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SURFACE DEFECT DETECTION WITH NEURAL NETWORKS

Abstract. The research results of signal recognition using neural networks are presented. A multilayer perceptron with back-propagation error is implemented on Java. The optimal number of neurons in the hidden layer is selected for building an effective architecture of the neural network. Training network on different sets of signals with noise allowed teaching her to work with distorted information, which is typical for non-destructive testing in real conditions. Experiments were performed to analyze MSE values and accuracy.
Keywords: composite materials, neural networks, multilayer perceptron with *back-propagation training, defect, function of activity.*

Problem statement and purpose of research. The global economic pressures have gradually led businesses to become more competitive. In order to sustain or increase current level of performance in the highly competitive global market, industry should improve quality of the production process. Early and accurate detection of defects is an important aspect of quality improvement. The accuracy of manual inspection is not good enough due to fatigue and tediousness. The solution to the problem of manual control is an automated system for checking parts based on machine vision. Automated part inspection systems mainly involve two challenging problems, namely defect detection and defect classification.

One of the methods nondestructive controls of composite materials is eddy current. It can be carried out without contact of transducer and the object and obtain acceptable results of control even at high speeds displacement transducer. Eddy current method based on registration of changes in the eddy current density, so the received signal can influence the outer eddy currents. The surface of composite materials is characterized by roughness and this creates additional noise.

Modern technologies allow to create computer systems with involving neural networks [1] for whom the as input parameters can be used characteristics of electromagnetic signals.

The purpose of this work is to create a neural network for the classification of electromagnetic signals that are obtained by scanning the composite material, as well as for solving problems of defect detection.

Main part. Each artificial neural network is a set of simple elements - neurons that are connected in some way. The particular form of executable network data conversion due not only characteristics of neurons that make up its structure but also its architectural features such as topology interneuron links directions and methods of information transfer between neurons and learning tools[2, 3].

Multilayer neural networks of direct distribution are nonlinear systems that enable better qualified than conventional statistical methods. Multilayer perceptron (MLP) has a plurality of input nodes that provide the input layer with one or more hidden layers of neurons and output layers. Each neuron of MLP which learns based on back propagation algorithm has nonlinear smooth activation function often use nonlinear logistic sigmoid function type or hyperbolic tangent [3, 4].

It is important to highlight that a neural network may have many hidden layers or none, as the number of neurons in each layer may vary. However, the input and output layers have the same number of neurons as the number of neural inputs/ outputs, respectively.

Neural network training consists of several steps[4]:

- selecting the initial network configuration using, for example, the following heuristic rule: the number of neurons in the hidden layer is determined by half the total number of inputs and outputs;

- conducting a number of experiments with different network configurations and choosing one that gives the minimum value of the error functional;

- if the quality of training is insufficient, the number of layer neurons or the number of layers should be increased;

- if a retraining phenomenon is observed, it is necessary to reduce the number of neurons in the layer or to remove one or more layers.

The network learning process includes setting values weights and bias of network to optimize network performance. Setting performance for networks with direct propagation is determined by the mean squared function (mse) between the outputs of the network (a) and targeted outputs (t) and defined by the formula [2, 3]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (1)$$

After training and testing neural network the network object can be used to calculate the answer for any input value.

When scanning compositeg materials using an eddy current transformer, there is a smooth change in the waveform from unimodal with a maximum amplitude (defects exceed the control zone) to bimodal with the highest dips. Such changes are modeled using the expression [5]:

$$y(x) = \exp(-1{,}5x\uparrow 2\ ) - k \cdot \exp(-3x\uparrow 2\ ) \qquad (2)$$

The article uses multilayer perceptron (MLP). For the training of MLP the algorithm of back - propagation training is used [2, 3].

The creation of a neural network is performed in the Java programming language.

So, let's start implementing. Initially, we are going to define six classes: *Neuron, Layer* (class is abstract and cannot be instantiated) that describes the layers, *InputLayer class* that describes the input layers (class inherits attributes and methods from the Layer class), *HiddenLayer* class that defines the middleware (class inherits attributes and methods from the Layer class), *OutputLayer* class describes the output layer (class inherits attributes and methods from the Layer class), *NeuralNet* (the values of the neural net topology are fixed in this class)[1].

