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USE OF RADIAL-BASIS NEURAL NETWORKS FOR CLASSIFICATION OF SIGNALS

Abstract. The results of the study radial basis and probabilistic neural networks for solving the problems of classification of signals in defectoscopy are represented.

Keywords: radial basis, probabilistic neural networks, defect, classification.

Introduction. Lately actively developing a new area of applied mathematics − the theory of neural networks. Developed by a huge number of functioning algorithms and neural networks training, work is underway to create algorithms to optimize their structure in order to improve performance, quality results, reducing training time. Neural network technologies have been used in economics, medicine, industry and many other areas of science and technology can solve almost any problem associated with modeling, forecasting, optimization [1].

In the area of neural network technologies considerable amount of research is necessary to engineering problems, in particular, the aviation and space industry. In this area, there is a trend towards the production of modules with a high level of automation, which requires an increasing number of intelligent solutions that would be able to handle a wide range of products, to assess the quality of the product in order to minimize the control and assistance from a human operator. [2]

Details and body aircraft and spacecraft are made of composite materials. In carrying out non-destructive testing of such products receive signals of different shapes. Shape of the signal gives an idea of the character of the defect. One should take into account the surface roughness of the composite material, which adds a different intensity and noise complicates the recognition of the waveform, and accordingly, the type of defect.

To reduce the load on the expert to improve the quality and efficiency of defective products must perform a preliminary automated analysis of the information obtained. The result of this analysis is to classify products (the simplest case - the presence or absence of the defect).

To solve complex classification problems are increasingly using neural networks, which are capable of modeling various processes, adaptation and ability to work with noisy data [1].

Formulation of the problem. The paper presents a comparative analysis of the application of radial basis and probabilistic neural networks for the classification of noisy signals with eddy current defectoscopy of composite materials.

Theoretical foundation. Network of radial basis functions − a neural network feedforward signal, which comprises intermediate (hidden) layer radially symmetric neurons. This neuron transforms the distance from a given input vector corresponding to the "center" for some nonlinear law (usually Gaussian function). In turn, the radial function – a function *f (x),* which depends only on the distance between x and the fixed point of X.

Bayesian classification algorithm assumes that the density distribution can be represented as a mixture of Gaussian distributions with diagonal covariance matrices. To do this, write down the basic formula of the Bayesian classifier

$$a(x) = \arg\max_{y \in Y} \lambda_y P_y p_y(x), \tag{1}$$

where Y − many answers (classes), x belongs to the set of objects X, P_y − a priori probability of class Y, $p_y(x)$ − the likelihood function of class Y, λ_y − cost of error on the object of class Y.

Represent the density $p_y(x), y \in Y$ of the classes k_y component mixtures. Each component has an n-dimensional Gaussian density with parameters: $\mu_{yj} = (\mu_{yj1},...,\mu_{yjn})$ − center and $\sum_{yj}=diag(\sigma_{yj1},...,\sigma_{yjn})$ − covariance matrix for j=1, …, k_y. Therefore, a mixture of densities represented:

$$p_y(x) = \sum_{y=1}^{ky} \varpi_{yj} P_{yj}(x), \tag{2}$$

A density of each component of the mixture (looks like Gaussian) will present:

$$p_{yj}(x) = N(x; \mu_{yj}, \sum{}_{yj}) \tag{3}$$

subject to the normalization of weights and non-negativity $\sum_{j=1}^{k_y} \varpi_{yj} = 1, \varpi_{yj} > 0$.

Express the density of each component $P_{yj}(x)$ through a weighted Euclidean distance from x to the center of the object components μ_yj (t. E. Substitute in the basic formula of the Bayesian classifier (1) instead P_y (x) of formula (2) with (3)), we obtain:

$$a(x) = \arg\max_{y \in Y} \lambda_y P_y \sum_{j=1}^{ky} N_{yj} e^{(-\frac{1}{2} p_{yj}(x, \mu_{yj}))}, \tag{4}$$

where $N_{yj} = (2\pi)^{-\frac{\pi}{2}} (\sigma_{yj1}, ..., \sigma_{yjn})^{-1}$ — normalization factors.

