Research on Ultrasonic Quantitative Evaluation Technology of Complex Defects Based on Neural Network

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Abstract. As one of the five non-destructive testing methods, ultrasonic testing is widely used because of its accurate positioning, high sensitivity and simple operation, but the method is still difficult to locate and quantify complex shape defects. The large amount of data required for ultrasonic imaging leads to low detection efficiency. Based on this, the article establishes an inversion system for evaluating complex shape defects, which includes ultrasonic A-scan technology, BP neural network, image processing technology and signal processing technology. The system is verified by simulation and experiment. The results of the defect inversion are as follows: the similarity coefficients are all greater than 0.89, the maximum value can reach 0.95; the area error is less than 11\%, the minimum value can reach 1.2\%; the centroid x error is less than 12\%, the minimum value can reach 1.58\%; the centroid y error is less than 11\%, the minimum value can reach 2.15\%. The result of defect inversion further verifies the accuracy and reliability of the complex defect inversion system.

1. Introduction

With the rapid development of science and technology, various industrial fields such as aviation and high-speed rail have put forward higher requirements for the performance of materials. However, various defects may occur during the production and use of the material. These defects seriously affect the mechanical properties of materials, reduce the life cycle of products, and cause huge losses to the national economy[1-2]. For example, a major derailment accident of the high-speed train ICE-1 occurred in the town of Asheide, Celle, Germany in June 1998, causing 101 deaths and 194 injuries. The investigation revealed that the cause of the accident was a series of defects in the steel ring on the double steel wheel due to metal fatigue. Therefore, how to effectively detect defects has become a key issue in industrial production. Ultrasonic testing, as one of the five major non-destructive testing methods, is widely used due to its strong penetrating ability, high sensitivity, simple operation, and harmlessness to human body [3-4].

Ultrasonic testing can judge defects with the characteristics of ultrasonic reflection, refraction, transmission and attenuation [5-6]. Although ultrasonic testing technology has been widely used in many fields, its application has certain limitations due to its own reasons: (1) It is difficult for ultrasonic
testing to detect the complex defects. The technique of positioning and quantification complex shape defects need to be improved. Jing et al. successfully reconstructed the defects by using ultrasonic imaging technology to study irregular defects, combined with elastic reverse-time migration algorithm, but the accuracy of the defect quantification needs to be improved [7]. (2) It is slow and costly for the ultrasonic testing to image defects. Holmes et al. succeeded in imaging defects with clear results by using full-matrix data as the basis of the full-focus method for the first time, but the processing speed is not high enough and real-time imaging is complicated because the amount of data required during the imaging process was relatively large [8]. (3) There are few studies on using artificial intelligence algorithms to improve the accuracy of quantitative detection of defects. Most of them are used for classification detection [9]. Xiao et al. used an improved ultrasonic measurement model and a support vector machine model to classify defects in metal objects, but they did not perform quantitative analysis on the defects [10]. Li et al. realized quantitative detection of surface cracks on metal objects based on laser ultrasound using improved neural networks and particle swarm algorithm [11]. Although they achieved quantitative detection of defects, they didn’t conduct experimental verification and the internal defects of specimens was not analysed [12-15].

In order to achieve quantitative analysis and rapid imaging of complex defects, this paper proposes a new defect detection system that includes BP neural network, signal processing technology, image processing technology and pulse reflection method. In the detection system, the ultrasonic pulse reflection method has the advantages of high sensitivity and easy operation to obtain the pulse reflection wave containing defect-related information; the signal processing technology is used to extract the characteristic values of the ultrasonic echo that are sensitive to the defect; the powerful nonlinear mapping ability of the BP neural network is used to establish the nonlinear relationship between the defect and the signal, the rapid inversion of the defect is realized based on the established nonlinear relationship.

The organization structure of this article is as follows. Section 2 describes the defect inversion system based on BP neural network, signal processing technology and image processing technology. Section 3 introduces the flow of finite element simulation and experiment. Section 4 introduces the data expansion, feature extraction and optimization based on signal processing technology. The fifth section realizes the defect imaging based on BP neural network technology and image processing technology, which analyses the error of the imaging results. Conclusions are provided in Section 6.

2. Ultrasonic Inspection System

The ultrasonic inspection system designed in this paper is shown in Figure 1, it is mainly composed of 5 parts, ultrasonic inspection system, signal processing system, image processing system, BP neural network system and defect pseudo-colour image generation system.

