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TECHNICAL SCIENCES

INFLUENCE OF ARCHITECTURE AND TRAINING DATASET PARAMETERS ON THE NEURAL NETWORKS EFFICIENCY IN THERMAL NONDESTRUCTIVE TESTING

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ABSTRACT

Describes the perspective of the use of artificial neural networks in automated thermal non-destructive testing and defectometry systems. The influence of backpropagation neural networks architecture on the efficiency of defect classification and accuracy of determining their depth and thickness are analyzed. Considered the influence of volume and quality of training dataset on the efficiency of defect classification and accuracy of defectometry. Performance of neural networks is evaluated by quantitative indicators, such as MSE, relative error and Tanimoto criterion. The optimal neural network architecture for using in active thermal testing was established on the basis of experimental researches.

Keywords: nondestructive testing, thermal testing, neural networks, thermograms processing, composite materials

Introduction.

Methods of thermal nondestructive testing (TNDT) at the present stage of development allow to identify hidden defects (flaw detection) and to determine their size (defectometry). TNDT is used to test the quality of a wide range of products with internal technological defects in the form of cracks, bundles and extraneous inclusions. An active TNDT is of particular interest because of its many advantages, which can greatly expand the list of possible objects of testing (OT).

A characteristic feature of active TNDT is the correlation of all informative parameters with each other. Therefore, to improve efficiency of defect classification and accuracy of defectometry, a comprehensive analysis of OT thermal fields should be performed. Decision to determine defect type is made on the analysis of multidimensional space of nonlinearly related diagnostic features. In most cases, it is impossible to establish a unique defect in a particular class by traditional methods. Same factors complicate the process of defects depth or thickness accurately measuring. This problem requires search for new modern methods of data processing. In particular, artificial neural networks (NN) are used to automate defects recognition and improve testing and defectometry efficiency, as well as to construct thermal tomograms of OT [1].

The use of neural-based automated systems can solve problems that are difficult or impossible to solve by traditional mathematical or statistical methods. At the same time, performance of neural network systems will depend on the parameters of the networks used, rather than on predefined analytical rules.

Problem Statement.

Dynamic thermal field is described by the function $T(x,y,\tau)$. By considering the temperature dynamics at each point of thermograms (pixels) corresponding to coordinates of OT surface, it is possible to construct a temperature profile – a graph of temperature changes over time for a given area. As a rule, in defect-free areas the nature of temperature change is constant and is known. It is possible to enter some reference temperature $T_{nd}(x_{nd}, y_{nd}, \tau)$, which is assumed to be defect-free. In the defect zone, regular nature of the thermal field is disturbed and local temperature differences $T_d(x,y,\tau)$ occurs, which lead to a change in temperature profile. Thus, it is possible to calculate the value of temperature difference between defective and defect-free areas:

$$\Delta T(x,y,\tau) = T_d(x,y,\tau) - T_{nd}(x_{nd}, y_{nd}, \tau)$$

The time τ_{opt} at which the value of $\Delta T(x, y, \tau)$ at this point of OT becomes maximum is called the optimal testing time:

$$\Delta T_{max}(x,y,\tau) = \Delta T_{max}(\tau_{opt})$$

Analyzing the shape, amplitude and time characteristics of temperature profile, as well as the frequency, phase and power characteristics of temperature signal, it is possible to make conclusions about the size, position and depth of defects. However, results of such analysis depend significantly on the quality of recorded thermograms, their number, presence of noise, OT heating parameters, experience of operator etc. In this regard, special methods of digital processing of thermographic images, such as artificial neural networks, are used to improve testing accuracy.

Using multilayer feedforward backpropagation neural networks, it is possible to construct regression models of any function. The complexity of function is determined by number of hidden layers and number of neurons in each of them. Therefore, it is important to determine the optimal number of layers and number of neurons when building a network model. In thermal nondestructive testing, this task is complicated by the high level of noise and unpredictability of input data.

A particularly important step in creation of neural network systems is the formation of training datasets. The completeness and quality of input vectors dataset for network learning directly depends on its efficiency. There is a need to ensure high representativeness of training data. Therefore, analyzing the effect of representativeness level of training dataset on performance of neural networks in thermal testing is an important task.

