DEFECT IDENTIFICATION BY AN ULTRASONIC CYLINDRICAL PHASED ARRAY

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In this paper, a new method is presented for defects classification by ultrasonic cylindrical phased array. Firstly, a finite element model is conducted to simulate the defects identification by the cylindrical phased array transducer. A series of simulation are done for 4 types of defects with different sizes by a 64-element cylindrical phased transducer with the center frequency of 500 kHz. Then, the Wavelet-packet transform decompose algorithm is used to four-levers decompose, reconstruct and extract the feature of these echo signals. Finally, the reconstructed signals are used to the deep neural network to the defect classification. The accuracy of the known defects classification is 100%, which means the method is feasible for classification by ultrasonic cylindrical phased array.

Keywords: Ultrasonic cylindrical phased array; Defect classification; Wavelet-packet transform; Deep neural network

1. INTRODUCTION

Ultrasonic phased array technology is widely used in industrial Non-Destructive Testing (NDT) field through the last decades, such as high speed railway locomotive axles, turbine rotors and borehole wall [1-2]. The traditional planar phased array transducer is usually used to scan the object with flat surface and the transducer should rotate rapidly around the borehole axis in order to scan all the directions of the borehole wall. Compared with the traditional transducer array, the ultrasonic phased array transducer can scan the borehole wall without rotation of the transducer beam. Zhang [3] investigated the main parameters affecting the ultrasonic phased array transducer. On the other hand, conventional defects identification usually depends on the specific professional knowledge, and the experience of the operating personnel which could cause the instability and individual differences of the analysis results easily [4]. Recently, the neural network was adopted to classify the identification of defects [5], while the recognition accuracy is still restricted and the learning process of the neural networks is quite time-consuming. Shi [6] experimentally studied the defect classification using a deep neural networks combined with a wavelet packet transform method, while the theoretical analyses was not given in the manuscript.

To imaging the inner surface of a borehole wall, an ultrasonic cylindrical phased array transducer is presented to fulfill the whole scanning process for the inner surface. Based on this, the finite element method is conducted to simulate the defects identification by the cylindrical phased array transducer, the wavelet-packet transform (WPT) and deep neural network was also conducted to improve the recognition accuracy.

2. SIMULATION OF THE CYLINDRICAL PHASED ARRAY

Fig. 1(a) illustrates the 3D model of a cylindrical phased array, while the physical description is shown Fig. 1(b). The elementary transducers of the array are located on the outside surface of a cylinder. In this paper, we used the 64-element rectangular phased transducers, o' is the center of the cylindrical phased transducer array and the radius of circle array is R. The 64 elementary rectangular transducers are equally distributed around the dotted line as shown in Fig. 1(b). In each simulation process, only 8 rectangular transducers of the 64 elementary cylindrical phased transducers are chosen to generate the ultrasonic waves. The coordinate position F is considered as the defect point. And the 8 transducers are modulated with different phase to focus the ultrasonic waves in the defect point. The distance between the coordinate position o' and F is 20 mm. The center frequency of the ultrasonic wave is set as 500 kHz and the system is both used for signals generation and reception. As the the focusing point is far from the transducer array, then the focusing ultrasonic wave can be approximately treated as the plane wave.

As shown in Fig. 1(a), the length of the transducer in the columnar axis direction is greater than the width, then a 2D finite element (FE) model is conducted to simulate the defects identification by the

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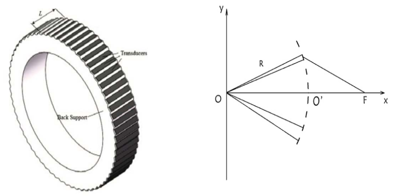
cylindrical phased array transducer. The commercial finite element software COMSOL is used to simulate the wave propagation in the defects specimens. Water is the internal medium, and the square and spherical defect under the transducer is made of aluminum. In this simulation, the delayed time for the four transducers above the X axes is set as 0s, 1.14e-7s, 1.957e-7s and 2.298e-7s, while that of the other four transducers is set symmetrically to the four transducers above the X axes. Fig. 2 shows the snapshots of wave propagation in square and spherical defects. It is clearly to find that the generated waves are precisely focused on the defects and the focusing wave can be treated as the plane wave.