Ultrasonic A-scan is used to collect ultrasonic signals containing defect information. While moving, the probe receives the ultrasonic signals reflected in different directions of the defect, forming different data sources. Compared with a single data source, the defect information contained in multiple data sources is more comprehensive, which is beneficial for the defect location analysis and quantitative analysis; Based on the signal processing system, this paper extracts and finds the features which is sensitive to defects from both the time domain and frequency domain, and the features can be input into the BP neural network; By using image processing technology, the test block image can be binarized. The binarized image can be used as the output of neural network; In the BP neural network, all its information is distributed and stored in each neuron in the network, which has strong robustness and fault tolerance. Due to the parallel distributed processing method, it is possible to perform a large number of calculations quickly. It can meet the real-time requirements of the defect inversion system [16-18]. By using this defect inversion system, various information such as the shape, location and size of the defect can be accurately detected.
3. Simulation and experiment

3.1. Simulation

3.1.1. Defect test block

In this article, the finite element software COMSOL is used to establish the simulation model of different hole defects. In the simulation, two types of defects with circular and isosceles triangle shapes were set, as shown in Figure 2. The radius of the circular defect is set to \( r \), the base of the triangular defect is set to \( a \), \( h \) represents the height of the triangle; the centroids of the two defects are located on the axis of \( x=50 \text{mm} \).

![Figure 2. Schematic diagram of defects](image)

![Figure 3. Fitting relationship between amplitude and angle \( \theta \).](image)
3.1.2. Materials and other parameters

Aluminum is widely used because of the characteristics of high strength, low density and corrosion resistance. And often being used as the standard test block for ultrasonic pulse detection because of the better ultrasonic conductivity, lower ultrasonic attenuation and scattering, the material used in this paper is Aluminum, with density is 2870kg/m$^3$ ($\rho=2870kg/m^3$), the Young’s modulus is 71GPa ($E=71GPa$), the poisson’s ratio is 0.33 ($\nu=0.33$). The material at the defect is replaced with air. Table 1 shows the signal excitation, grid parameters and time step parameters. In the simulation, the probe moves along the x-axis, with the consideration of the relationship between the size of the included angle and the ultrasonic amplitude. As shown in Figure 3, the amplitude will increase in an S-shape as the angle increases. Considering the probe diameter $D$ and the detection angle $\theta$, this paper gives equation (1) to calculate the maximum step distance of the probe step. According to the probe diameter of 10mm and the best detection angle range of 75.2°~90°, the range of the step length is less than 3.34mm. The step length selected in this paper is 2mm. Each defect must be inspected four times during the inspection process. The probe positions for the four inspections are located at $x=50mm$, $x=52mm$, $x=54mm$, and $x=56mm$. The received ultrasonic signals are defined as UT1, UT2, UT3 and UT4 respectively.

$$l \leq \frac{D^2}{4\lambda \tan \theta}$$  \hspace{1cm} (1)

Where $D$ denotes the probe diameter, $\theta$ denotes the angle between the probe and the defect.

| Table 1. Defect size (unit: mm). |
|-------------------------------|
| Isosceles triangle             | Round                  |
| Base ($a$) | Height ($h$) | radius ($r$) |
| 4   | 3       | 1      |
| 4.25 | 3       | 1.5    |
| 4.5  | 3       | 2.5    |
| 5   | 5       | 3      |
| 5.5  | 4       | 3.5    |
| 5.75 | 4       | 4.5    |
| 6   | 4       | 5      |

| Table 2. Simulation parameters. |
|--------------------------------|
| Parameters | Calculation formula | Value |
| Signal stimulus $Y(t)$ | $Y(t) = A(1 - \cos(2\pi f_0 t/5)) \sin(2\pi f_0 t)$ | $f_0=2.5MHz$ |
| Grid parameters $l_{\text{max}}$ | $l_{\text{max}} \leq \lambda/12$ | 0.2018mm~0.016mm |
| Time Step $\Delta t$ | $\Delta t \leq l_{\text{min}}/c_p$ | 0.005μs |
| Probe stepping | $l \leq \frac{D^2}{4\lambda \tan \theta}$ | 2mm |

$A$—signal amplitude; $f_0$—center frequency of pulse function; $l_{\text{max}}$—maximum cell size; $\lambda$—ultrasound wavelength; $l_{\text{min}}$—minimum cell size; $c_p$—ultrasonic velocity. $l$—probe step distance; $D$—probe diameter.
3.2. Experiment

3.2.1. Preparation of test block
In order to study the law between ultrasonic signals and defects, the material selected in this experiment is 2024 aluminium, and 10 different defects are prefabricated internally by the wire cutting method. The test piece is a cubic with a length of 60mm, a width of 60mm, and a height of 40mm, as shown in the Figure 4.

