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Application of the Virtual Identification to the Ferromagnetic Materials Defects Classification

***Abstract**. Automatic algorithms which include classifiers require effective systems of the data acquisition in order to create probability groups. Their role is to process the information to the basic figure of the model with a significant number of the details. In the presented work the authors depict individually created solution to the problem of ferromagnetic materials nondestructive testing with ramified and loss nonlinear characteristics and large values of magnetic permeability. All required parameters are subject to the nondestructive eddy current test.*

***Streszczenie.** Algorytmy automatyczne wymagają zastosowania efektywnych systemów akwizycji danych do formowania grup podobieństwa. Ich rolą jest przetworzenie informacji w zbiorach danych do postaci podstawowych reprezentacji modeli. W pracy autorzy przedstawiają rozwiązanie problemu klasyfikacji materiałów ferromagnetycznych z charakterystyką rozgałęzioną. Wymagane parametry podlegają identyfikacji metodą badań materiału w polu magnetycznym. (**Zastosowanie wirtualnego systemu do klasyfikacji defektów materiałów ferromagnetycznych**).*

Keywords: nondestructive testing, virtual instrument, classification, identification.
Słowa kluczowe: badania nieniszczące, wirtualny instrument, klasyfikacja, identyfikacja.

Introduction

The fundamental principle of the nondestructive testing of ferromagnetic materials is to determine the eddy currents changes inside the volume as a function of magnetic field strength as well as of the variable frequency [1]. Essential here is the observation of trajectories following either the impedance module or the impedance argument change. Another method belonging to the inductive method of testing ferromagnetic objects is the examination of the magnetic hysteresis loop. The observation of hysteresis loops comprises the acquisition process of the magnetic flux density or magnetization changes as the function of the magnetic field strength. In the article, the authors present the method of the acquiring, the conditioning, and the classification of a discrete image of the differential weight function, analogical to the weight function of the Preisach model, and its gradient images.

Automatic classifications of multidimensional objects are the processes that require the adoption of models that explicitly depict their basic properties and characteristics. The application of an automatic process requires the selection of a model with a high sensitivity to geometrical defects.

Unlike conventional algorithms for the flaw detection, as part of the specified problem solution, the authors propose to apply the system described with the ramified and loss characteristic i.e. the density function. That one, known as a weighted surface in the classical Preisach model, could be determined during the experiment, by well-known identification algorithms. The surface, regardless of the inputs, delivers a continuous observation space and characteristics of the material that is the function of the R^3 space. It allows determining that surface and assigning any materials or material defects to given similarity groups with marked characteristics [2, 3, 4, 5, 6, 9].

The essence of the model parameters identification process relies on the experimental method selection. The objects, tested with ferromagnetic properties are suitable for examination by means of dynamic methods.

The fundamental method presented in the paper is the eddy currents changes examination inside the tested detail as a consequence of the magnetic field value *H* as well as the frequency value [2].

Measurement system

The methodology of experimental research requires the measurement of two quantities: the current value in the magnetizing circuit and the voltage induced (electromotive force) in the measuring coil, assigned with the magnetizing coil, coupled with the tested sample that plays a role of a magnetic core.

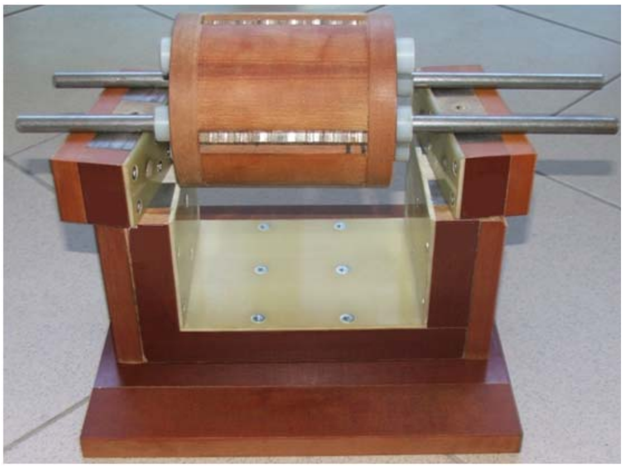

Fig. 1. The device for examination of cylindrical samples

The authors focused on the AC-bridge, linked with a magnetic circuit owing to couplings: M_1, M_2 and M. The bridge contains linear elements: resistors R_1, R_2, R_3, R_4, inductive coils: L_2, L_4 as well as the voltage source $e(t)$. L_1 and L_3 are coils with nonlinear ferromagnetic cores inside: a reference component and the tested sample, respectively (Fig. 2).