(a) (b)

Fig. 1. (a) 3D model of a cylindrical phased array. (b) Physical description of a cylindrical phased array.

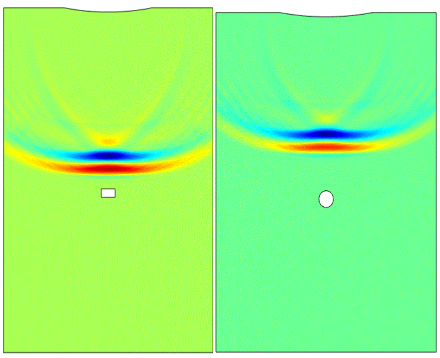


Fig. 2. The snapshots of wave propagation in square and spherical defects.

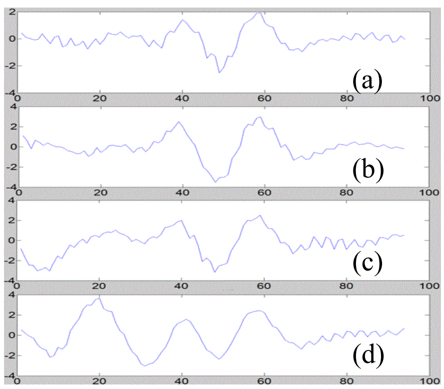


Fig. 3. The scattered echo of four different defects. (a) sphere defect of 2mm diameter; (b) 2mm*1mm square defect; (c) 2mm*4mm square defect; (d) 2mm*8mm square defect.

Fig. 3 illustrates the four-scattered time-domain signal of these four different defects. Each kind of the defect contained 60 samples, the scattered echo signals are reflected from the four kinds of defects, respectively. It can be concluded from Fig. 3 that the scattered echo signals of the square defect (Fig. 3(a)) differ greatly from sphere defect (Fig. 3(b)-(d)). When thickening the thickness of the square defects from 1mm to 8mm, the amplitude of the first wave crest increased to 3.5. While there is little difference in the other two wave crests.

3. ANALYSIS OF THE DEEP BELIEF NETWORK MODEL

Fig. 4 illustrates the basic framework of the deep belief network, a visible layer and an invisible layer are included in an RBM, respectively. The visible layer and the invisible layer are connected with both-way junction while there is no connection among the same layer. A typical deep belief network model (DBN) is built up with a serious of restricted Boltzmann machines (RBM), which could also be treated as a directed acyclic graph built up with a lot of random variables. The units of invisible layer are trained to catch the correlation of the high order data. In the sorting network, the tag units are added into the top RBM at training time. '1' is set if the tag unit is "on", while '0' are set for others which are "off".

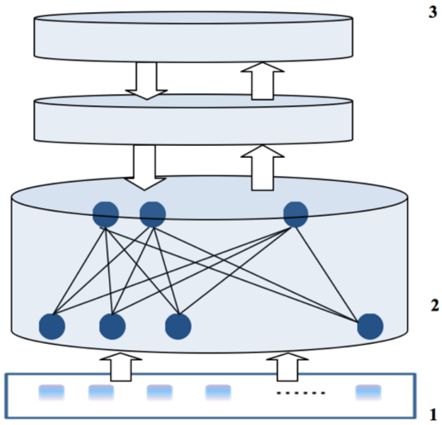


Fig. 4. The framework of the deep belief network. Step1: observation vector; Step 2: one RBM; Step 3: sorting machine.

Then, unsupervised learning algorithm is used to train the lower layers in the network, and generate the first initial parameter values for the DBN. Next, setting the output of the first layer as the input of the next layer. The unsupervised learning algorithm is progressed by training the layer step by step. After times of training and initial process, the unsupervised learning algorithm is used to fine adjustment of the whole DBN structure.

The DBN structure was then used to classify the four kind of different scattered echo signals mentioned above. The classification was conducted by a 94-1000-500-500-4 DBN structure which included three invisible layers, the numbers of the nodes are 100, 500, 500, respectively. There are three RBMs and the structures are 96-1000 (visible layer nodes number-invisible layer nodes number), 1000-500, 500-500, and the final layer is the Softmax sorting machine which conduct the pattern classification.

