ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ, СИСТЕМНИЙ АНАЛІЗ ТА КЕРУВАННЯ

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ANALYSIS OF APPLICATION OF NEURAL NETWORKS TO IMPROVE THE RELIABILITY OF ACTIVE THERMAL NDT

Background. The relevant question of increasing the informative content and reliability of the thermal non-destructive testing is considered in this article. The most promising algorithms of digital processing of sequences of thermograms are given.

Objective. The main aim of this research is to determine the advantages and disadvantages of the application of each considered method of digital processing of thermograms. Secondary, the possibilities of testing automation with the use of the selected methods of digital processing of thermograms are analyzed in this article.

Methods. Computer simulation software was used to obtain the artificial sequence of the thermograms. Methods of wavelet analysis, principal components analysis and neural networks were used to process the received data.

Results. The simulation of active thermal testing process is carried out in this research. The artificial thermogram sequence with a high level of noise is obtained for the object of testing. In order to quantify the results of application of considered methods, relative errors of determining the area of defects were calculated. Also values of Tanimoto criterion are obtained. The advantages of the neural network processing of digital data in thermal non-destructive testing have been established and proved in this article. Shape of defects on a binary map built by the neural network was closest to true compared with principal components analysis method. The effectiveness of neural networks is also confirmed by quantitative estimates.

Conclusions. The method of wavelet transformation has a high sensitivity. This method is ineffective in the conditions of uneven heating and high noise. The principal components analysis method allows increasing the SNR and improving the visual perception of thermograms, but does not provide complete separation of information about defects and noises caused by uneven heating. Methods of artificial neural networks theory provide the best reproduction of the shape and size of the defects, but the training process requires significant time and computing resources.

Keywords: wavelet analysis; principal components analysis; neural networks; thermogram processing.

Introduction

Thermal non-destructive testing (TNDT) is widely used in various fields of industry due to its contactlessness, high performance and effectiveness. The thermal field of the object of testing (OT) is recorded and visualized using the thermal imager. Received thermograms represent the distribution of the intensity of object's thermal field, and their quality depends on many factors. The results are influenced by parameters of the infrared radiation detector, preferences of testing, external conditions, thermophysical characteristics of the object. In this regard, thermal images are characterized by high levels of noise. The form of thermal imprints of defects is often distorted, so in many cases it is impossible to uniquely estimate the parameters and characteristics of defects. The issue of increasing the informativeness of thermograms is important in order to ensure high reliability of testing.

Thermograms are digital images that represent the distribution of pixel values of temperatures on the OT surface, thus, for their analysis the methods of digital signal processing are used. One of the modern approaches is the use of wavelet transformation applied to the temperature profiles at the points of the thermogram. As noted in [1], this allows increasing the SNR, aligning the image field and increasing the sensitivity of detecting structural defects. Significant interest is also caused by the statistical method of principal components analysis (PCA) [2]. This method is used in the theory of pattern recognition to solve classification tasks and to reduce the size of the initial data. The use of artificial neural networks in thermal testing is also promising [3, 4]. A comparative analysis of different methods of thermogram processing was made in [5] and some recommendations are given. However, still an important issue is the assessment of efficiency and the choice of the most optimal and versatile modern method of thermogram processing. The main requirements for such a method are high noise immunity, informativeness, the ability to automate the procedure of testing and data processing.

Problem Statement

The aim of the study is to evaluate the efficiency of the use of neural networks for the thermogram processing with a significant level of noise in order to increase the informativeness and reliability of active TNDT. This study focuses on the technique of thermogram processing and describing the process of conducting research using neural networks and comparing the results with the wavelet analysis method and the PCA method, since previous studies have demonstrated their advantages over other methods of thermograms processing.

Description of the source data

Active TNDT is based on the analysis of the dynamic thermal field, which is described by the function $T(x, y, \tau)$. In this case is considered the character of the change of instantaneous values of temperature in time at the points of the OT surface. As a rule, during conducting of active thermal diagnostics the object is firstly heated, and then the certain time is allocated to cool it. Throughout the process of heating-cooling, the temperature field is recorded with the thermal imager. As a result, a sequence of thermograms representing the change in the temperature field on the surface of the OT in time is recorded with a certain frame rate [6]. In the defect zone, the regular nature of the thermal field is violated and there are local temperature differences $T_d(x, y, \tau)$ appeared, that lead to changes in the temperature profile.

