaches 0. 917, which means that this feature extraction method feature extraction is very effective for defect echo signals of ultrasonic testing.

4. Intelligent defect recognition based on the neural network and genetic algorithm

Ultrasonic defect echo signal is a typical transient signal. It contains large amount of information, the waveforms of different types of defect echo are so similar that it is difficulty for flaw detection personnel to recognize and distinguish them according to their experiences. However, artificial neural network offers powerful robustness and self-organizating, self-learning, self-adaptability and parallel data processing capacity. Therefore, it is feasible to perform the defect classification recognition of welds by using pattern recognition method based on the neural network. The genetic algorithm, as a new global optimization search algorithm, has the advantages such as strong adaptability, global optimization, parallel processing. It is very suitable for optimization design of neural network. Combining the genetic algorithm with neural network in the actual applications can make use of the advantages of each method, and it has become an important development trend of neural network technology.

Based on the MATLAB platform and its accessory neural network toolbox, this paper designs and establishes additional momentum BP neural network, RBF network, LVQ network and additional momentum BP network by using GA optimization. Then, we perform the training for these models. Finally, using four neural network models after the training, we perform the pattern classification recognition test for weld defect samples measured actually during ultrasonic flaw detection.

In the 60 samples（including three types of defects: adding wire, porosity and cracks, 20 samples for each type）, the sampled 36 samples (12 samples for each type) form a training sample set, and use the rest 24 samples as the sample to be recognized. Use optimal subspace entropy values and characteristic vectors for wavelet packet decomposition of defect echo signals as input pattern vector of the network, and its dimension is 10. The number (n) of neurons in the input layer of neural network also is 10. The number (m) of neurons in the output layer of neural network depends on the number of sample target pattern, where output target vector is set as (1 0 0), (0 1 0), (0 0 1) (3 in total), corresponding to adding wire, porosity and cracks respectively. The number (m) of neurons in the output layer is 3. Four networks are designed as single hidden layer network structure. To ensure that function approximation performance is met while the comparison of network performance is easy, the number of nodes (l) in the initial hidden layer of network models are 40. Therefore, initial neuron composing ($n-l-m$) of four network models are 10-40-3 structure.

After performing the training for four neural networks by using 36 training samples, perform the classification and recognition as input neural network classifier of the samples to be recognized, then perform the network test by using the rest 24 samples. Comprehensive testing results of the networks are shown in Table1.

Table 1 Statistical table for neural network classification recognition results of weld defect samples

Item / Type	Training samples			Testing samples			Comprehensive recognition rate
	Number of samples	Number of correct classification	Correct recognition rate	Number of samples	Number of correct classification	Correct recognition rate	
Network □	36	36	100%	24	21	87.5%	95%
Network □	36	36	100%	24	22	91.7%	96.7%
Network □	36	36	100%	24	22	91.7%	96.7%
Network □	36	36	100%	24	22	91.7%	96.7%

Notes: □ additional momentum BP network; □RBF network; □LVQ network; □additional momentum BP network using GA optimization

From the classification results in the table1, we can see that for training sample, correct recognition rate of the designed four types of neural network classifiers are 100%. For testing samples, the lowest recognition rate is also above 87.5%. This means that the design structures of the networks are basically rational, has strong learning capacity, and is capable to perform the modeling according to the specified input and output relationship. Meanwhile, the tests also show that the correct recognition rate and convergence speed of additional momentum BP network after using GA algorithm optimization are obviously increased comparing with additional momentum BP network without the optimization.

The above results show that it is very effective that performing intelligent recognition of weld defects in the ultrasonic testing using the neural network classifier. For different types of neural network classifiers, due to their differences on the network topological structures and learning algorithm mechanisms, their training convergence speed and recognition accuracy rate also are different; combining the genetic algorithm (GA) with neural network can make use of the advantages of each method, and the convergence speed and recognition rate of additional momentum BP network after performing GA optimization are increased obviously comparing with that before the optimization.

In addition, recognition results in Table 1 also further demonstrate that Wavelet packet decomposition optimal subspace entropy value and feature extraction method used in this paper are very effective. The dimension of characteristic vectors of the extracted weld defect signal is lower, the separability is higher. Therefore, the complexity of structure of neural network classifiers is reduced greatly, and has the advantages such as good separability, higher classification recognition rate.

5. Intelligent defect recognition system design based on the MATLAB

When performing ultrasonic flaw detection, the signals received by the ultrasonic defectoscope contain a great deal of useful information which reflects defects and features of the materials. But the existing ultrasonic testing units aren't provided with advanced signal processing and interpretation software, so the information can not be fully used. This requires selecting a platform suitable for signal processing and system design because it is important to the implementation of analysis method and the programming of application software. Since the MATLAB software offers powerful data computation, signal processing and system analysis functions while it can provide the users with convenient environment in which the users can design the graphic interfaces according to the requirements. This paper uses the MATLAB software as development platform, performs the preliminary design of signal processing and intelligent defect recognition system for ultrasonic flaw detection of metal materials. This system has the features of user-friendly, easy operations, and it can achieve data acquisition of echo signals, defect signal feature extraction and intelligent defect recognition.

The main function modules and interfaces of the system include as follows: collecting ultrasonic original waveform with the signal collection module, selecting the defects with the signal interception module, eliminating the interference with the noise reduction processing module, performing the wavelet noise reduction, extracting the related characteristic signals from defect signals, performing data compression, and performing automatic recognition of defect types by selecting different neural network classifiers using the intelligent recognition module [8]. In addition, they also include the functions such as the establishment of defect database (including the database of typical defect signals such as cracks, porosity, adding wire, incomplete penetration), the training of network nerves, and performance analysis of the system. With the expansion of sample database and continuous improvement of network performance, the system can be updated and improved gradually so that the accuracy rate of defect type recognition is further increased.

4. Conclusions

Noise interference in the ultrasonic echo signals is an important factor that affects the defect analysis and evaluation. In this paper, we use the wavelet packet noise reduction method to process the echo signals. The results show that this method can effectively filter and eliminate noise interference, and the characteristic information of initial signal is reserved to the greatest extent while the signal to noise ratio is increased.

The advantages and disadvantages of defect signal feature extraction methods directly affect the classification results of subsequent defect recognition. This paper gives optimal subspace entropy value and feature extraction method for wavelet packet transform of defect echo signals, performs the feature extraction of the signal measured actually, and performs the separability evaluation for the extracted characteristic vectors by using the classification separability criterion. The results have proven that this method is very effective.

With the MATLAB platform, we establish four network models of BP, RBF, LVQ and BP network with genetic algorithm, and respectively perform the training and recognition tests for them based on the weld defect samples. The results show that the weld defect recognition of ultrasonic testing using neural network classifiers is very effective, but the training convergence speeds and recognition rates of different neural networks are different, where the convergence speed and recognition rate of the BP network with genetic algorithm optimization is increased obviously comparing with BP network without the optimization. The testing results have further proved the good effect of the wavelet packet transform feature extraction method used in this paper.

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