The resulting algorithm is similar to the neural network, which consists of three

levels or layers. The first layer is formed k_1 + ⋯ + k_M Gaussians P_yj (x), y ε Y, j

= 1, ..., k_y .. At the entrance they take the description of the object x, the output give estimates of the closeness of the object x to the centers μ_{yj}, equal component density values at x. The second layer consists of the M adders calculating the weighted average of these estimates with weights ω_{yj}. At the exit of the second layer appear estimate the closeness of the object x to each of the classes of equal value of the density classes P_{yj} (x). The third layer is formed by a single unit argmax, makes the final decision to classify the object x to one of the classes. Thus, the classification of the object x is estimated its proximity to each of the centers μ_{yj} the metric P_{yj} (x, μ_{yj}), j = 1, ..., k_y. The object belongs to the class, at whose center, it is closer.

Described three-level classification algorithm called network with radial basis functions or RBF-network (radial basis function network). The neural network of radial basis functions in the general case contains three layers: the conventional input layer that performs the distribution of the sample data for the first layer of scales; hidden layer neurons with radially symmetric activation function and output layer.

Education RBF-network is reduced to restore the density of each of the classes. The learning outcomes are the centers μ_{yj} and variance Σ_{yj} component j = 1, ..., k_y. It may be noted that, in assessing the variance actually select metrics P_{yj}, by means of which will be calculated the distance to the center μ_{yj}. When using the described algorithm for each class is determined by the optimal number of components of the mixture.

To construct RBF-network must satisfy the following conditions.

Firstly, the presence of the standards provided in the form of weight vectors in the hidden layer neurons. Secondly, the availability of a method for measuring the distance of the input vector and the reference. Usually a standard Euclidean distance. Third, a special feature activation of neurons in the hidden layer, specify the chosen method of measuring distances. Is commonly used Gaussian function, greatly enhances small difference between the input and the reference vectors. The output of the hidden layer neuron reference - a function (Gaussian distribution) which depends only on the distance between input and reference vectors.

Education layer samples neurons network involves conducting a preliminary clustering to find the reference vectors and certain heuristics to determine the values.

The neurons of the hidden layer are connected by a full mesh scheme with the output layer neurons, which carry a weighted sum.

In solving the problem of classification can be estimated probability density for each class, to compare the probability of belonging to different classes and select the most likely. This is what happens when we train the neural network "solve" the problem of classification. The network tries to determine the (approximate) probability density.

Usually probability density estimate is based on kernel estimators. In this case, the reason, if the observation point is located in this space, it indicates that at this point there is a certain probability density. Clusters of closely lying points indicate that at this point the probability density is large. Near observation has more trust in the level density, and further from him confidence decreases and tends to zero. In the method of nuclear grade at the point corresponding to each observation, put some simple function, then they are added and, as a result, we obtain an estimate for the total probability density. The most commonly used kernel functions take a simplified Gaussian function:

$$f(X) = e^{-\frac{|X - X_i|^2}{2\sigma^2}}, \qquad (5)$$

where Xi - i-th sample of one of the recognized classes,, X - unknown sample, σ - parameter that specifies the width (deviation) of nuclear Gaussian function and determining its impact. To determine the probability density function for the entire k-th class, the Gaussian function for all training vectors are summed up:

$$\varphi(X)=\sum_{i=1}^{L_k} e^{-\frac{|X-X_i|^2}{2\sigma^2}}\ ,\qquad (6)$$

where Lk - the volume of training sample k-th class.

Approximation method using probability density functions of nuclear largely similar to the method of radial basis functions, and thus we come to the probabilistic neural network. Such a network is an implementation of methods of nuclear approximation, decorated in the form of a neural network.