A simulation of the heating and cooling of the OT was performed using the COMSOL Multiphys-ics software. The tools of MATLAB software, which contains a wide range of built-in functions for digital signal processing, were used to study the methods of thermogram processing [7].

A computer model of steel plate with 20 mm thickness and 100 mm sides was created as a testing sample (Fig. 1, *a*). Artificial defects of square shape with 15 mm, 10 mm and 5 mm side and thickness of 5 mm were placed in the middle of the sample model at a depth of 10 mm. The heating has been carried out for 8 seconds by the heat flux with a power density of 10 kW/m^2, which was applied to one of the faces of the OT. Cooling lasted 12 s. To take into account the influence of the unevenness of heating and the presence of noise in real thermal testing, two sources of low power heat flows located on the edges of the plate were added to the model.

A sequence of 20 thermograms with an interval of 1 s between them was obtained as a result of the simulation. Parameters of the sample were intentionally chosen so that the thermal imprints of defects on the surface of OT were blurred due to the effect of thermal diffusion, which greatly complicates the analysis of the thermogram visually, without the use of additional processing means. The thermogram in optimal testing time is shown in Fig. 1, *b*.

Wavelet analysis

Fourier transform is considered to be one of the most sensitive methods of thermogram processing. Analyzing the shape, amplitude and time characteristics of the temperature profile, as well as the frequency, phase and power characteristics of

| a | b |

Fig. 1. Simulation of OT: *a* — the layout of the defects, *b* — the thermogram in the optimal testing time (9 s)

the temperature signal when applying the Fourier transform, we can make conclusions about the size, position and depth of defects. At the same time, the results of such analysis essentially depend on the quality of the recorded thermograms, their number, presence of noise, parameters of heating the OT, experience of the operator, etc. The disadvantages of using the Fourier transform for thermogram processing are described in [8, 9].

In order to eliminate the negatives of Fourier analysis, the use of wavelets was proposed. By its physical content, wavelet transform differs from Fourier transform by form of a basis function. If Fourier transform decomposes signal into a series by a sine or cosine, then wavelet analysis involves the use of a wide variety of other basis functions. In [10] it is proposed to use Gaussian or Morlet wavelets in the thermal testing due to their similarity to the shape of temperature signal. At the same time, this study indicates that the shape of signals in thermal testing is smoothed, whereas wavelet analysis is used mainly in the tasks of detecting and processing short-term radio pulses.

Wavelet images have the same features as Fourier's images. The result of wavelet transform also contains a real and imaginary part. It is possible to detect the position of defects using the phase of wavelet transformation [11].

The representations of absolute value and phases of wavelet shapes were obtained by the application of wavelet transformation to the initial sequence of thermograms (Fig. 2). The representations of wavelet shapes have a uniform field, which is expressed in a small number of parasitic lines, and a better contrast. However, the size and shape of the defects are distorted. At the same time, the images retained the representation of artificial

structures that simulate the uneven heating. On this basis, emphasize the drawbacks analogous to Fourier analysis method, and poor suitability of method for analysis of thermograms with fuzzy contours of defects and uneven heating.

The wavelet transforms the one-dimensional time function signal into a two-dimensional function of scale and shift, which results in significant computing costs. To determine the optimal wavelet transformation parameters, it is necessary to make additional calculations based on the thermophysical characteristics of the OT, which not always can be performed with the required accuracy. In general, the question of using wavelets in thermal testing is controversial. Considering the presence of a large number of parasitic structures, the construction of a binary map of defects location based on the results of this method is not feasible.

Principal components analysis

The method of principal component analysis is based on Karunen-Loev transformation. This method is widely used in statistics to reduce the space of features without significant loss of information.

