The application of virtual instruments to the identification and automatic classification of the defect images

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Abstract — Automatic algorithms which include classifiers require effective systems of 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. Owing to the differences between the probability groups, the classifier allocates the images to a selected class. At the same time the assessment of details' quality is created.

In the presented work the authors depict individually created solution to the problem of nondestructive testing of materials with ramified and lossy nonlinear characteristics and large values of magnetic permeability.

All required parameters are subject to nondestructive eddy current test. The difference between interpretation methods are only in the proposed data conditioning. The authors have paid attention to the selection of classifying algorithms, distinction of function classes as well as the methods of identification.

I. INTRODUCTION

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

II. 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, coupled with the magnetizing coil by coupled by the tested sample that plays a role of a magnetic core. The authors concentrated on the ac bridge linked with a magnetic circuit owing to couplings C_L, C_{L1} and C_{L2}. 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: a reference component and the tested sample, respectively.

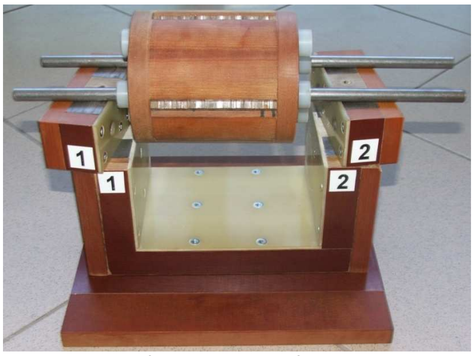

Fig. 1. The device for examination of cylindrical samples

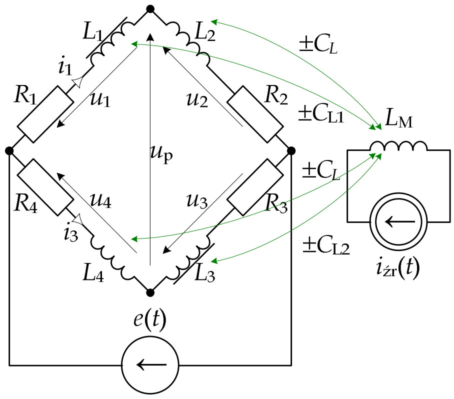

Fig. 2. The scheme of the ac bridge

The basic image is the weight function obtained by means of measurement conducted with the ac bridge (Fig. 2), through the examination of unbalanced voltage u_p. 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.

III. EXPERIMENTAL RESULTS

Every process of identification requires the determination of mathematical model parameters [1], [2]. The classification of materials defects requires the acquisition of a number of the characteristic classes as large as possible. Analyzing the behavior of the weight function of the Preisach model one can observe two significant properties i.e. the values are always nonnegative and they are always symmetrical with respect to the normal axis of α-β plane, going through the (0,0) point [4]. In addition, in the case of examined cylindrical samples, the function does not possess any extrema. Only the extremal value can be determined. The individual properties of the density function make it difficult to analyze the data concerning their classification [3].

The reasons stated above suggested alternative solutions. As a result the idea of applying differential and bridge measurements was conceived.

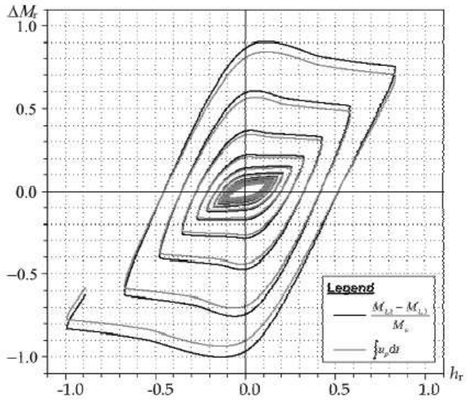

Fig. 3. The sample's incremental differential curves of two elements

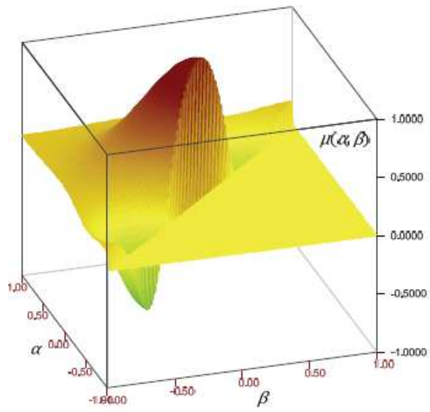

Fig. 4. A sample of the differential surface

The graphical representation of an analyzed data series is presented in Fig. 3. One curve is the integrated voltage u_p; the second one is the difference of the magnetization values M_{L1} and M_{L3} divided by the saturation magnetization M_s. M_{L1} and M_{L3} 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 were determined [4], [5].

The multifunction measuring cards and LabVIEW virtual programming environment were implemented, for measurement, data analysis and visualization. The system acquires data from the selected circuit and the density function surface is calculated based on the classical algorithm (1), where α' and β' are always interpreted as measuring point coordinates [1], [3].

$$\mu(\alpha,\beta) = -\frac{\partial^2 F(\alpha',\beta')}{\partial\alpha\partial\beta} \tag{1}$$

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].

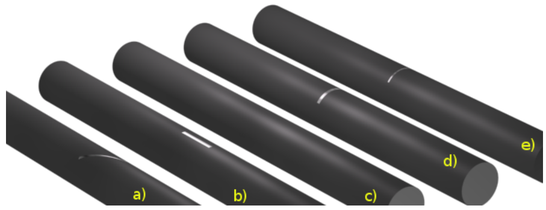

Fig. 5. The defect models of a cylindrical sample

The authors considered the factor of learning process errors of the neural classification and identification system for materials defects of cylindrical samples. The slotted defects of different sizes are presented in Fig. 5. They were positioned at selected angles relative to the axis of the tested samples. The results, shown in Fig. 3 and Fig. 4, have been prepared for the sample (Fig. 5e) 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.

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 using artificial networks in the eddy current detection method.

IV. REFERENCES

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