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O.L. Starodubtsev, V.S. Khandetskyi

NEURAL NETWORKS OPERATION SPEED ESTIMATION FOR IDENTIFICATION OF SIGNALS IN DEFECT DETECTION

Annotation. Using the computer simulation, we determined the degree of influence of structural parameters and learning methods of multilayer perceptrons with back propagation algorithm on their operation speed when identifying the defect detection signals for composite materials. The obtained results have a practical importance for real-time studies.

Key words: neural networks, defect detection, composite materials.

Introduction. The main task in defect detection of composite materials using the eddy current method is to identify the defect signals distorted by noise [1].

The highest reliability of the defect signal identification, additively mixed with white Gaussian noise, has been shown by three neural networks (NN) - multilayer percetrons with a back propagation algorithm [2]. Acceptable from a practical point of view, the reliability of the defect identification was obtained at the noise level of up to 30% of the defect signal amplitude.

At the same time, the question of the defect detection speed is also important in practical conditions of non-destructive control. Due to relatively small sizes of existing defects, compared with the total area of the studied products, two approaches can be used to indicate the exact location of the defect - either directly during the real-time scanning an signals processing, or after scanning the entire surface of the product and indicating the defects by defining its coordinates relative to the representative points. In a number of practical tasks, the second approach is very difficult, especially for defect detection of significant size products.

Problem statement. The purpose of the work is to obtain a statistical data for the estimation of the different NN operation speed depend upon the number of the NN hidden layers, the type of generated and added to the defect signal noise, the method of NN layers initialization.

Main part. To solve this problem, the program developed in Octave programming environment was used. We operated with multilayer percetrons contained from 2 to 4 hidden layers and 21 inputs and 1 output.

The program generated samples of noise different types with 15% intensity comparatively the amplitude of the defect signal. The noise samples added to defect signal after which the learning of NN with a given level of error and their testing was realized. Then the program determined the corresponding number of convergence epoch (cycles).

As a studies types of noise, based on the physical properties of carbon fibers reinforced plastics were taken: Gaussian white noise, wavelet noise, simplex noise.

Gaussian white noise characterizes the uniform stochastic roughness of the surface of composite materials. Wavelet noise is a gradient noise corresponding to the properties of an object that has different levels of detail. In particular, it is characteristic of quasiperiodic structures, including texture of reinforcing fabric, which is formed by crossing bundles of fibers [3]. Simplex noise is a gradient noise generated by the construction of a multidimensional noise function with low computational costs.

The following approaches were used in the study to accelerate the convergence of NN with conservation of a given level of identification error [4-7]:

1. Optimization of choice of the neurons initial weights. In the developed program, two tools were used:

- setting randomly small values for all NN weights (classical approach);

- use of the previous mode for the first hidden layer with the installation of consecutively double reinforced weights for the last layers (according to [3], during learning there is a tendency to increase the scale of the change in weight coefficients in the direction from the first layer to the last).

2. In the program, to exclude NN learning in a certain group of input data sequences, their random alternation was applied.

3. Using the best estimates of reliability of the defect signal identification [2], three NN with different numbers (2, 3 and 4) of hidden layers were selected for studying the speed operation. There are a multilayer perceptrons with back propagation algorithm and learning in accordance with Quasinewton Levenberg-Marquardt's algorithm.

However, in the first NN the weights tuning is carried out by the method of gradient descent with perturbation (hereinafter the NN #1). In the second the learning algorithm is added by Bayes regularization (NN #2). In the third, only gradient descent method is used for the neurons weights tuning (NN #3).

For all NN was given the same precision. The results of the conducted studies are presented in Tables 1 - 4.

Table 1

Quantity of the convergence epochs at the different parameters for NN#1

Quantity of NN hidden layers	Types of weights tuning	Type of noise	Quantity of epochs
2	Classical	Gaussian white	3724
		Wavelet	4122
		Simplex	3451
	With weights doubling	Gaussian white	2632
		Wavelet	4382
		Simplex	2818
3	Classical	Gaussian white	6258
		Wavelet	6989
		Simplex	3956
	With weights doubling	Gaussian white	3824
		Wavelet	4597
		Simplex	4126
4	Classical	Gaussian white	11349
		Wavelet	17834
		Simplex	8235
	With weights doubling	Gaussian white	6814
		Wavelet	13720
		Simplex	7844

In Tables 1-3 data we registered the minimum, maximum and average ratio of the quantity of epochs at the change of each parameter, while coinciding the others. The most influential on the speed of NN convergence we determined those parameters, the individual variation of which when coinciding the others, leads to the maximum average ratio of the epochs quantity.

Table 2

Quantity of the convergence epochs at the different parameters for NN#2

Quantity of NN hidden layers	Types of weights tuning	Type of noise	Quantity of epochs
2	Classical	Gaussian white	3108
		Wavelet	4490
		Simplex	2311
	With weights doubling	Gaussian white	2893
		Wavelet	4324
		Simplex	2021
3	Classical	Gaussian white	5486
		Wavelet	6114
		Simplex	3327
	With weights doubling	Gaussian white	4832
		Wavelet	5232
		Simplex	2502
4	Classical	Gaussian white	10884
		Wavelet	12930
		Simplex	7914
	With weights doubling	Gaussian white	8913
		Wavelet	10814
		Simplex	4239

Table 3

Quantity of the convergence epochs at the different parameters for NN#3

Quantity of NN hidden layers	Types of weights tuning	Type of noise	Quantity of epochs
2	Classical	Gaussian white	3003
		Wavelet	3390
		Simplex	2751
	With weights doubling	Gaussian white	2811
		Wavelet	3422
		Simplex	2834
3	Classical	Gaussian white	5899
		Wavelet	6547
		Simplex	3827
	With weights doubling	Gaussian white	5421
		Wavelet	6303
		Simplex	5011
4	Classical	Gaussian white	13112
		Wavelet	13737
		Simplex	9921
	With weights doubling	Gaussian white	12802
		Wavelet	12912
		Simplex	10120

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Table 4

The ratio of epochs quantity when one studied parameter is changed

Quantity of NN hidden layers			NN type			Types of weights tuning			Type of noise		
Min.	Max.	Aver.	Min.	Max.	Aver.	Min.	Max.	Aver.	Min.	Max.	Aver.
2,10	4,55	3,32	1,10	2,39	1,42	1,01	1,87	1,21	1,19	2,55	1,68

From Table 4 it can be seen that the most influential parameter on the speed of NN convergence is the quantity of its hidden layers (k_{aver} =3.32, $k_{max.}$=4.55). The type of added noise ($k_{aver.}$=1.68, $k_{max.}$= 2.55) and the NN type ($k_{aver.}$= 1.42, $k_{max.}$= 2.39) are also significant. The type of the weights tuning ($k_{aver.}$=1.21, $k_{max.}$= 1.87 is less influential.

Conclusions. The obtained simulation results indicate the unequal influence of various parameters on the NN convergence speed at the identification of the defect noisy signals.

The most influential parameter is the number of hidden NN layers, the type of added noise and the learning and tuning NN parameters are also significant. Less influences are the ways of initializing the weights of neurons in hidden NN layers.

The obtained results have practical importance for real-time probing of composite materials.

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