3.2.2. Ultrasonic experimental system
The schematic diagram of the ultrasonic testing experimental platform is shown in Figure 5, which is mainly composed of AFG3102 signal generator, MDO3014 oscilloscope, ultrasonic probe and computer. In this inspection system, the test piece is fixed in the inspection bracket, and the ultrasonic probe is located at the centre of the upper surface of the test piece, and moves along the x-axis to obtain defect information in different directions. The ultrasonic wave is generated by controlling the signal generator, and then enters the material through the dual crystal probe and the couplant to propagate. At the same time, the dual crystal probe collects the reflected echo signal, and the oscilloscope displays the collected ultrasonic signal and saves it in the computer. At least three repetitive tests are performed for each test position, and then the average value is taken to represent the test result.

3.3. Comparison of experiment and simulation
The collected signals are normalized due to the difference in magnitude before the comparative analysis, Figure 6(a) shows the comparison between the experimental signal and the analogy signal collected on the triangular defect. Figure 6 (b) is a comparison diagram of the signals collected on the circular defect. It can be seen from the figure that the trend similarity between the signals is higher and the difference is smaller, which proves the correctness of the finite element simulation.

4. Data expansion and feature extraction

4.1. Data expansion
In this paper, 190 working conditions are obtained by changing the shape, location and size of defects, including 182 simulated working conditions and 8 test working conditions. 760 sets of ultrasonic signals were obtained by changing the position of the ultrasonic probe (UT1, UT2, UT3, UT4), including 728 sets of analogy signals and 32 sets of experimental signals. In order to reduce the generalization error and make the neural network training more robust, it is necessary to expand the data. In this paper, three different levels of random Gaussian noise (10dB, 15dB, and 20dB) are added to the simulation data set. Therefore, a total of 2944 sets of ultrasound signals can be used as training sets.
4.2. Feature extraction

The signal contains a lot of information about defects in time domain, frequency domain and morphological features. In order to realize the automatic extraction of features, this paper defines the feature values specifically. Figure 7 shows a schematic diagram of the time-domain envelope and frequency-domain feature definitions. The selection of features is the prerequisite for qualitative and quantitative analysis of defects. The pros and cons of features directly determine the accuracy and reliability of defect inversion. Before training, it is necessary to remove features that are not highly related to defects, and only retain feature values that are highly sensitive to defects to avoid the disaster of dimensionality. Generally speaking, sensitive eigenvalues have the following characteristics: (1) The selected feature is independent of other features. (2) The difference between different defect characteristics is large. (3) The number of features must be the smallest set that can fully distinguish different defects. By analyzing the relationship between feature values and defects, based on the above-mentioned principle of sensitive features, this paper extracts a total of 11 feature values that are sensitive to defects, namely: peak $I_m$, $T_F$ for amplitude reduction, and 0.1 $I_m$ straight line duration $T_{10}$, 0.5$I_m$ straight line duration $T_{50}$; spectral peak $I_f$, low frequency component $f_l$, frequency difference $f_{90}$ at -1dB; shape factor $Scorff$, standard deviation $SD$, normalized energy $NE$, amplitude mean $m$.

Figure 6. Comparison of experimental and simulated signals. (a). Experimental and simulated signal comparison diagram of triangle defect. (b). Experimental and simulated signal comparison diagram of circular defects.

Figure 7. Schematic diagram of feature definition. (a). Time domain characteristics. (b). Frequency domain characteristics.
4.3. BP neural network parameters

The determination of neural network structure is more complicated, especially the number of hidden layer neural networks. When the number is too small, it will easily lead to poor convergence or even non-convergence of the network; when the number is too large, it will easily lead to "over-fitting" of the network. This paper uses the trial-and-error method to determine the optimal structure of the neural network. Table 3 shows the relevant parameters of the neural network. 2944 sets of ultrasonic signals are used for neural network training, 24 sets of ultrasonic signals are used for neural network testing, the extracted 11 feature values are used as the input of the neural network, and the logical value of the binary grid is used as the output of the neural network.