Algorithm of the method of principal component analysis (PCA) applied to the processing of sequences of thermograms was first described in [12]. The authors used PCA to test the carbon fiber cylindrical products. Improvement of the visual perception of thermograms and the increase of SNR was proved in the course of the study. At the same time, there is a need to change the transformation parameters for each separate control task, which requires additional time expenditures. Classification of defects is complicated, because the
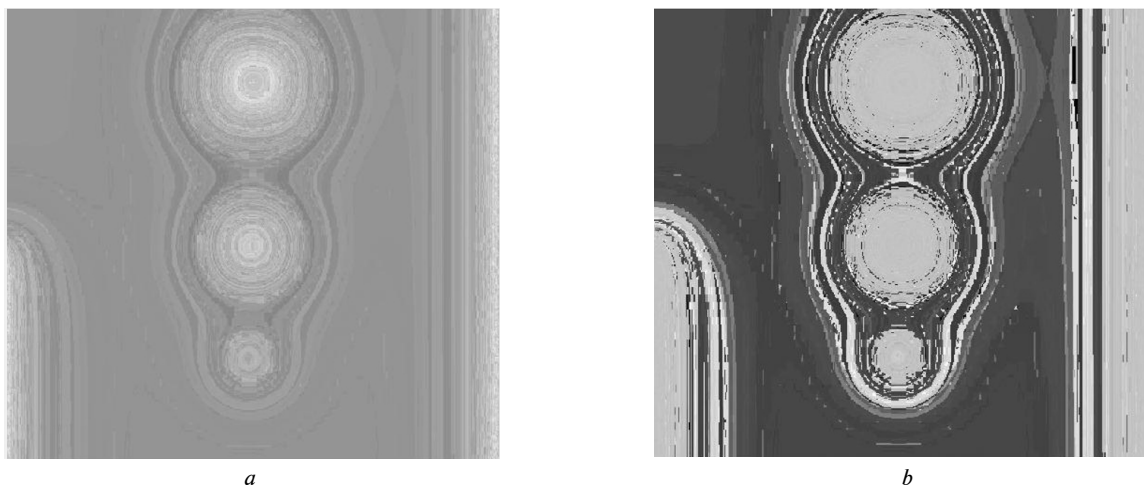

a   *b*

Fig. 2. Image of the results of wavelet transform at the 1st frequency: *a* — absolute value, *b* — phase
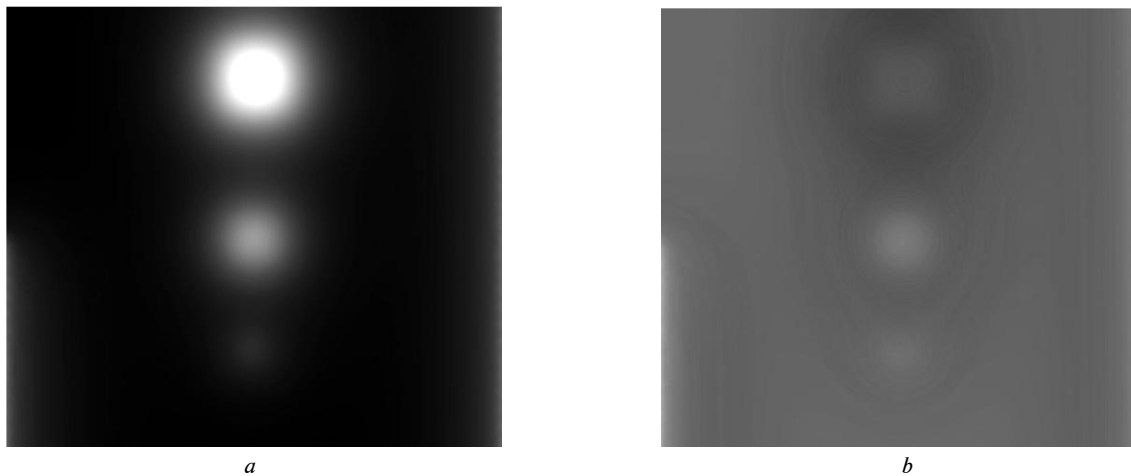
Fig. 3. Projections of initial sequence: *a* − on first principal component, *b* − on second principal component

method does not provide unambiguous separation of information about defects and noises.