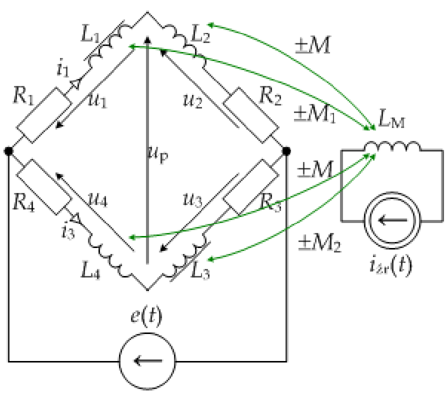

Fig. 2. The scheme of the AC bridge

As the basic image, the classifying function obtained by means of measurement conducted with the AC bridge (Fig. 2) through the examination of unbalanced voltage u_p (1) has been selected.

$$u_p \approx \frac{1}{2}\frac{d(\Psi_1 - \Psi_3)}{dt} \tag{1}$$

where Ψ_1 and Ψ_3 are magnetic fluxes, adequately in the model and test elements.

The conditions of its stability imply that the voltage u_p equals 0 when the parameters of the paired ferromagnetic elements are identical. Nonzero value of u_p indicates that the properties of the tested component and of the reference are different. The problems of the standard sample selection were not discussed in the article. The authors focused only on the numerical images of the classifying functions.

The designed program has been used to study the samples. This one is an application of virtual instrument, realized in LabVIEW, with the front panel shown in the Fig. 3.

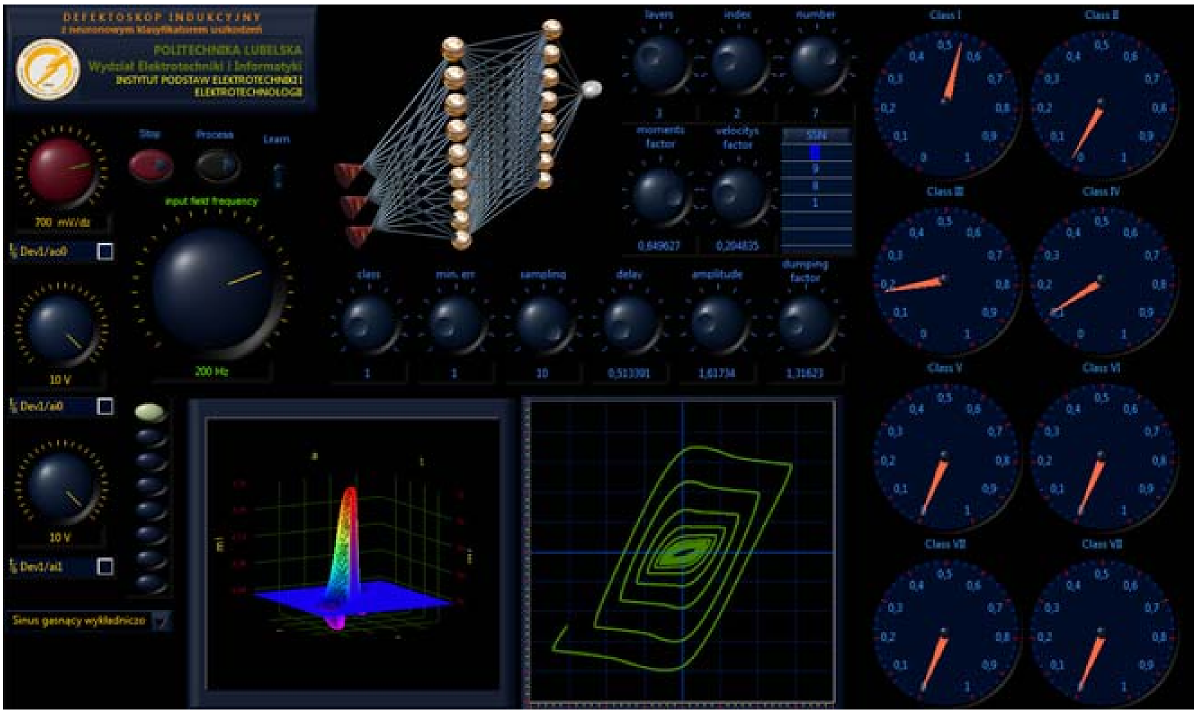

Fig. 3. The front panel of virtual instrument

The presented application allows users to change and control basic signal parameters of the magnetizing current, triggering parameters, perceptron topology parameters, and signal acquisition parameters. As the indicators of the object state the graphical presentation of the differential surface and the plot of the differential hysteresis are available.