Each output neuron denotes a class. To simulate noise, a normally distributed random number generator is used. An example of a unimodal signal with a noise level of 0.05 is shown in figure 1

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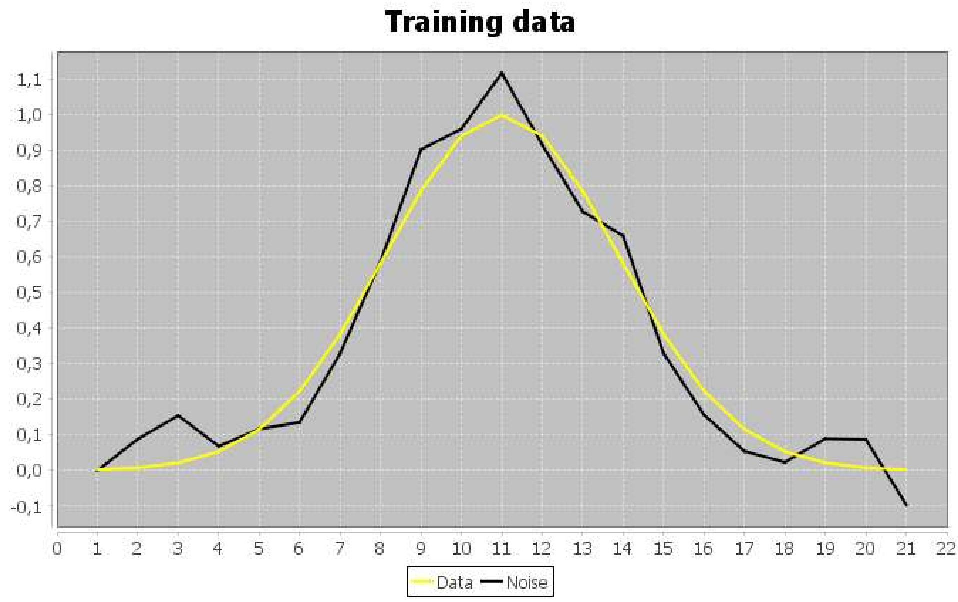

Figure 1 - Ideal signal (yellow color) and signal with noise (black color)

Many algorithms for the functioning and training of neural networks have been developed, and for each task it is necessary to configure the network in different ways. Therefore, research was conducted to determine the best network parameters, such as: activation functions of input and hidden neurons and determining the number of neurons in the hidden layer. Hyperbolic tangential activation function (Hypertan) and logistic sigmoidal activation function (Siglog) were used in experiments.

Parameters *MSE* (1) and *accuracy* was used for evaluate the neural network. The parameter accuracy is formed on the basis of the expected and real data provided by the neural network.

We performed many experiments to try to find the best neural network to classification. The training was conducted signals with noise (0.05). Linear and tangential functions were used in the output layer. The test results are shown in tables 1 and 2:

Table 1

Linear output function

Experiment	Number of neurons in hidden layer	Activation function	MSE	Total accuracy
#1	9	HYPERTAN	0.00995573339897946	75%
#2	12	SIGLOG	0.00996491835677809	83,333%
#3	10	HYPERTAN	0.00998401197657948	50%
#4	12	HYPERTAN	0.00999360929493481	66,666%
#5	11	HYPERTAN	0.00999502512706538	75%
#6	8	SIGLOG	0.00999869481576378	83,3333%
#7	8	HYPERTAN	0.02022418703632457	75%
#8	10	SIGLOG	0.02092368752492168	75%
#9	11	SIGLOG	0.02203575970296707	75%
#10	7	HYPERTAN	0.03168826834581766	58,3333%

Table 2

Hypertan output function

Experiment	Number of neurons in hidden layer	Activation function	MSE	Total accuracy
#11	9	HYPERTAN	0.00994917320039824	83,333%
#12	12	HYPERTAN	0.00997003565737264	50%
#13	11	HYPERTAN	0.00999157530952272	75%
#14	10	HYPERTAN	0.00999878881273251	100%
#15	9	SIGLOG	0.02377328083679948	41,667%
#16	7	HYPERTAN	0.02908783694768615	83,334%
#17	10	SIGLOG	0.04146528401729575	50%
#18	12	SIGLOG	0.05339244636898565	100%
#19	8	HYPERTAN	0.05342303501442618	75%
#20	8	SIGLOG	0.05983305704878905	41,667%

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Experiment #14 and #18 have same total accuracy measure (100%). Therefore, we selected experiments #14, because he has low MSE values among the two experiments.