Consider the algorithm of PCA to process the simulated sequence of thermograms. In this case, the number of thermograms $n = 20$, the number of rows and columns in the thermograms $m = 533$ and $k = 480$, respectively. After the transformation of the sequence, we have an initial matrix X with a dimension of 20×255840 elements. The size of the covariance matrix will be $n \times n$, that is, 20×20 elements. Let's leave the first 3 principal components, then the dimension of the matrix W^T will be 3×20, and the dimension of the resulting matrix Y will be 3×255840. After the decomposition of the matrix Y, we obtain a sequence of three images, which represent the projection of initial data for three principal components. An example of projections for first and second principal components is shown in Fig. 3. Contrasting was applied to the images to align the histogram for better visual perception.
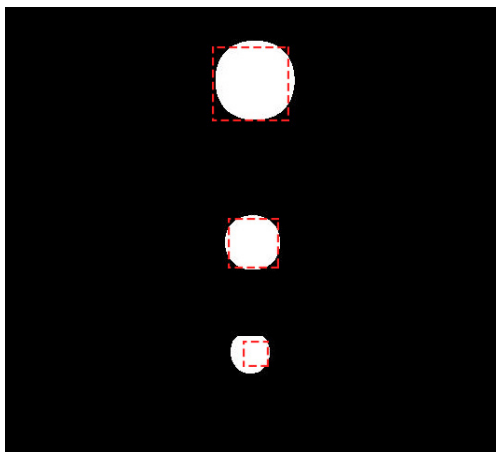

Fig. 4. Binary map of defects, obtained by the results of principal components analysis

The image on first principal component differs in blurred contours of defects and its similarity to the thermogram in optimal testing time. On second principal component, the shape and size of defects are more clearly displayed, as well as uneven heating sources are detected.

Applying binarization by threshold level operation to the projection image on first principal component, we can get a binary defect map, shown in Fig. 4. Note the high correspondence of the sizes of first and second defects to actual values shown in the red contour. The size of third defect in dimensions of 5 mm on a binary map is determined with higher error.

PCA allows to form a database of own vectors, which will correspond to a certain type of defects. Thus, the task of classification of defects can be solved. However, when classifying by PCA, the space of attributes separates to best fit the input data set, rather than obtaining the optimal class boundary. Therefore, when the testing conditions changes, for example the presence of uneven heating or other obstacles appears, the efficiency of the method drops sharply.

Neural networks

Neural Networks (NN) are mathematical models built on the principles of organization of biological neural networks of nervous system. The use of NN demonstrates high performance in classification tasks, image recognition, image processing, and more. The main advantage of NN is their ability to learn, which allows the network to automatically study hidden patterns in input data sets. NN work with complex nonlinear dependencies, solving multi-parameter problems [13, 14]. This al-

lows them to be used effectively for regression tasks, image classification, clustering, etc.

The classical NN consists of several layers of artificial neurons. Each neuron of one layer is connected with all neurons of the next layer with synaptic weights $w_{i,j}$. The neurons of input layer $[i_1, i_2, ..., i_n]$ intended for receiving and transmitting to network the input vector $X = [x_1, x_2, ..., x_n]$, where n — number of vector elements (counts in the signal). Neurons of hidden layers are designed to perform transformation of input data. Each artificial neuron receives a weighted sum of input data with bias:

$$A = \sum X(j) \times W(i, j) + b(i),$$

where $X(j) = [x_1, x_2, ..., x_j]$ — output vector of neurons of previous layer, j is the number of neurons in previous layer, i is the current neuron index, and $b(i)$ is the bias of current neuron.

Next, calculated value of A applies to the activation function (usually logistic, tangential or sigmoid). Thus, the equation of an artificial neuron with bias in general can be written as:

$$y = f(wx + b).$$

The initial value of current neuron is transmitted to the next layer. The value of neurons in initial layer $[o_1, o_2, ..., o_n]$ is the output data or the answer of NN. Choice of number of hidden layers, number of neurons in them, and choice of activation functions is carried out mainly empirically.

In thermal testing, NN can be used for task of defect classification and defectometry. Vectors containing thermal profiles in points (pixels) of a thermogram are given on NN input during its training for work with sequences of thermograms.

In this case, samples of defective and defect-free areas are submitted, which corresponds to class number (for example, 0 is defect-free, 1 is defective). A trained NN detects hidden dependencies and changes in temperature signals that are characteristic of a certain class of defects or defect-free areas. Thus, different modern NN can be used to build defect maps, defect classification and defectometry [15].