Table 3 Parameters of neural network.

| Name                  | Value | Name          | Value |
|-----------------------|-------|---------------|-------|
| Input layer           | 11    | Initial weight| init  |
| Hidden layer          | 45    | Learning rate | 0.01  |
| Output layer          | 1     | iterations    | 1000  |
| Activation function   | sigmoid | Expected error| 0.0001 |

5. Results and discussion

5.1. BP neural network parameters

In order to quantitatively analyze the difference between the actual value and the predicted value, this paper uses three parameters to evaluate the predictive performance of the defect inversion system. The parameters are as follows:

5.1.1. Similarity coefficient ε

The similarity coefficient ε can be evaluated by the correlation between the results, which can effectively characterize the pros and cons of the inversion result. The larger the similarity coefficient, the more accurate the inversion result. The calculation equation (2) is as follows:

\[
\varepsilon = \frac{\text{cov}(g', g)}{\sqrt{\text{Var}(g') \text{Var}(g)}}
\]  

(2)

Where cov is the covariance, Var is the variance, \(g'\) denotes image to be evaluated; \(g\) denotes original image.

5.1.2. Area error

The area can intuitively indicate the accuracy of the defect size, and the calculation equation (3) is as follows:

\[
E_s = \frac{|M - M'|}{M}
\]  

(3)

Where \(M\) is the number of grids with pixel value “1” in the original binarized image; \(M'\) is the number of grids with pixel value “1” in the binarized image to be evaluated.

5.1.3. Centroid error

Centroid can be considered as the geometric center of the defect, which can intuitively reflect the accuracy of the defect shape and position inversion. The calculation equation (4) is as follows:

\[
E_{xt} = \frac{|x - x'|}{x} \\
E_{yt} = \frac{|y - y'|}{y}
\]  

(4)
Where $E_x$ and $E_y$ are the error of the centroid $x'$ and the centroid $y'$ respectively; $x$, $y$ are the original defect centroid coordinates; $x'$, $y'$ are the centroid of the defect to be evaluated.

5.2. Quantitative analysis of defects

Figure 8 shows the defect inversion result based on BP neural network. (a) is the inversion result of four sets of ultrasonic signals of defect A (triangle $a=5\text{mm}$, $h=3\text{mm}$, $x=50\text{mm}$, $y=15\text{mm}$), (b) is defect B (triangle $a=5\text{mm}$, $h=3\text{mm}$, $x=30\text{mm}$, $y=20\text{mm}$) the inversion results of the four sets of ultrasonic signals, (c) is the inversion result of the four sets of ultrasonic signals for the defect C (circular $r=2.5\text{mm}$, $x=50\text{mm}$, $y=18\text{mm}$), (d) is the inversion result of four sets of ultrasonic signals of defect D (circle $r=2.5\text{mm}$, $x=30\text{mm}$, $y=25\text{mm}$).

![Figure 8. Pseudo-colour image of the defects. (a). defect A. (b). defect B. (c). defect C. (d). defect D.](image)

![Figure 9. Histogram of error parameters. (a). Histogram of similarity coefficient. (b). Histogram of area error. (c). Histogram of centroid x error. (d). Histogram of centroid y error.](image)

It can be seen from the figure that there are many noises in the inversion results, but the overall shape of triangles and circles can be basically distinguished. In order to further describe the accuracy of the inversion, this paper calculates the error parameters of the inversion results.
Figure 9 shows the histogram of error parameters. The inversion errors of the four signals are averaged and used as the overall average error of the defect, as shown in the dark blue histogram in the Figure 9. It can be seen from the figure that the similarity coefficients of the four defects are all above 0.8, the average similarity coefficient can reach up to 0.93, indicating that the inversion result is closer to the real result; There are only four area errors greater than 10%, and the smallest average area error can reach 4.43%, which shows that the inversion accuracy of the defect size is relatively good; Only one error of centroid x is greater than 12%, and the others are less than 12%. The average centroid x error is at least 6.36%, the centroid y error is less than 12%, and the average centroid y error is at least 5.09%. These data show that the location of defect inversion is relatively accurate.

By analyzing the error parameters, it can be known that this defect detection system can accurately obtain the relevant information of the shape, location and area of the defect. The imaging speed is fast, the amount of data required is relatively small, the defect display is intuitive, and it is of great significance for the detection of complex defects.

6. Conclusion
Based on the BP neural network, this paper proposes a complex defect quantitative evaluation system, in which less data can be used to achieve defect imaging and improve imaging efficiency. Based on this detection system, the similarity coefficients are all greater than 0.89, the maximum value can reach 0.95, indicating that the inversion result is closer to the real result; the area error is less than 11%, the minimum value can reach 1.2%; the centroid x error is less than 12%, the minimum value can reach 1.58%; the centroid y error is less than 11%, the minimum value can reach 2.15%. According to the error parameters of the inversion results, it verifies the accuracy and reliability of the system for defect imaging and quantitative analysis. In future work, data fusion technology can be used to achieve the fusion of different ultrasound signal inversion results, and research of three-dimensional imaging can also be carried out.