4. THE ECHO SIGNALS EXTRACTION AND CLASSIFICATION

The Wavelet-packet transform is an extension method of wavelet-transform. It can decompose the wavelet-transform signals at the high frequency part, then decomposed the signals into different frequency band. The Mallat algorithm used in WPT is as follows:

$$\begin{cases} C_k^{2n,j-1} = \sum_{l\in z} \overline{h}_{l-2k} C_l^{n,j}, \\ C_k^{2n+1,j-1} = \sum_{l\in z} \overline{g}_{l-2k} C_l^{n,j}, \end{cases}$$

$C_k^{2n,j-1}$ and $C_k^{2n+1,j-1}$ represent the WPT coefficient in the subspace. Mallat algorithm is utilized to decomposing the origin signal into 5 levels, then we can get the WPT coefficient of 32 nodes. According to these reconstructed 32 nodes, we can calculate the energy of each frequency band and normalize the vector. After the feature extraction by WPT method, the nodes are shortened from 94 to 32, which greatly reduce the calculation time. Similarly, the DBN is used to classify these four kind of extracted feature. In this situation, the classification is conducted by a 94-1000-500-500-4 structure. The DBN was build up with 2 RBM, 32-100 and 100-50, the final layer is the Softmax sorting machine as before.

The normalized energy feature of the four scattered echo signals is then plotted in Fig. 5. They are the extracted feature of four different defects mentioned above. Each defect contains 20 extracted feature signals.

The DBN is trained with these 20 extracted feature of 32 nodes in each defect, totally 80 extracted signals. And the DBN learns about the feature of these four defects. Then the trained DBN is used to test another 120 feature signals of unknown defects and classify the feature.

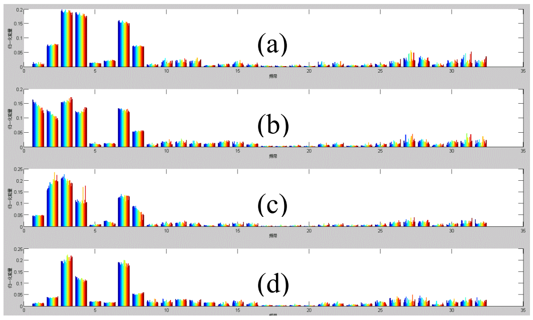


Fig. 5. The normalized energy feature of the four scattered echo signals. (a) 2mm*1mm square defect; (b) 2mm*4mm square defect; (c) 2mm*8mm square defect; (d) sphere defect of 2mm diameter.

Table 1 shows the results of the classification and the consuming time. The results indicate that the DBN method is feasible to this cylindrical phased array and the result of the identification is approving. Furthermore, compared to the original flaw echo signals, the extracted feature has greatly reduced the consuming time and saved the computational space, thus proved the efficiency of the classification process.

Table 1. Results of the classification and the consuming time.

data	defects	samples	results				correct	accuracy	time
			2mm spherical	2*1mm square	2*4mm square	2*8mm square			
flaw echo	2mm spherical	30	30	0	0	0	30	100%	3371.6s
	2*1mm square	30	0	30	0	0	30	100%	
	2*4mm square	30	0	0	30	0	30	100%	
	2*8mm square	30	0	0	0	30	30	100%	
	conclusion	30	30	30	30	30	120	100%	
extracted feature	2mm spherical	30	30	0	0	0	30	100%	177.2s
	2*1mm square	30	0	30	0	0	30	100%	
	2*4mm square	30	0	0	30	0	30	100%	
	2*8mm square	30	0	0	0	30	30	100%	
	conclusion	30	30	30	30	30	120	100%	

5. CONCLUSIONS

The feasibility of the defect defection and identification by the cylindrical phased array transducer is investigated based on the FEM analyses. Two types of defects (square and sphere) are investigated. The influence the size and shape of the defects are both considered in numerical simulation. It is found that the accuracy of the defects identification is up to 100%. Changing the thickness of the square defects, the scattered echo signals differ slightly. Compared with the defects identification with the firsthand data, the WPT method greatly can greatly improve the accuracy of the defect identification and reduce the computation consumption. Moreover, the WPT method and deep neural network can greatly reduce the training time and classifying process. This paper will be of valuable help for the inner surface defection and detect identification.

ACKNOWLEDGEMENTS

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