The authors of the paper [16] investigated the possibilities of using NN for testing of multilayer products. The resulting binary map of defects was not inferior in quality to similar maps obtained by traditional methods. The advantages of using NN in this work are demonstrated only on a qualitative level. In general, detailed research on the use of NN for tasks of thermal testing has practically not been carried out, so this issue needs further study.

Consider the work of the NN during processing the simulated sequence of thermograms. To do this, a single-layer backpropagation neural network was built in MATLAB software using the Neural Network Toolbox. The number of neurons in input layer corresponds to number of thermograms in the sequence and is $i = 20$. Number of neurons in hidden layer $j = 3$, number of neurons in output layer $o = 2$. Hyperbolic tangent was used as activation function. Levenberg–Marquardt training algorithm was used in this study. Also, other modifications of backpropagation algorithms can be used [17].

Training dataset that consisted of samples of temperature profiles at points of defective and defect-free zones was used to train the network. Total number of training samples is 7350. Of these, 4070 samples of defects temperature profiles, 3280 samples of temperature profiles in defect-free areas. It is worth noting that only defects that were most confidently visible on optimal thermograms were
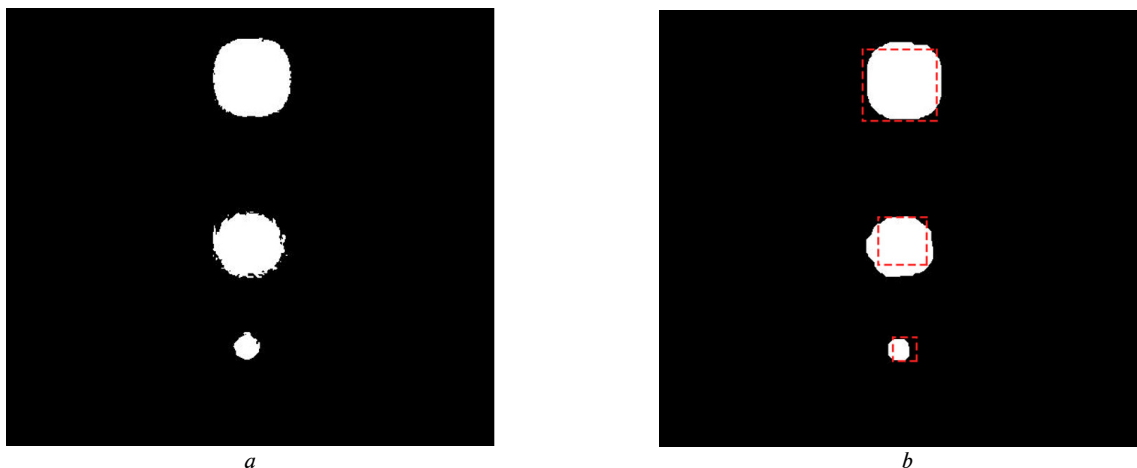

Fig. 5. The result of NN processing: *a* — without post processing, *b* — with morphological filtering of binary map

used to form samples of defective areas. The total training dataset was divided into three parts — training, test and validation sets. The training set comprised 70 % of total set of samples, the test and validation sets comprised 15 % of total number of samples. According to answer of NN, each pixel of thermogram corresponded to a certain class — defective (1) or defect-free (0).

A binary map of defects (Fig. 5, *a*) was built based on answer of the network. It is worth noting the high accuracy of the network and the lack of artifacts in image. Dimensions of defects with size of 15 mm and 5 mm are determined most accurately. A high error is observed in defining a 10 mm defect. Unlike the previously discussed methods, the form of detected defects is closer to actual one. This is particularly well seen in Fig. 5, *b*, which shows a binary map after operation of morphological image open.

The NN showed high noise immunity, as there is no uneven heating or other artifacts on the binary map. Construction of binary map was carried out with high precision in automatic mode without additional operations, which demonstrates superiority of NN technologies to other methods of digital thermogram processing.

Discussion

In order to quantify the results of application of considered methods, relative errors of determining the area of defects were calculated. Also values of Tanimoto criterion are obtained, used in theory of pattern recognition to determine quality of recognition [18]. The Tanimoto criterion is calculated according to formula:

$$T = \frac{N_{\text{r.d.}} - N_{\text{m.d.}}}{N_{\text{r.d.}} - N_{\text{f.d.}}},$$

where $N_{\text{r.d.}}$, $N_{\text{m.d.}}$, $N_{\text{f.d.}}$ — the number of real defects (defected points), missed, and false defective points on thermogram, respectively.

