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Classification of Acoustic Signals of Discharge Processes in Insulation Based on the Shape of Their Wavelet Spectra

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Abstract—A description of the results of the recording of acoustic signals, which indicate the isolation disruption of high-voltage power equipment, are presented. The description is invariant with relation to the time shift and nonlinear monotonous amplitude distortions. Signal classification, as the basis for the automatic control and monitoring of power equipment, was carried out.

Key words: mathematical modeling, acoustic diagnostics, image analysis, optimal decision making, wavelet analysis.

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As is known [1] acoustic signals arising at discharges in isolation carry information on the state of high-voltage equipment and can serve as a basis for damage prevention. Existing methods of power equipment diagnostics are based on expert evaluations. This work offers a method for the automatic classification of signals on the basis of an analysis of the wavelet-spectra format of the recording of acoustic signal by acoustic pressure sensors.

According to the terminology of acoustic diagnostics [1] the analyzed signals are divided into four classes: resulting from the “individual spark discharge” (class V_1); “individual partial spark discharge” (class V_2); “numerous discharges” (class V_3); “vibroimpact mechanical processes” (class V_4). The first three classes are connected with different degrees of danger from damage, and the fourth one, with an accident-free situation.

Assume that the conversion class of an acoustic signal not deriving its resultant from the class the signal belonged to is set and the invariant of these conversions is known. Then the problem of classification is naturally solved in terms of these invariants, since they do not contain information on the signal differences inside the classes. These invariants are called the signal format. Classification success depends on how invariant values differ for the signals of different classes.

The specificity of the acoustic signals that serve to solve the problem of classification appears lie in the local properties of the envelope and signal spectrum. To characterize the local properties of the signals, we have opted for their presentation as a wavelet Meyer expansion [2]. Specific types of signals and their wavelet spectra are presented in Fig. 1.

For the analysis of the specificity of wavelet spectra of the signals from each class on the basis of test signals we have built a mathematical model of the wavelet spectrum signal of each class.

Assume that $f(\omega, t)$ is the module of the value of the wavelet image of an acoustic signal in the moment t on the frequency ω. Following the work in [3–5] denote the pair (ω, t) as the point in the field of vision $X = \{(\omega, t): \omega \in (0, \Omega), t \in (0, T)\}$, and $f(\omega, t)$ is the display brightness f of the wavelet spectrum of the signal in the point $\mathbf{x} \equiv (\omega, t) \in X$.

An analysis of the brightness of specific subimages of the wavelet spectra of the signals serves to show that they can be approximated by piecewise-constant functions of type $f(\mathbf{x}) = \sum_{j=1}^{N} c_j \chi_j(\mathbf{x})$. Here $\chi_j(\mathbf{x}) = \begin{cases} 1, & \mathbf{x} \in A_j \\ 0, & \mathbf{x} \notin A_j \end{cases}$ is the indicated function of the set A_j of the field of vision, at all points of which the image $f(\mathbf{x})$ has the same brightness c_j, $j = 1, \ldots, N$. The sets A_j, $j = 1, \ldots, N$ do not intersect and in total make up the selected fragment of the field of vision. The display brightness $f(\mathbf{x})$ is regulated according to the disparities $c_1 \le \ldots \le c_N$. Classes V_1, V_2, V_3 differ by their numbers and the form of set A_j, $j = 1, \ldots, N$: for the classes V_1 and V_2 we have selected the value $N = 3$ and for V_3, $N = 2$. The types of sets with constant brightness for the classes V_1, V_2, V_3 are given in Fig. 2.

The images of the wavelet spectra of the signals from class V_4 are not characterized by the expressed areas with the same brightness, therefore we have used the images $f(\mathbf{x}) = c = \text{const}$, $\mathbf{x} \in X$ as their models.

