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NEURAL NETWORK APPLICATION IN THE DEFECTOSCOPY

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Abstract: At present avery perspective solution of indications classification in the defectoscopy is neural network application. One of the fields is classification of indications into classes, that are characterized by the signal shape, eventually by the signatures relating to the signal shape. The nondestructive defectoscopy of steam generator tubes of nuclear power plants by multifrequency eddy current method is the field, in that the use of classifiers, based on neural network is very perspective.

The contribution concentrates on the choice of suitable neural network structures, on the choice of the training set and of the suitable representation of indications. The success of selected solutions is compared on real records of steam generator tubes with artificial defects and with imitation of construction element.

Keywords: eddy-current, neural network, expert system

1 INTRODUCTION

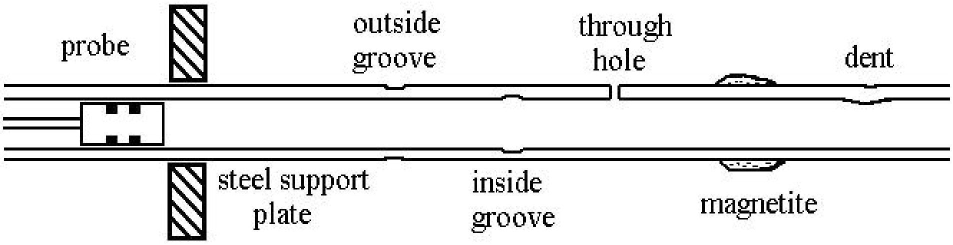

Figure 1. Defect types

Eddy current testing is one of methods of nondestructive testing. In our case it is the testing of heat-exchanger tubing using a differential probe [1]. Tubes are made from nonmagnetic material. The shape of output signal from the probe reflects properties of tested material. The fundamental problem is to determine according to the signal shape, whether there is some defect, structural element, roughness or impurity in the tube, etc. Potential defect location in the signal are called indications.

Indication can be processed using different representations, which can describe the primary signal. Among the fundamental problems belongs researching of indication in the signal (violent change of the signal, the choice of the boundary of indication,...), adjustment of indication for classification (creation of signature vector - e.g. Fourier coeficient [2], distances of extremums and their angle) and the classification of indication signature (fundamental and quantitative).

The output signal from the probe includes measurement data for different frequencies. Signals of different frequency describe changes in material in the different depth of tested tube. Higher frequencies can better map the changes of internal structure (e.g. internal scratch), lower frequencies can better describe the changes of outside cover (e.g. presence of support). Some methods based on the signal properties have been developed in the defectoscopy.

2 SIGNAL PROPERTIES

We have used a differential probe. Computer can read output signal of this device and backup it into data files for future use. Typicaly data files contains four sets of measurement data of the same tube in different frequencies (in our case it‘s typicaly 25 kHz, 100 kHz, 200 kH and 700 kHz).

Signal consists of two parts (two normalized directions) which can be drawn on complex surface. Every type of specific object (defect, support plate, etc.) has it‘s own characteristic signal shape. But not only shape, but also rotation (or more precise angle between x-axis and signal min/max peaks) can offer usefull information. Rotation angle of defect shape can be used to determine the loss of material (see figure 3.).