This criterion can be used to compare the effectiveness of different methods of thermogram processing only if parameters and location of defects in sample are known in advance. The main feature of Tanimoto criterion is concurrently use of missing defective points and points that were falsely identified as defective. This allows associating this criterion with reliability of testing. Value $T = 100 \%$ is possible only in the case where probability of correct detection of defects $P_{\text{c.d.}} = 100 \%$ and probability of false alarm $P_{\text{f.a.}} = 0$. Conse-

quently, high values of Tanimoto criterion correspond to high reliability of TNDT results. Accordingly, a decreasing of values of this criterion indicates deterioration in reliability of testing. Simplicity of calculations makes Tanimoto criterion a convenient indicator for comparison and estimation of methods of thermogram processing.

Data from binary defect map was used for calculations. Since the binary map based on the results of wavelet transformation is not informative, a quantitative assessment of effectiveness of this method is not given. The relative error of determination of area and values of Tanimoto criterion for PCA method and artificial neural networks are given in the Table. It is worth noting that, in other configuration of OT, other conditions of testing and defect parameters, the error values may differ significantly from ones in the table. The unpredictability of results when initial parameters are changed is a characteristic feature of all existing methods of digital thermograms processing.

Table. Evaluation of defining the size of defects

Parameters	PCA	NN
Relative error, %	23	16.7
Tanimoto criterion, %	48.1	63.2

Method of wavelet transform allows getting a clear image of all structures that are present in thermograms of initial sequence due to high sensitivity. In the presence of noises, this method is ineffective. Ability to classify defects by this method requires additional study. Automation processing of sequences of thermograms is complicated, because for effective application method requires preliminary calculation of initial parameters for each separate testing procedure.

The method of principal components analysis allows increasing SNR. The main advantage is reduction of dimension of input data. The possibility of classifying defects by this method has not been proved. The main disadvantages are low noise immunity and a sharp decrease in the efficiency of method when changing testing conditions. Building of binary maps requires a qualitative assessment and choice of the most informative main component, which complicates automation of control. Value of Tanimoto criterion, $T = 48.1 \%$, indicates that there is a high probability of misidentification of defects.

Methods based on the use of artificial NNs are highly effective in analyzing thermograms with high levels of noise. NN provide the best reproduction of shape and size of defects in comparison

with other methods of digital thermogram processing. Building of binary maps takes place in automatic mode. The Tanimoto criterion at the level of $T = 63.2\%$ confirms the increase of reliability of testing compared to PCA method. Versatility and high adaptability make it possible to use NN effectively to solve a wide range of tasks. The disadvantages include the need to form a bulk training data base, with learning process requiring significant time and computing costs. Therefore, it is recommended to test same type of products, which will require only one-time training of network.

Conclusions

Methods of digital thermogram processing can improve image quality compared to optimal thermogram, increase SNR and, as a consequence, reliability of testing. The main problem of most methods is low noise resistance.

According to results of comparative analysis, the neural network thermograms processing showed best results. Shape of defects on a binary map built by the NN was closest to true compared with PCA method. The effectiveness of NN is also confirmed by quantitative estimates. NN allow in long run not only to build a map of defects, but also to determine their type, size and depth. Versatility of algorithms and high adaptability make NN the most promising method of thermograms processing.

Topical tasks for further research are study of ways to optimize architecture and process of NN learning, analysis of possibilities of using different types of NN in specific tasks of non-destructive testing. The greatest interest is development of automated systems of thermal testing on the basis of NN. It is expected that such an approach will reduce role of operator in decision-making process, improve accuracy of defining the defects size and probability of testing. Automated intelligent systems of thermal defectoscopy and defectometry can be used to solve a wide range of problems in various fields of industry.

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АНАЛІЗ ЗАСТОСУВАННЯ НЕЙРОННИХ МЕРЕЖ ДЛЯ ПІДВИЩЕННЯ ДОСТОВІРНОСТІ АКТИВНОГО ТЕПЛОВОГО НЕРУЙНІВНОГО КОНТРОЛЮ

Проблематика. Розглянуто актуальне питання підвищення інформативності та достовірності теплового методу неруйнівного контролю. Наведено найбільш перспективні алгоритми цифрової обробки послідовностей термограм.