Recent works review.

Authors of [2] investigated possibilities of using neural networks to test products made of multilayered materials. Possibility of using neural network classifiers in active TNDT is noted and proved. Neural network is used to classify defects by depth. The benefits of using NN are shown only at a qualitative level. There is no study of NN effectiveness in determining depth or thickness of defects, impact of network architecture or quality of training dataset on the result of its work.

Modern methods of digital thermogram processing and thermal tomography are also described in work [3]. Authors considered the possibility of applying artificial neural networks in thermal nondestructive testing. The efficiency of different architectures of neural networks in the tasks of thermal tomography is analyzed. However, the accuracy of defect depth estimation is given only at a qualitative level.

Work [4] is devoted to optimizing the structure of input data for neural networks used to determine depth of defects in TNDT. Ten different sets of input data have been used for training and verification of the neural network designed to determine depth defects in infrared thermographic nondestructive testing. The input data sets include raw temperature data, polynomial fitting, principle component analysis, Fourier transform and others. The influence of NN architecture on research results was not analyzed in this paper.

In work [5] authors propose a fast method using artificial neural networks for internal defects depth evaluation from the thermal contrast. Influence of different training algorithms on the learning speed and root mean square error is considered for aluminum OT. The impact of other parameters on accuracy of defect depth estimation was not performed.

Therefore, in existing works, some aspects of the use of NN in active TNDT have been investigated. However, authors do not take into account the interaction of individual parameters of neural networks on results of their work. There are no studies on choice of the neural networks optimal architecture and their parameters in tasks of complex analysis of thermal fields – simultaneous classification and determination of defects depth and thickness by results of active thermal nondestructive testing.

Aim of research.

The aim of this research is to determine the optimal neural network architecture and training dataset requirements for use in active thermal testing in defect classification and defectometry tasks. Research is based on computer simulation data and experimental validation.

Description of the input data.

Computer simulation allows to estimate the influence degree of different neural networks parameters and training datasets on the performance of complex analysis of thermal fields system. By creating appropriate computer models, it is possible to vary such parameters of training dataset as its volume, representativeness, number of thermograms in a sequence etc. This is a significant advantage in absence of a large number of physical test specimens.

During the research, a computer simulation of an active TNDT test specimen made of carbon fibre reinforced polymer (CFRP) was performed. Each layer has a thickness of 1 mm, total thickness of the plate is 5 mm. Plate has a square shape with 100 mm side. Models of square shaped artificial defects at depth of 1, 2 and 3 mm are placed inside the plate. These defects have transverse dimensions of 10, 8, 6 and 4 mm and a thickness of 1, 2 and 3 mm. The scheme of test sample is shown on fig. 1, a. Common models of various defect types are air-contaminated, aluminum and paper inclusions. Materials of defects used in model have thermal conductivity more (aluminum), less (air) or the same (paper) as the OT main material. The standard COMSOL Multiphysics libraries were used when creating the model.

A two-sided testing scheme is selected for the simulation. A pulsed heat source with a power density of 10 kW / m^2 is attached to the front surface of OT. Duration of heating pulse was 1 s, the duration of cooling stage 14 s. Thermograms were recorded from OT back surface during the entire heating / cooling procedure. The result of testing is a sequence of 50 thermograms with 400 x 400 pixels resolution. The optimal thermogram for defect detection at a depth of 1 mm is shown on fig. 1, b. The resulting dataset was exported to MATLAB for further processing.

Three additional computer models of five-layer CFRP training models were created to form a training dataset for classification, determination of defects depth and thickness via NN. Each model of training sample has dimensions similar to the test sample model and contains artificial defects of a specific type. Defects inside one specimen differ in dimensions (10 to 4 mm), depth and thickness values (1 to 3 mm). This arrangement of defects allows to expand the variety of training dataset.