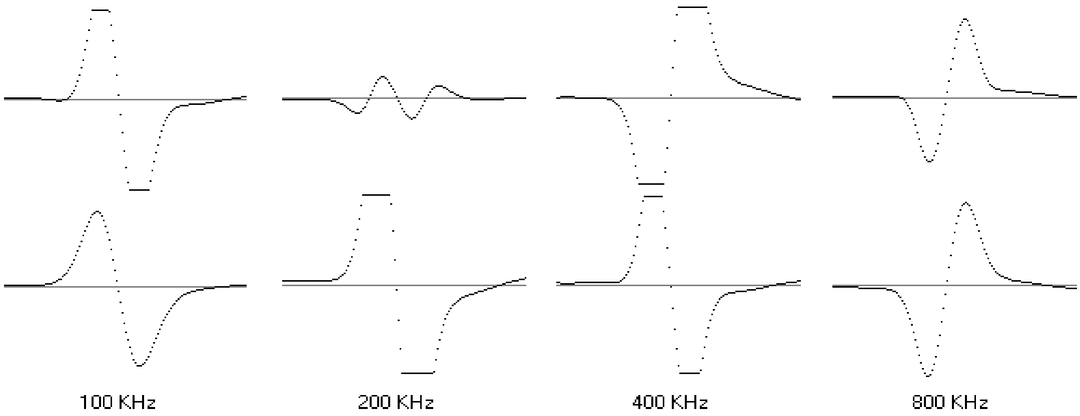

Figure 2. Same indication in different frequencies

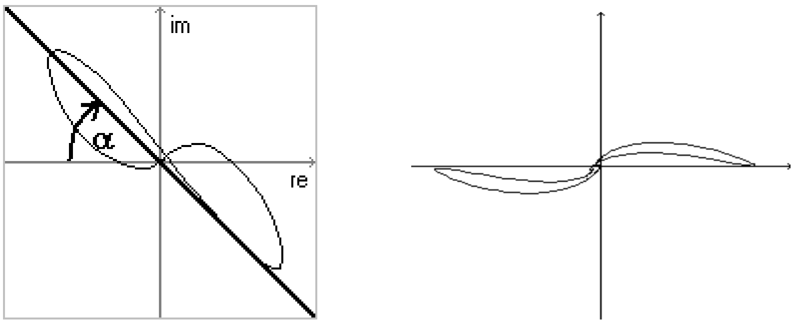

Figure 3. Characteristic shape of defect (100% hole) and support plate

Data of indication can be converted into different representations for different reasons. For examle when we need to reduce dimension of indication data or to filter data noise, etc. Most of signal shapes are closed curves, so we decided (as first step) to use Fourier coeficients **(2)** to describe indications.

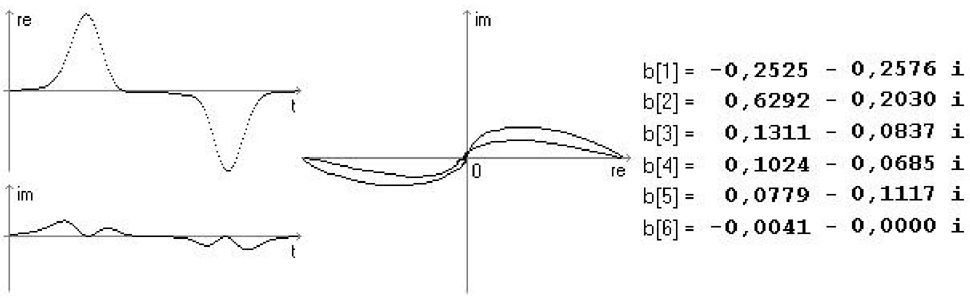

Figure 4. Different representations of support plate

3 DATA REPRESENTATION – INVARIANT PATTERN VECTOR (IPV)

Let *m* is closed curve with parametrized representation *f(t) = x(t) + i.y(t), where* $t \in \langle a, a+t \rangle$.

Function *f* is closed and periodical with periodicity t. Let $f \in C^{r-1}_{<a,a+t>}$ and on interval $\langle a, a+t \rangle$ is defined systém of orthonormal functions:

$$\left\{ h_k(t) = \frac{1}{\sqrt{t}} . e^{i\frac{2pkt}{t}} \quad | \quad k \in Z \right\} \tag{1}$$

Let $w = \frac{2pk}{t}$, $g(t) = f(t).e^{-iwt}$ and $a_k = \frac{1}{\sqrt{t}}.\int_a^{a+t} g(t)\,dt \quad | \; k \in Z$. (2)

For $t \in \langle a, a+t \rangle$ we can assume that $f(t) = \sum_{k \in Z} a_k h_k(t)$ (3)

To reconstruct the curve we need only limited amount of Fourier coeficients (a_{-p},…,a_0,…,a_p). So we can write:

$$f(t) = \sum_{k=-p}^{p} a_k.\frac{1}{\sqrt{t}}.e^{iwt}\ ,\ t \in \langle a, a+t \rangle \tag{4}$$

The fundamental problem is to calculate expression $\int_a^{a+t} g(t)\,dt$. There are different ways to approximate this function (step functions, partially linear function, least-square method).