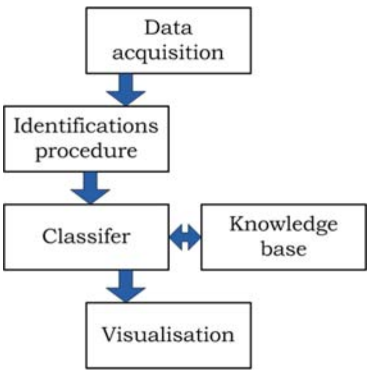

Fig. 4. The block diagram of the application

Virtual instrument

The essence of the designed virtual instrument is the assigning the result to the similarity group, represented by the model class. The task of data interpretation is the role of virtual instruments. The proposed version the system has to determine the qualitative value of the tested detail.

The indicators, placed on the right side of the front panel indicate the boost value of the neuron in the classifier output layer. Its values are changed between 0 and 1. One can therefore concluded that, the indications can be interpreted as a coefficient of the similarity of the test results to the master class. The figure 4 shows the diagram of the main application. The virtual instrument includes:

- data acquisition block,
- identification procedure,
- classifier,
- knowledge base,
- visualization.

1) *Acquisitions module*

The data acquisition block was carried out using the multifunction card from National Instruments. Two analog input channels were used, with the sampling frequency of 500 kHz and one output channel with the same sampling frequency – 500 kHz.

The signal from the output channel is adjusted to the power amplifier ADS 4000 with maximum power output of 4 kW. The data acquisition's module was developed by application of available LabVIEW functions. The current value of the magnetizing circuit, and the imbalance AC bridge voltage waveform have been collected.

2) *Identification*

Every identification process requires the determination of some mathematical model parameters [1, 2].

The classification of any materials defects requires the acquisition of as large as possible number of the characteristic classes. Analyzing the behavior of the weight function of the Preisach model one can observe two significant properties: values are always nonnegative and values are always symmetrical with respect to the normal axis of α-β plane, going through the (0,0) point [4]. In addition, the analyzed function does not possess any extremes in the case of examined cylindrical samples. Only the extremal value or values can be determined. The individual properties of the density function make it difficult to analyze the data concerning their classification [3, 7].
The reasons stated above suggest alternative solutions. As a result the idea of applying differential and bridge measurements is conceived.

The graphical representation of an analyzed data series is presented in Fig. 3. The curve depicts the integrated voltage u_p and the one is the result of the difference of the magnetization values M_1 and M_3 divided by the saturation magnetization M_s. M_1 and M_3 were calculated by integrating voltage differences between nodes of the branches of the bridge. The range of the selected characteristics was defined using the relative values of the magnetic field strength h_r.

The quantitative comparison is not as crucial as the qualitative comparison. In the range of increasing input values the extrema can be detected which implies their presence in the weight function. After the completion of the selected calculation process the Preisach surface was obtained (Fig. 4).

By analyzing selected voltages and currents from the measuring circuit (Fig. 2), the formation mechanism of the differential surface, including more than one extreme and negative values in the class of the density function was determined [4, 5].

The important algorithm is the automatic search of the class allocation. The authors made use of a transformation of the density function to the gradient surface domain. The obtained images increased the number of differentiation details. The automatic algorithm calculates the extremal values of surface components or gradient modules (and their positions) in the domain of a density function. On a basis on distances between characteristic points (see Fig. 4) and (0,0) point, the input values of the artificial interpretation data system have been calculated [4].

(2) $$\mu(\alpha,\beta) = -\frac{\partial^2 F(\alpha',\beta')}{\partial\alpha\partial\beta},$$

The classical algorithms (2), proposed by many other authors were applied, in order to determine the density function $\mu(\alpha, \beta)$ values in the α, β domain and the discrete differential function F, based on the measurement data file. Contrary to the general principles this method was applied to calculate the differential curves (Fig. 2). This one has specific properties: clearly separated extremes as well as clearly defined rise or fall curves.

3) *Classification*

The density function, as an object, defined in R^3 space is sufficient for classification requirements.

As the first basic criteria, the fundamental conclusion was formed on its position in regard to the maximum value (Fig. 5). While modeling process of the closed hysteresis loop is done, the one maximum value in the vicinity of (0,0) point usually exists.