As a result of testing, we chose the following neural network architecture: 21 neurons in the input layer, 10 neurons in the hidden layer and 2 neurons at the output. The hypertan activation function used in hidden layer and output.

The graph shows a comparison between the real (yellow line) and the estimated (black line) signal values (Figure 2). The neural network works perfectly.

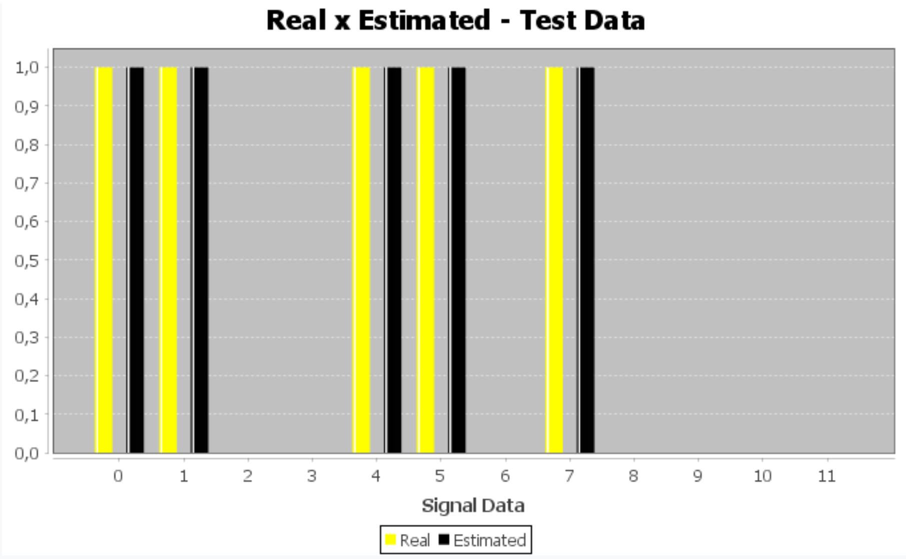

Figure 2 - The expected class along with the classification estimated by the neural network

The neural network is trained on signals with noise, and then tested on signals with different noise levels. The results are shown in table 3.

Table 3

Noise level		
training	testing	MSE
0.05	0.05	0.009998219707589661
0.05	0.1	0.009974832345368063
0.1	0.1	0.015766026730132145
0.1	0.15	0.01686189145885091
0.15	0.15	0.03283785458113339
0.15	0.2	0.014996758480474942
0.2	0.2	0.07208712408865446

Now let's do the reverse test. A neural network learns from more noisy data than testing is done. The test results are shown in table 4:

Table 4

Noise level		
training	testing	MSE
0.2	0.05	0.010012569938241766
0.15	0.1	0.009969095902656683
0.1	0.1	0.009998217002776047
0.05	0.15	0.009983868328343774

Conclusions. Defect detection has been an attractive area of research for pattern recognition scientists. Research has shown in principle the possibility of using neural networks for signal recognition. The neural network is implemented by means of the Java language; the number of neurons in the hidden layer was selected. Training network on different sets of signals with noise allowed teaching her to work with distorted information, which is typical for non-destructive testing in real conditions. Training is best done on signals with a low level of noise and then the neural network shows the best results of signals recognition.

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Обнаружение поверхностных дефектов с помощью нейронных сетей

Представлены результаты исследования распознавания сигналов с использованием нейронных сетей. Многослойный персептрон с алгоритмом обратного распространения ошибки реализован на Java. Для построения эффективной архитектуры нейронной сети выбирается оптимальное количество нейронов в скрытом слое. Обучение сети на разных наборах сигналов с шумом позволило научить ее работать с искаженной информацией, что характерно для неразрушающего контроля в реальных условиях. Эксперименты были выполнены для анализа значений MSE и точности.

Знаходження поверхневих дефектів за допомогою нейронних мереж

Представлені результати дослідження розпізнавання сигналів з використанням нейронних мереж. Багатошаровий персептрон з алгоритмом зворотного поширення помилки реалізований на Java. Для побудови ефективної архітектури нейронної мережі вибирається оптимальна кількість нейронів в прихованому шарі. Навчання мережі на різних наборах сигналів з шумом дозволило навчити її працювати з перекрученою інформацією, що характерно для неруйнівного контролю в реальних умовах. Експерименти були виконані для аналізу значень MSE і точності.

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