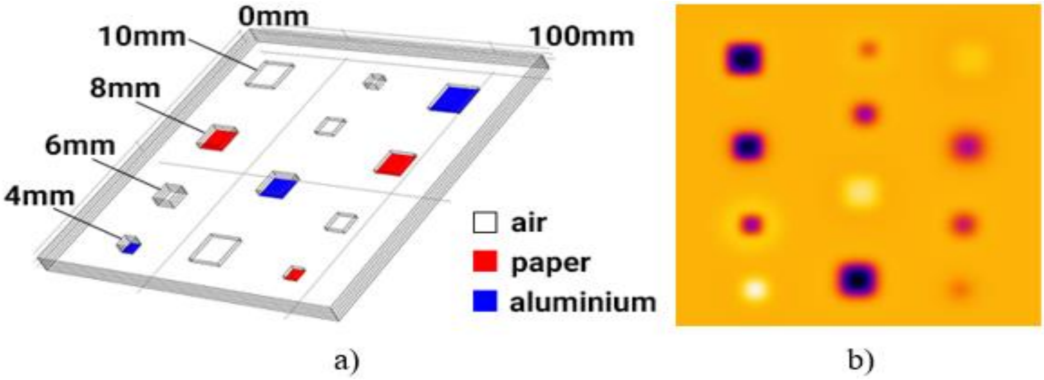

Fig.1. Computer model of testing sample: a) – schema, b) – optimal thermogram

Total number of training pairs in the received set of input vectors was 27933. Of these: 14950 examples of thermal profiles of air cavities defects, 3123 specimens of defect thermal profiles of aluminum inclusions, 3494 specimens of defect thermal profiles of paper inclusions. Levenberg-Marquart algorithm is used for NN training. NN training was conducted on a PC with the following characteristics: Intel Core i7 3770k 3.5GHz processor, 16GB RAM, NVidia GeForce GTX 760 graphics card.

Influence of the number of neurons in hidden layers.

Only a small amount of works is devoted to research on the choice of optimal NN architecture in active TNDT. This is due to fact that the network architecture may differ for each specific task. To formulate recommendations for choosing NN architecture, it is necessary to set initial conditions in the form of OT parameters and testing conditions. In the following, influence of different NN architectures on the data processing results obtained from computer simulation is considered.

According to the results of previous studies, it was found that the use of NN architecture with two hidden layers is optimal for active TNDT tasks [3]. This deepens the overall properties of network, making it more versatile. At the same time, it is proved that excessive increase in the number of hidden layers does not increase the efficiency of NN. On the contrary, too complicated architecture can lead to retraining, which will impair the approximate properties of network [6].

To research the optimal number of neurons in the hidden layers choice for NN in the active TNDT, several NN architectures with different numbers of neurons in hidden layers were implemented and trained, results of which are shown in Table 1. In the table, Np_1 – number of neurons in first hidden layer, Np_2 – in 2nd hidden layer.

Table 1.

Efficiency of NN depending on the number of neurons in two hidden layers

Criterion	$Np_1 = 3$ $Np_2 = 1$	$Np_1 = 6$ $Np_2 = 2$	$Np_1 = 12$ $Np_2 = 4$	$Np_1 = 18$ $Np_2 = 6$	$Np_1 = 24$ $Np_2 = 8$
Training time, min	47	164	219	732	993
Classification network MSE	0,0730	0,0214	0,0070	0,0068	0,0069
Temperature profiles classification error, %	48,05	23,15	10,52	9,47	10,08
Tanimoto criterion, %	62,95	74,52	89,48	89,95	89,69
Depth estimation training time, min	5	108	140	538	742
Depth estimation network MSE	0,162	0,084	0,052	0,050	0,052
Depth estimation relative error, %	±24,19	±13,60	±5,07	±4,96	±5,31
Thickness estimation training time, min	16	93	142	631	864
Thickness estimation network MSE	0,065	0,057	0,037	0,041	0,039
Thickness estimation relative error, %	±5,05	±4,69	±2,41	±3,63	±3,12

As can be seen from Table 1, the complexity of defect classification NN architecture allows to improve its efficiency only to a combination of $Np_1 = 12$ and $Np_2 = 4$. Further increase in the number of neurons in layers does not significantly improve accuracy and reliability of classification. At the same time, the complexity of architecture significantly increases training time.