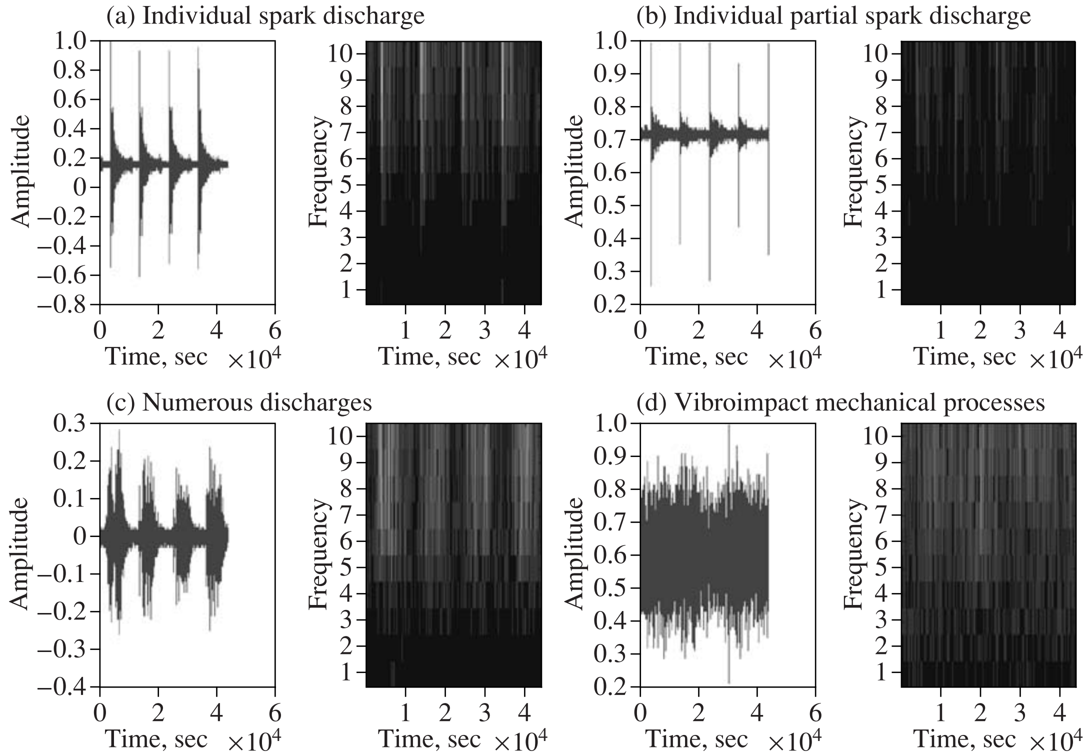

Fig. 1. Specific type of signals and their wavelet spectra: a, class V_1; b, class V_2; c, class V_3; d, class V_4.