Neural network PNN (Probabilistic Neural Network) consists of three layers: input, output, and radial. Radial elements are taken one by one to each student observation. Each of them represents a Gaussian function centered at this observation. Each class corresponds to one output. Each element is connected with all the radial elements belonging to its class, and with all the other radial elements it has zero connection. Thus, the output feedback element simply adds all the elements belonging to its class. The values of the output signals obtained proportional nuclear estimated probability of belonging to the corresponding classes, and normalizing them to the unit, we obtain the final estimate of the probability belong to the classes.

Practical implementation. At the scanning of product from composite materials spatial basis of signals received lower limit diameter area of the electromagnetic control. Amplitude of signals in every point of abscissa is determined by the projection defect in the product on the plane perpendicular to the direction of the eddy currents**.** The area is the integral informative characteristic of such signals.

Smooth change of the form of signal from unimodal with maximal amplitude (defects exceed a control zone) to bimodal with the most failure of the top(point defects) is modeled by means of expression[3]:

$$y(x)=\exp(-1{,}5x^2)-k\cdot\exp(-3x^2)\ ,\qquad (7)$$

where *k* varies from 0 to 1 and *x* from -2 to 2 in 0.1 increments. The result signals of different forms: for k = 0 ÷ 0.35 - narrow unimodal signal describing the long crack, the length of which exceeds the control zone. When changing k = 0.35 ÷ 0.55 obtain gentle unimodal signal characteristic cracks of lower dimension; at k = 0.6 ÷ 1 a bimodal signal, which is characteristic of small cracks (for k = 1 − a point defect).

Area model signal is informative characteristic of eddy current signals and is calculated by integrating the expression (4) on the abscissa from before, and the difference is known [4] of the areas under the two Gaussian curves unspecified, with parameter values $\sigma=1/\sqrt{3}$ and $\sigma'=1/\sqrt{6}$:

$$Q = \sqrt{\frac{2\pi}{3}}(1 - \frac{\sqrt{2}}{2}k)\,, \qquad (8)$$

where Q is measured in units of square relative length equivalent to the reduced diameter coil eddy current transducer.

To solve the problem of classification of signals obtained by scanning the composite materials used in the radial-basis (RBF) and probabilistic (PNN) neural networks.

Signal Classification was performed in two ways: by area, using the expression (7), the coordinates with regard to the expression (6). In each of the methods used two types of noise pollution: a random variable distributed according to the normal law, and additive white Gaussian noise.

Developed a simulation software environment MATLAB R2011a IFR Neural Network Toolbox [5].

In the case of signal classification area first define the vector of indices of classes, according to which a matrix of connections in diluted form. Then, using the formula (7), for each value of k from 0 to 0.1 1 was filled with the matrix Q, the number of which corresponds to each value of the index vector classes. For training neural networks use a vector containing the values of the area ideal signals.

After learning of neural networks on ideal signals were noisy signals. First, the expression (6), a random value, distributed according to a normal distribution with mean 0 and standard deviation of from 0 to 0.2 in increments of 0.05 [4]. For noisy signals used by white Gaussian noise environment function awgn (x, snr, 'measured'), where x is a vector signal scalar snr specifies the signal / noise ratio in decibels. If the value of x is complex, the function adds awgn integrated noise. In this case, the power of x is measured automatically. To calculate the area of noisy signals used trapezoidal rule [4].

Next noisy signals are processed by the neural network and the results were recorded in the results matrix.

Checking the operation of the neural network was carried out on 1000 input vectors for different noise levels. The results of the experiment are shown in Fig. 1 and 2.