For depth and thickness estimation NN, the results are similar. Increasing the number of neurons in the hidden layers has a significant effect on training time, but can improve accuracy of defectometry only to architecture $Np_1 = 12$ and $Np_2 = 4$. Further increase in the number of neurons is impractical because it does not significantly reduce measurement errors.

Influence of volume and quality of the training dataset.

An important step in the creation of neural network systems is optimal formation of training dataset. The number of training pairs corresponding to different types of defects or samples of signals from one defect has a direct impact on the representativeness of training dataset. In examples considered, the temperature profiles of all points of artificial defects embedded in training specimens of five-layer CFRP were used to train NN for relevant tasks. However, due to generalizing properties of NN, there is no need to represent absolutely all received training signals to network during the training [7].

Table 2 summarizes the NN training results using different number of training samples *Ns*. The principle of representativeness was maintained during formation of the training dataset. Only the number of temperature profiles that described defects of each type with each depth and thickness value was reduced.

Table 2.

Efficiency of NN depending on the volume of training dataset

Criterion	***Ns* = 27933**	***Ns* = 7000**	***Ns* = 350**	***Ns* = 140**
Training time, min	219	52	4	1
Number of epochs for defects classification NN	413	161	104	70
Classification network MSE	0,0070	0,0079	0,0081	0,0668
Number of detected defects	12	12	12	9
Area estimation relative error, %	11,74	16,46	29,69	45,39
Temperature profiles classification error, %	10,52	14,32	23,44	52,44
Tanimoto criterion, %	89,48	81,93	76,83	60,86
Depth estimation training time	140 min	28 min	0 min 44 s	0 min 12 s
Number of epochs for depth estimation NN	823	370	181	84
Depth estimation network MSE	0,052	0,053	0,052	0,110
Depth estimation relative error, %	±7,97	±22,71	±24,53	±42,97
Thickness estimation training time	142 min	20 min	0 min 45 s	0 min 4 s
Number of epochs for thickness estimation NN	870	306	195	50
Thickness estimation network MSE	0,037	0,041	0,052	0,106
Thickness estimation relative error, %	±2,41	±3,11	±4,37	±10,09

As can be seen from table 2, reducing the training dataset size by 4 times (to the number of training pairs *Ns* = 7000) leads to a slight deterioration in accuracy of defect area estimation (with a relative error of 16.46%) and accuracy of temperature profiles classification (with an error of up to 14, 32%) compared to the basic training dataset. Further decrease in the volume of training dataset leads to a significant deterioration of all indicators of the network. At the same time, training time is also rapidly decreasing.

Similar are the results for defects depth and thickness estimation NN. For the depth estimation network, reducing the number of training samples by 80 times does not increase network MSE, but it significantly affects the value of depth estimation relative error, which increases by 3 times (from ± 7.97 % to ± 24.53 %). For the defect thickness estimation network, results are similar.

The representativeness of training dataset has a significant impact on NN effectiveness. In the examples described above, temperature profiles of all 12 artificial defects, which were laid in OT, as well as defect-free sections, were used to train defect classification, depth and thickness estimation NN of defects of five-layer CRFP specimen. However, the generic properties of NN allows training on a limited number of sample signals. In this case, the representativeness of sample dataset become worse. But no quantitative studies on the effect of training dataset quality on results of thermogram sequence processing have been performed to date.

For purpose of conducting relevant research, five NN models were built and trained, then the best of them selected. The representativeness of training dataset was varied by selecting the number of defects *Nd*, the samples of temperature profiles of which were included in training dataset. A value of *Nd* = 2 means that samples of temperature profiles from two defects of each type are included in training dataset. Accordingly, at *Nd* = 1, samples from one defect of each type are included in the training dataset. Results are summarized in Table 3.

Table 3.