Мета дослідження. Визначити переваги та недоліки, області застосування сучасних методів цифрової обробки термограм з метою підвищення їх інформативності. Аналіз обраних методів проводиться для визначення можливостей автоматизації теплового неруйнівного контролю.

Методика реалізації. За допомогою засобів комп'ютерного моделювання отримано штучну послідовність термограм об'єкта контролю. Для обробки отриманих даних використовувалися методи вейвлет-аналізу, аналізу головних компонент і штучні нейронні мережі.

Результати дослідження. Проведено моделювання процесу активного теплового контролю. Отримано штучну послідовність термограм об'єкта контролю із високим рівнем завад. Для кількісної оцінки результатів застосування розглянутих методів розраховано відносні похибки визначення площі дефектів. Також отримано значення критерію Танімото. Встановлено та доведено переваги засобів нейромережної обробки цифрових даних у тепловому неруйнівному контролі. Форма дефектів на бінарній карті, побудованій за допомогою нейронної мережі, була близькою до істинної порівняно з методом аналізу головних компонент. Ефективність нейромереж підтверджується і кількісними оцінками.

Висновки. Метод вейвлет-перетворення має високу чутливість. Цей метод неефективний в умовах нерівномірного нагріву та значних завад. Метод аналізу головних компонент дає змогу збільшити співвідношення сигнал/шум і поліпшити візуальне сприйняття термограм, але не забезпечує повного відокремлення інформації про дефекти і завади, що викликані нерівномірним нагрівом. Методи теорії штучних нейронних мереж забезпечують найкраще відтворення форми і розміру дефектів, але навчальний процес вимагає значних витрат часу та обчислень.

Ключові слова: вейвлет-аналіз; аналіз головних компонент; нейронні мережі; обробка термограм.

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АНАЛИЗ ПРИМЕНЕНИЯ НЕЙРОННЫХ СЕТЕЙ ДЛЯ ПОВЫШЕНИЯ ДОСТОВЕРНОСТИ АКТИВНОГО ТЕПЛОВОГО НЕРАЗРУШАЮЩЕГО КОНТРОЛЯ

Проблематика. Рассмотрен актуальный вопрос повышения информативности и достоверности теплового метода неразрушающего контроля. Приведены наиболее перспективные алгоритмы цифровой обработки последовательностей термограмм.

Цель исследования. Определить преимущества и недостатки, области применения современных методов цифровой обработки термограмм с целью повышения их информативности. Анализ выбранных методов проводится для определения возможностей автоматизации теплового неразрушающего контроля.

Методика реализации. С помощью средств компьютерного моделирования получена искусственная последовательность термограмм объекта контроля. Для обработки полученных данных использовались методы вейвлет-анализа, анализа главных компонент и искусственные нейронные сети.

Результаты исследования. Проведено моделирование процесса активного теплового контроля. Получена искусственная последовательность термограмм объекта контроля с высоким уровнем помех. Для количественной оценки результатов применения рассмотренных методов рассчитаны относительные погрешности определения площади дефектов. Также получены значения критерия Танимото. Установлены и доказаны преимущества средств нейросетевой обработки цифровых данных в тепловом неразрушающем контроле. Форма дефектов на бинарной карте, построенной с помощью нейронной сети, была более близкой к истинной по сравнению с методом анализа главных компонент. Эффективность нейросетей подтверждается и количественными оценками.

Выводы. Метод вейвлет-преобразования имеет высокую чувствительность. Этот метод неэффективен в условиях неравномерного нагрева и значительных помех. Метод анализа главных компонент позволяет увеличить соотношение сигнал/шум и улучшить визуальное восприятие термограмм, но не обеспечивает полного отделения информации о дефектах и помехах, вызванных неравномерным нагревом. Методы теории искусственных нейронных сетей обеспечивают наилучшее воспроизведение формы и размера дефектов, но процесс обучения требует значительных временных и вычислительных затрат.

Ключевые слова: вейвлет-анализ; анализ главных компонент; нейронные сети; обработка термограмм.