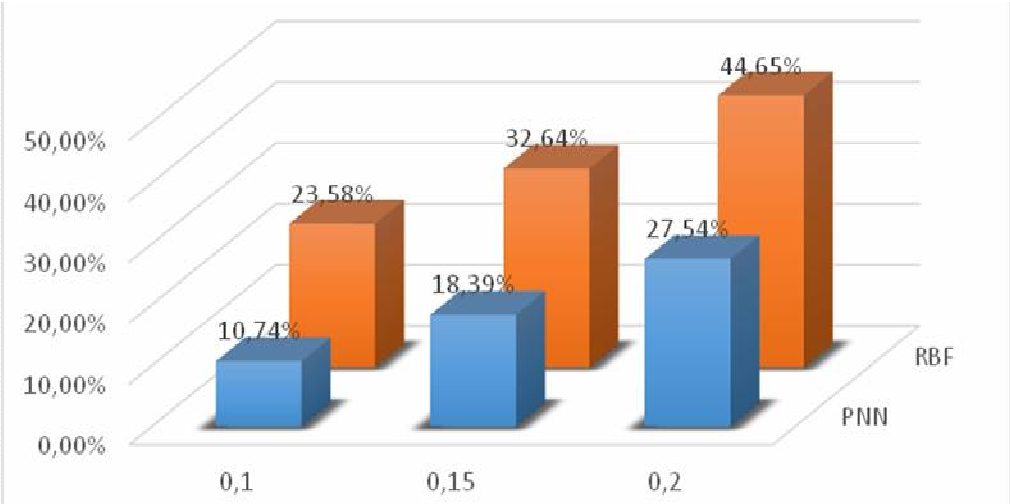

Figure 1 – Tolerances of neural networks in the classification of signals, noisy random variables distributed according to a normal distribution with a mean of 0 and a standard deviation of 0 to 0.2

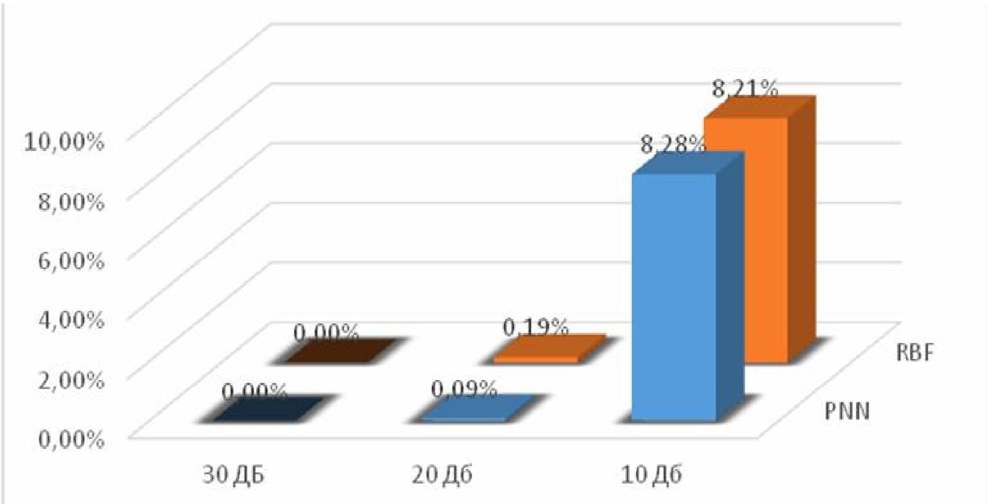

Figure 2 – Tolerances of neural networks in the classification of signals, noisy white Gaussian noise

When classifying signals, which are given by the difference of exponents (6), 10 first selects the values that define the 41-component vector of inputs, and relate each of them to one of three classes. Layer has 10 neurons samples: 5 for the first, 2 for second class and 3 - for the third class. Summation layer comprises three neuron in accordance with the number of classes into which the input vectors.

Defines a vector of indices of classes, according to the connection matrix which is constructed in a dilute form. Then, using the expression (6), for each value of k from

0 to 1 in increments of 0.1 is filled matrix, wherein each signal corresponds to the values of the vector indices classes.

For training neural networks used a vector which contains ideal signals consisting of 41 coordinates. For the simulation of signals from noise to the expression (6) added random variables distributed according to the normal law and then white Gaussian noise.

Verifying the functioning of the neural network was carried out on 1000 input vectors for different types of noise. For each value of the noise measurements performed in 1000 and identify common errors relative work:

$$P = \frac{n}{N} \times 100\%, \tag{9}$$

where n - the number of recognition errors, N - total number of measurements. The results of the experiment are shown in Fig. 3 and 4.