Efficiency of NN depending on the representativeness of training dataset

Criterion	***All defects***	***Nd* = 2**	***Nd* = 1**
Training time, min	219	121	65
Number of epochs for defects classification NN	413	390	256
Classification network MSE	0,0070	0,0077	0,0081
Number of detected defects	12	11	10
Area estimation relative error, %	11,74	17,03	23,44
Temperature profiles classification error, %	10,52	15,71	19,09
Tanimoto criterion, %	89,48	86,94	80,96
Depth estimation training time	140	103	80
Number of epochs for depth estimation NN	823	847	869
Depth estimation network MSE	0,052	0,054	0,050
Depth estimation relative error, %	±7,97	±12,19	±14,14
Thickness estimation training time	142	81	40
Number of epochs for thickness estimation NN	870	754	421
Thickness estimation network MSE	0,037	0,042	0,028
Thickness estimation relative error, %	±2,41	±5,95	±13,24

As can be seen from Table 3, with the decrease in representativeness of training dataset, error in determining defects area and temperature profiles classification error increases. At the same time, MSE of defect detection and classification network increases slightly from 0.0070 to 0.0081. With the worsening of representativeness, the number of detected defects decreases.

For depth and thickness of defects estimation networks, reducing the representativeness of training dataset does not lead to a clear increase in network MSE. However, the error in determining these parameters in this case increases (for depth estimation network from ± 7.97 % to ± 14.14 % in case Nd = 1; for thickness estimation network from ± 2.41 % to ± 13.24 % in case of Nd = 1). For all networks with a decrease in representativeness, the training time is also reduced, because training dataset volume decreases. In general, deliberate reduction of training dataset representativeness is not recommended, as errors in determining defect parameters increase markedly with decreasing learning time.

Experimental validation.

In order to conduct experimental validation, two training and one test specimens of multilayered fiberglass were developed. This material is used as a construction material for manufacture of parts responsible for high strength. Developed specimens are square plates of five layers of fiberglass. Total thickness of each sample is 5 mm, thickness of one layer is 1 mm. The plate is 100 mm side. Artificial defects of various types and sizes were laid in test specimen at depths of 1mm, 2mm and 3mm. Scheme of location of defects is shown in fig. 2, a.

During the experiment, a scheme of two-sided active TNDT was used. The power of infrared heating source is 1 kW. To minimize the effects of heat radiation from the heating source, a steel shield plate that contains hole and fixtures for OT is provided. OT plate is located 100 mm from the heater. The distance from OT to the Testo 876 infrared camera is 400 mm.

Sequence containing 20 thermograms obtained in the result of experiment. Obtained results reflect the process of thermal field of OT changing at the stage of heating. Recorded thermogram sequences were exported to a PC. Initial processing of thermograms was carried out using proprietary Testo IRSoft software. Resolution of each obtained thermogram is 320 x 240 pixels. Thermograms are saved as images and corresponding arrays of pixel temperatures. Thermogram of test specimen at the optimal testing time is shown in fig. 2, b.