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References
[1] Delrue S., Aleshin, V., Sørensen, M., Lathauwer, L. (2017) Simulation Study of the Localization of a Near-Surface Crack Using an Air-Coupled Ultrasonic Sensor Array. J. Sensors, 17(4): 930.
[2] Goueygou M., Abraham, O., Lalaste, J.F. (2008) A comparative study of two non-destructive testing methods to assess near-surface mechanical damage in concrete structures. J. NDT and E International, 41(6): 448-456.
[3] Baniukiewicz, P., Chady, T., Sikora, R. (2014) Electromagnetic Nondestructive Evaluation (XVI). Ios Pr Inc Publishing, Haarlem.
[4] Mor, E., Aladjem, M., Azoulay, A. (2018) A sparse approximation method for Ultrasonic Monitoring the degradation of adhesive joints. J. NDT & E International, 98: 17-26.
[5] Nomura, H., Adachi, H., Kamakura, T. (2018) Feasibility of low-frequency ultrasound imaging using pulse compressed parametric ultrasound. J. Ultrasonics, 89: 64-73.
[6] Pal, B. (2015) Pulse-echo method cannot measure wave attenuation accurately. J. Ultrasonics, 61: 6-9.
[7] Rao, J., Saini, A., Yang, J., Ratassepp, M., Fan, Z. (2019) Ultrasonic imaging of irregularly shaped notches based on elastic reverse time migration. J. NDT and E International, 107: 102135.
[8] Holmes, C., Drinkwater, B.W., Wilcox, P.D. (2005) Post-processing of the full matrix of ultrasonic transmit–receive array data for non-destructive evaluation. J. NDT and E International, 38(8): 701-711.
[9] Latête, T., Gauthier, B., Belanger, P. (2021) Towards using convolutional neural network to locate, identify and size defects in phased array ultrasonic testing. J. Ultrasonics, 115: 106436.
[10] Xiao, H., Chen, D., Xu, J., Guo, S.F. (2020) Defects identification using the improved ultrasonic measurement model and support vector machines. J. NDT and E International, 111: 102223.

[11] Nayak, P., Mallick, R.K., Dhar, S. (2021) Novel hybrid signal processing approach based on empirical mode decomposition and multiscale mathematical morphology for islanding detection in distributed generation system. J. IET Generation, Transmission & Distribution, 14(26): 6715-6725.

[12] Nomura, H., Adachi, H., Kamakura, T. (2018) Feasibility of low-frequency ultrasound imaging using pulse compressed parametric ultrasound. J. Ultrasonics, 89: 64-73.

[13] Li, K., Ma, Z., Fu, P., Sridhar, K. (2018) Quantitative evaluation of surface crack depth with a scanning laser source based on particle swarm optimization-neural network. J. NDT and E International, 98: 208-214.

[14] Rao, J., Saini, A., Yang, J., Ratassepp, M., Fan, Z. (2019) Ultrasonic imaging of irregularly shaped notches based on elastic reverse time migration. J. NDT and E International, 107: 102135.

[15] Xu, W., Zhang, J., Li, X., Yuan, S., Ma, G., Xue, Z., Jing, X., Cao, J. (2022) Intelligent denoise laser ultrasonic imaging for inspection of selective laser melting components with rough surface. J. NDT and E International, 125: 102548.

[16] Xiao, Z., Ye, S., Zhong, B., Sun, C. (2007) BP neural network with rough set for short term load forecasting. J. Expert Systems With Applications, 36(1): 273-279.

[17] Qiu, S., Xu, H., Deng, J., Jiang, S., Lu, L. (2019) Transfer Convolutional Neural Network for Cross-Project Defect Prediction. J. Applied Sciences, 9(13): 2660.

[18] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahrroudy, A., Shuai, B., Liu, T., Wang, X., Wang G., Cai, J., Chen, T. (2018) Recent Advances in Convolutional Neural Networks. J. Pattern Recognition, 77: 354-377.

[19] Dempster, A.P. (2008) Classic works of the Dempster-Shafer theory of belief functions. Springer Publishing, Berlin.

[20] Zhang, D., Guo, Y., Hong, Y., Hou, Z., Pan, R. (2018) Research on data fusion technology of the online monitoring system for optics bonnet polishing. J. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 232(8): 1436-1443.