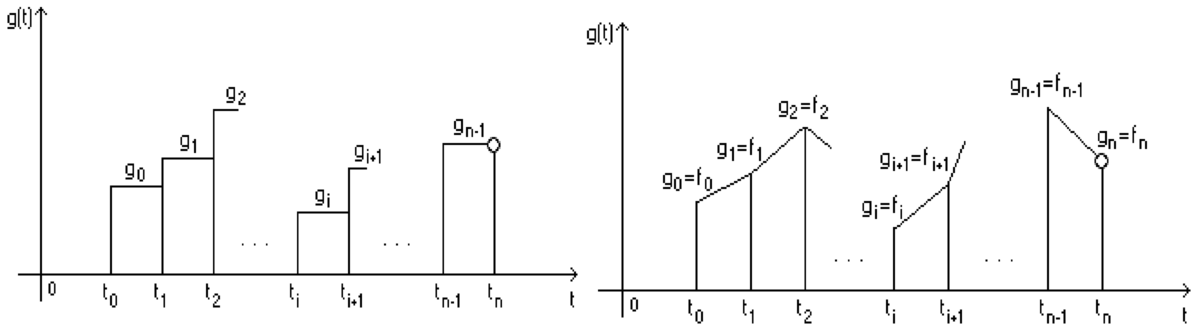

Figure 5. Methods of integral approximation

Using step function for integral approximation we can modify equations **(2)** to:

$$\begin{aligned} a_k &= \frac{1}{\sqrt{t}}\left(\int_{j=t_0}^{t_1} g_0.e^{-iwj} + \int_{j=t_1}^{t_2} g_1.e^{-iwj} + \ldots + \int_{j=t_{n-1}}^{t_n} g_{n-1}.e^{-iwj} \right) = \\ &= \frac{1}{\sqrt{t}}\left(\frac{1}{iw}\left(f_0.e^{-iwt_0} + (f_1 - f_0).e^{-iwt_1} + (f_2 - f_1).e^{-iwt_2} + \ldots + (-f_{n-1}).e^{-iwt_n} \right)\right) \end{aligned} \tag{5}$$

In addition, let $\Delta_0 = f_0$, $\Delta_i = f_i - f_{i-1}$, $\Delta_{n-1} = -f_{n-1}$.
and for w = 0 we can write

$$a_0 = \frac{1}{\sqrt{t}} \sum_{i=0}^{n-1} f_i (t_{i+1} - t_i) \tag{6}$$

and for $w \neq 0$ we can write

$$a_k = \frac{1}{\sqrt{t}} \frac{1}{iw} \sum_{j=0}^{n} \Delta_j.e^{-iwt_j} \tag{7}$$

Fourier coeficients depend on the following factors: choice of starting point, curve position and rotation according to absolute zero point and scale of the closed curve. These factors are unacceptable for classification. To eliminate these dependencies we can define IPV based on Fourier coeficients. Let

$$b_1 = \frac{|a_1|\, a_2}{a_1^2} \tag{8}$$

$$b_j = \frac{a_{1+j} a_{1-j}}{a_1^2}\ ,\ \text{for } j \geq 2 \tag{9}$$

Descriptor b_1 depends on curve rotation, but others descriptors are independent from all unacceptable factors defined at the begining of this section.