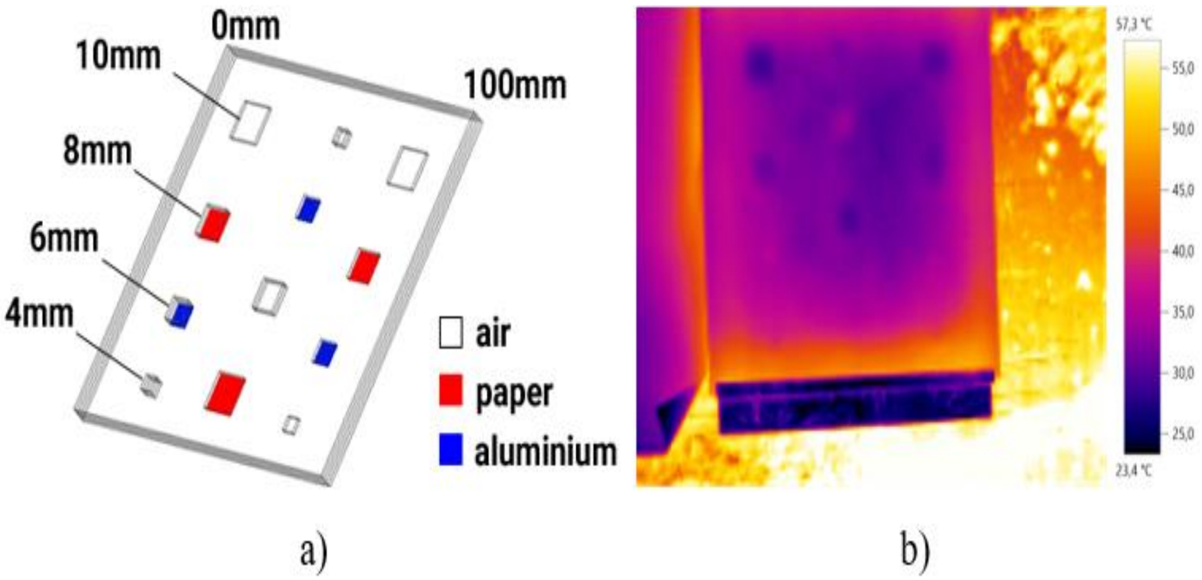

Fig.2. Experimental testing sample: a) – schema, b) – optimal thermogram

In order to form a set of training vectors for NN, two training specimens were developed and manufactured. Material, structure and geometric dimensions of the training specimens correspond to the same parameters of test specimen. The first training specimen contains only artificial defects in the form of air cavities. The second training specimen contains examples of artificial defects in the form of aluminum and paper inclusions. The total volume of training vectors set is 6545 training pairs.

The NN architecture with two hidden layers with the number of neurons in first hidden layer $Np_1 = 12$ and in second hidden layer $Np_2 = 4$ was initially selected. This architecture was determined to be the most optimal by results of computer simulation. However, network with specified architecture showed low results in processing of real experimental data. This can be explained by the presence of high noise level and imperfection of measuring equipment. Therefore, additional research was conducted to select the architecture of neural networks for defects classification and depth and thickness estimation.

Five NN of different architectures were trained for each task, of which the best by network MSE were chosen. Training results of NN with different architectures to process the thermograms of test specimen are shown in Table 4.

Table 4.

Efficiency of NN depending on architecture for experimental data

Criterion	$Np_1 = 12$ $Np_2 = 4$	$Np_1 = 24$ $Np_2 = 8$	$Np_1 = 30$ $Np_2 = 12$	$Np_1 = 35$ $Np_2 = 15$	$Np_1 = 40$ $Np_2 = 18$
Training time, min	17	21	28	31	45
Number of epochs for defects classification NN	156	138	141	121	172
Classification network MSE	0,0754	0,0059	0,0049	0,0022	0,0023
Depth estimation training time, min	9	14	14	18	27
Number of epochs for depth estimation NN	187	239	214	247	285
Depth estimation network MSE	0,1120	0,0893	0,0731	0,0590	0,0587
Thickness estimation training time, min	7	13	18	19	31
Number of epochs for thickness estimation NN	183	231	209	262	306
Thickness estimation network MSE	0,0873	0,0630	0,0236	0,0124	0,0131

Based on the data in Table 4, it be can concluded that the most optimal NN architecture for processing thermograms sequences of test specimen is $Np_1 = 35$ and $Np_2 = 15$. Further architecture complication does not show a significant improvement in results, but leads to training time increase. The use of less difficult architecture increases network errors.

Conclusions.

As a result of researches, high efficiency of NN in tasks of active TNDT is proved. According to computer simulations, NN architecture with two hidden layers and number of neurons in them $Np_1 = 12$ and $Np_2 = 4$ is the most optimal set of parameters compared to other architectures considered. However, experimental results have shown that in real conditions the architecture should be complicated to $Np_1 = 35$ and $Np_2 = 15$ neurons. Results are reliable in tasks of testing and defectometry of multilayer composites specimens in the laboratory. For other tasks, the NN architecture may differ and must be empirically determined.

Influence of training dataset volume on the effectiveness of NN has been investigated. It is proved that with a significant decrease in sample size, performance of NN deteriorates in proportion to volume changes. At the same time, training time is significantly reduced. It is found that with decreasing representativeness all performance indicators of NN deteriorate except training time, which is reduced slightly.

The main focus for further research is determination of NN architecture, which will be the most versatile for use in various thermal testing tasks. An important problem is also the pre-processing and optimization of input data for NN. This is especially true in terms of a limited number of training specimens.

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