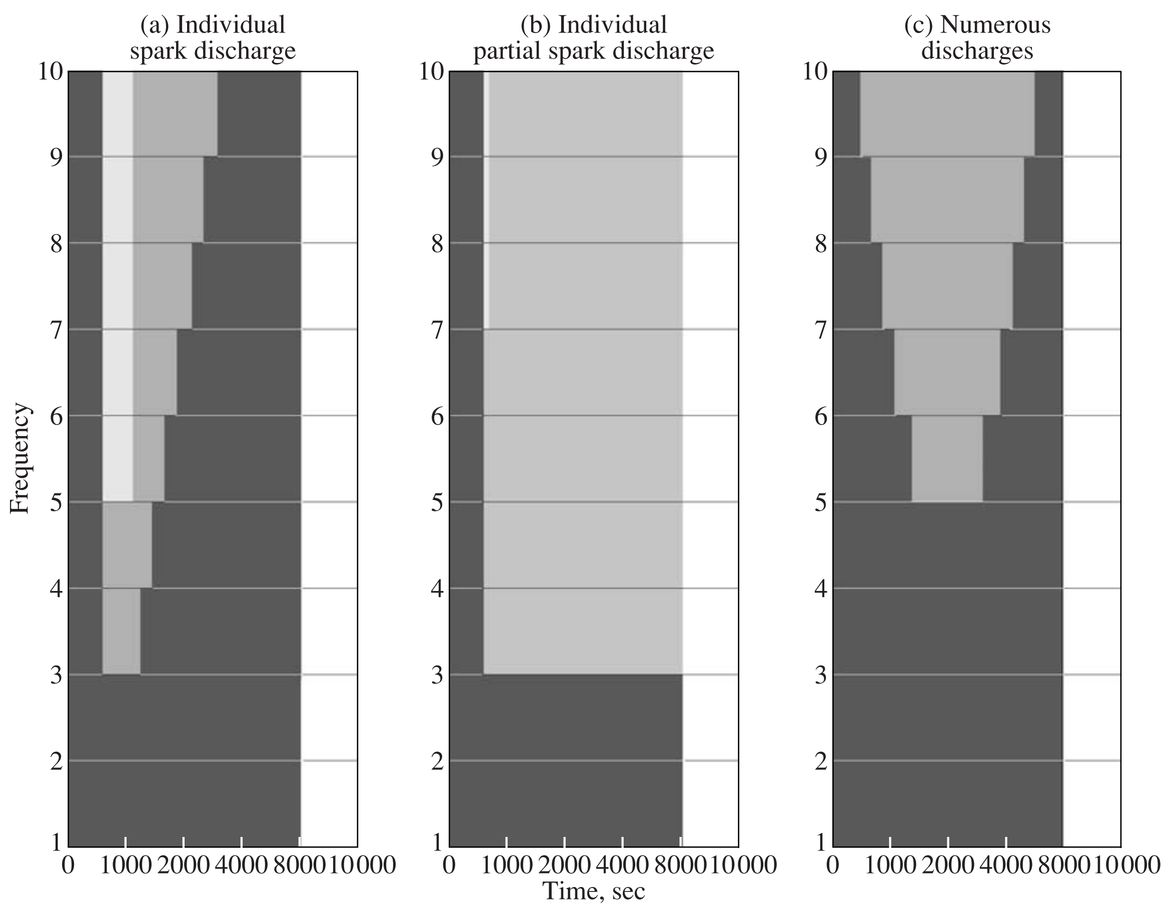

Fig. 2. Sets of constant brightness of the image fragments of the wavelet spectra: a, Class V_1, b, class V_2, c, class V_3.

Note that the choice of the basic function is conditioned by the fact that sets with similar brightness of images of the wavelet spectra of verified test signals obtained in the case of accidents (from the classes V_i, $i = 1, 2, 3$) were most different from each other and the images of the spectra of the signal from the class V_4 were closest to constant.

We will further equate the classes V_i, $i = 1, 2, 3, 4$ and the sets of specific fragments of the images of the wavelet spectra. These sets appear to be convex closed cones in the Euclidian space of all images set in the field of vision X, $\|f\|^2 = \int_X f^2(\mathbf{x})d\mathbf{x}$. For each of the cones V_i, $i = 1, 2, 3$, determine the projection P_ig of the presented fragment $g(\mathbf{x})$ of the selected image of the wavelet spectrum on the set of images V_i, $i = 1, 2, 3$ as a solution to the problem of the best approximation:

$$\|g - P_ig\|^2 = \min\{\|g - z\|^2 | z \in V_i\}, \quad i = 1, 2, 3.$$

For the fragments of the spectra images from the class V_4 we determine the projection as the solution to the problem.

$$\|g - P_0g\|^2 = \min\{\|g - z\|^2 | z = \text{const}\}.$$

As the invariant of the optional monotonous conversions of the brightness of the specific fragments of the images we select the functional

$$\tau_i(g) = \begin{cases} \|g - P_0g\|^2 / \|g - P_ig\|^2, & \|g - P_ig\|^2 \neq 0, \\ +\infty, \quad \|g - P_ig\|^2 = 0, & \|g - P_0g\|^2 \neq 0, \\ 0, \quad \|g - P_ig\|^2 = 0, & \|g - P_0g\|^2 = 0. \end{cases}$$

Indeed, if $g \in V_i$, $i = 1, 2, 3$, then $\tau_i(g) = +\infty$, and at $g = \text{const}$ $\tau_i(g) = 0$. The values of the functionals $\tau_i(g)$ for $g \notin V_i$, $i = 1, 2, 3$ serve as a measure of the image proximity of g to the classes V_i, $i = 1, 2, 3$: the value $\tau_i(g)$ is greater the closer the image format g is to the image format from the set V_i compared with the image format equal to the constant. Thus, if the value $\tau_i(g)$ for all $i = 1, 2, 3$ is lesser than the threshold value the presented image can be attributed to the class V_4, otherwise, to the class with the number k, if $\tau_k(g) \geq \tau_i(g)$, $i = 1, 2, 3$.

The algorithm described here has shown no mistakes in the selection from 28 verified signals.

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