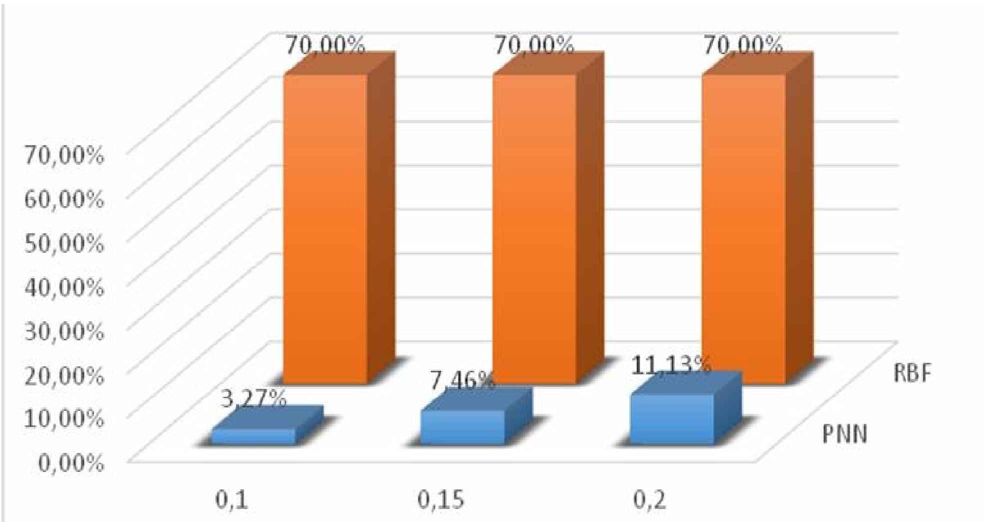

Figure 3. – Estimation of the error operation of neural networks for pattern recognition signals, noisy random variables distributed according to the normal law

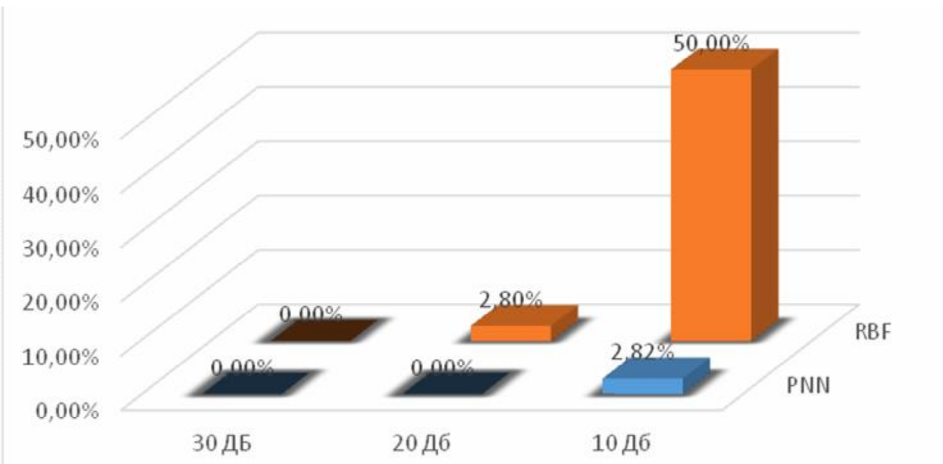

Figure 4 Evaluation of error operation of neural networks for pattern recognition signals, noisy white Gaussian noise

Conclusions. Studies have shown the fundamental possibility of the use of artificial neural networks to identify defective products from composite materials. In noisy results white Gaussian noise signal processing by neural networks occurs with greater precision, corresponding to reality, since noise present when scanning composite materials close to white Gaussian noise.

Comparing methods of signal classification can be said that probabilistic neural networks to more accurately determine the class to which the signal is described by the difference between the exponents and not on the area where the radial basis neural network shows better results.

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