4 USING OF NEURAL NETWORKS

Neural networks have the ability of generalization and universal approximation. The main result of general approximation theorem is, that the multilayer perceptron (MP) containing one hidden layer is adequate for approximation of arbitrary continuous function. But the theorem gives no solution of such network construction. The main problem is to construct optimal network, especially to gain sufficient number of representative data (the number of real data is relative small). Else it is not clear, whether the input space of signature vectors of indications is linear separable and with which complexity (size of network) according to the mapping into the classification classes. Briefly, the problem is not only choice of the optimal topology, paradigms of learning, but also choice of the free network parameters (learning rate, activation functions,...).

For classification there are usually used feed-forward suppervised NN [3]. The most popular are *multilayer perceptron (MP)* and *RBF (Radial Basis Function)* network. We decided (as first step) to use 3-layer perceptron. This network has input, hidden and output layer, adjacent layers are full connected. As network development environment we use *Stuttgart Neural Network Simulator* (SNNS). There are main network parameters used in experiments: initialization – random (-1, 1), update mode – topological order, learning function – backpropagation.

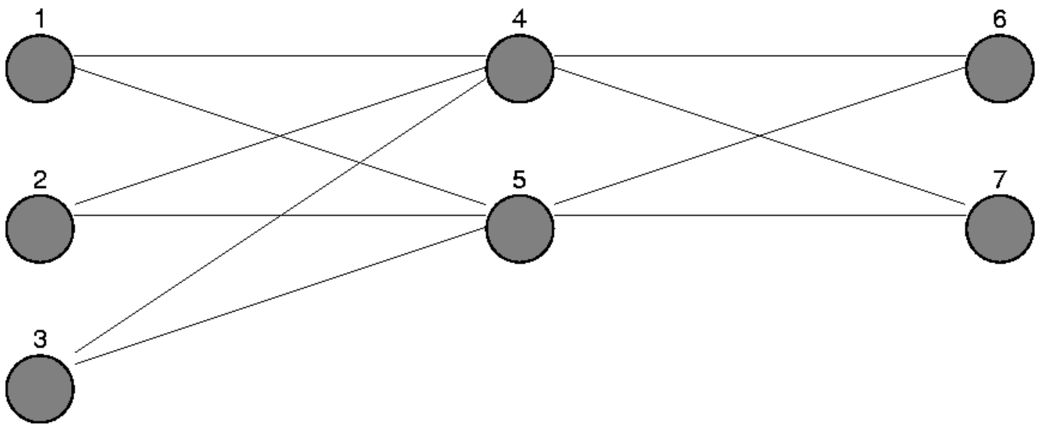

Figure 6. Example of 3-layer NN (configuration 3-2-2)

5 EXPERIMENTAL DESICIONS AND RESULTS

In the next section we'll try to explain basic steps of our experiments. Because we are use supervised NNs, we need to build database of indications as large as possible. Description of the class to which indication belongs must be saved in database too. Subsets of database data are then used to generate training a validating patern files. These files are used by NN and result can be imported back into database to analyze potential error of classification (we can find out differences between network classification answers and real class of indications). Classification can be divided into following steps:

- building database of indications (segment of indication data together with it's class description)
- generating training and validating sets to be used by NN (indication can be processed into different representations – ex. Fourier coefficients **(2)**, invariant pattern vector **(8) (9)** based on Fourier coefficients, complex surface image data, etc…)
- building network (topology, parameters, learning strategy, …)
- validating network (output analysis – classification success / errors)

We decided to use IPVs **(8) (9)**. We can export subset of database indications into vectors of FD. In our case, we use first six descriptors, so dimension of network input is twelve (six complex numbers). Dimension of newtork output layer depends on the required application (type of classification). In first step we decided to monitor four types of indications: support plate, defect (all types of material fals), air gap and other / unknown:

- indication belongs to specified class – network answer: yes / no – dimension of output is two (yes = [1, 0], no = [0, 1])
- to find out class to which inidication belongs – network answer: class number – dimension of output is four (generaly it‘s number of classes, example: support plate = [1, 0, 0, 0], defect = [0, 1, 0, 0])