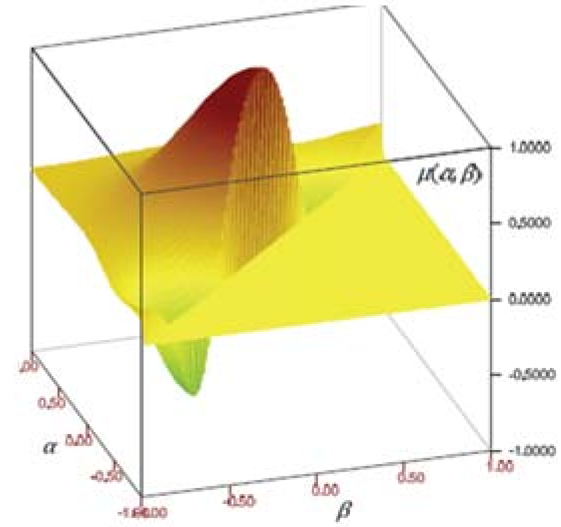

Fig. 5. The differential surface

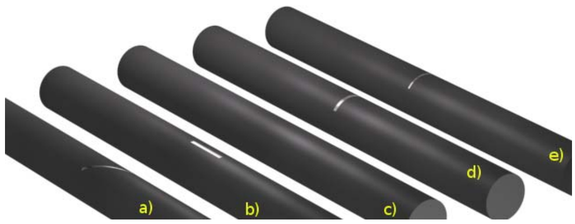

Fig. 5. Defect locations on the rod

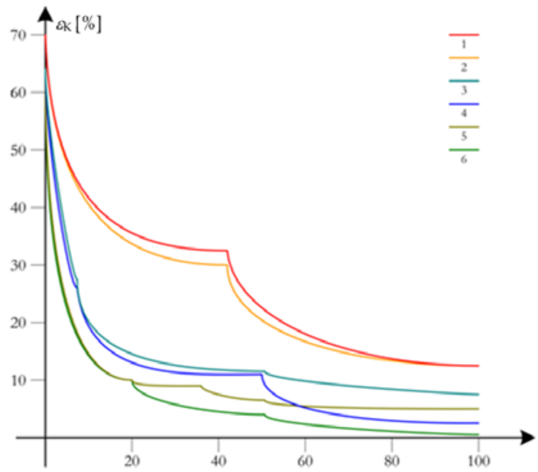

Fig. 7. The result of learning process: 1, 2 Kohonen or Hopfield structure, 3-6 multilayer perceptron

The Preisach model properties imply that the density function is nonnegative. As the result, the possibility to create of any automatic classifiers is restricted. A small number of characteristic properties is not a favorable factor. The supporting element in the examination of the surface plane is the calculation of local gradients. Their components or modules make a function of the another classifying property. The composition, projection or analysis of sample details on the surface plane image increases the number of characteristic properties. Owing to that the automatic classifier receives significant amount of information to form some probability groups [2, 5, 7].

While the experiments were conducted the authors focus on the analysis of the density function surface planes . In the case of neural network algorithms, there are some possibilities of applying discrete data values of the surface plane as the input vector. As a first experiment, two primitive classes were formed and a learning process was done. After calculating the error, the fault factor was determined.

The final applications were designed to form more then two class. In our research, the classifier was built in two versions. The first was the primitive classifier (similar to Bayes classifier) for two classes. Second – the neural classifier. In the input layer of multilayer perceptron, the nodes have been placed and they correspond to the specific features:

– the number of extremes,
– the distance of extremes and origin,
– the mutual distance between negative extremes,
– the distance positive extremes and origin,
– the number of gradient extremes, etc.

For greater number of the input parameters the more learning cycles had to be made.

Results description

The slotted defects of different sizes are presented in the figure 6. They were positioned at selected angles, relative to the axis of the tested samples. The results, shown in the figure 5, have been prepared for the sample (Fig. 6e) with the air gap, perpendicular to the axis of the cylinder. The defect's size (depth and width) determines the local increments of the differential surface (Fig. 4) and distance between the extremal values.

Conclusions

In the presented article, the problem of the classification and identifications process from the point of view the application of: the automatic algorithms, the neural classifier, the identification system and the factor of learning process errors were considered.

The virtual instrumentation tool was developed to further experiment on classification and identification problems of nondestructive testing. The proposed solution is a part of the data interpretation with artificial networks application in the eddy current detection method. The results of learning process show that the typical solutions of our research (multilayer perceptrons) returned some promising results and the work on the problem should be continued.

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