Lets define networks for classification application from previous section. Generally configuration of such type of networks may be one of these: 12-?-2 and 12-?-4. The best dimension of hidden layer is unknown and was calculated experimentaly. Good results were obtained (for network X-Y-Z) using equation:

$$Y = \frac{X - Z}{2} + Z \text{, let us assume that } X > Z \qquad (10)$$

Example of results:

- network configuration 12-8-4, full conection
- data files: 00-10-10, 00-11-11, 00-22-22, 00-33-33, 1a-50-01, 1a-50-06, 1a-50-09
- tested frequency 100kHz
- class 0 – defect, class 1 – support plate, class 2 – air gap, class 3 – other / unknown
- input: IPV (6 complex numbers), output: class number (winner output neuron)
- network configuration 12-5-2, full conection
- data files and tested frequency – same as above
- class 0 – defect, class 1 – all other (not defect)
- input: IPV (6 complex numbers), output: is defect? (yes = [1 0], no = [0 1])

Table1. Experimental results of detection of 4 classes using 12-8-4 network

TEST description	Training set	Validating set	Result (in %) (right-wrong-unknown)	Error type:pattern number x (teacher - network)
TEST1 network adaptability	patterns from all files 75 patterns	patterns from all files 75 patterns	100,00 0,00 0,00	none
TEST2 network classification of unknown pattern	patterns from files 00-xx-xx (41 patterns)	patterns from files 1a-xx-xx (34 patterns)	52,94 26,47 20,59	wrong: 1x0-3, 3x0-2, 1x1-0, 2x2-0, 2x3-1 unknown: 3x0-1, 2x1-3, 1x0-2, 1x0-?
TEST3 network classification of unknown pattern	patterns from files 1a-xx-xx (34 patterns)	patterns from files 00-xx-xx (41 patterns)	75,61 19,51 4,88	wrong: 1x0-1, 5x2-0, 1x3-0, 1x3-1 unknown: 1x0-1, 1x3-1

Now let‘s demonstrate, how the experimental results depend on network configuration changes. To solve task number 2 we can use for example network of 12-8-2 configuration. Dimension of hidden layer was increased from 5 to 8 neurons. But results for TEST1 from TABLE2 were a bit different:

- right: 96.00 %, wrong: 4.00 %, unknown: 0.00 %
- wrong: 3 x 1-0, unknown: none

Table 2. Experimental results of detection of 4 classes using 12-5-2 network

TEST description	Training set	Validating set	Result (in %) (right-wrong-unknown)	Error type:pattern number x (teacher - network)
TEST1 network adaptability	patterns from all files 75 patterns	patterns from all files 75 patterns	100,00 0,00 0,00	none
TEST2 network classification of unknown pattern	patterns from files 00-xx-xx (41 patterns)	patterns from files 1a-xx-xx (34 patterns)	64,71 35,29 0,00	wrong: 7x0-1, 5x1-0 unknown: none
TEST3 network classification of unknown pattern	patterns from files 1a-xx-xx (34 patterns)	patterns from files 00-xx-xx (41 patterns)	73,17 26,83 0,00	wrong: 4x0-1, 7x1-0 unknown: none

6 CONCLUSION

In previous sections we tried to explain and demonstrate, that neural networks can be used to solve this type application. To obtain better and more authentical results, we must perform much more experiments.

There are many ways how to continue realising our experiments. Neural networks and data preparing methods contains a lot of free parameters. Let‘s define main topics of possible experimental steps:

- changing data representation, wavelet analysis/functions seems to be a good choice
- changing network topology – example: feed forward four layer networks, dimension of network hidden layer, …
- changing network parameters – learning paradigm, initialization
- testing depences between results of different types of networks – example: 3 classes, 3 networks (configuration 12-?-2, first for class 0, second for class 1, …) , 1 network (configuration 12-?-3)

NN represents a nondeterministic procedure, so it‘s difficult to estimate quality of final results. But we tried to show that AI methods are very progressive and succesfull for solving such a type of problem [4].

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