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METHOD OF REFERENCE SIGNALS CREATING IN NON-DESTRUCTIVE TESTING BASED ON LOW-SPEED IMPACT

V. S. Eremenko[1]*, V. P. Babak[2], A. O. Zaporozhets[2]*****
[1] National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"
37, Pr. Peremohy, Kyiv, Ukraine, 03056, e-mail: nau_307@ukr.net .
[2] Institute of Engineering Thermophysics of NAS of Ukraine
2a, Marii Kapnist Str., Kyiv, 03057, Ukraine, e-mail: vdoe@ukr.net; a.o.zaporozhets@nas.gov.ua

The article describes the approach to the formation of a simulation model of information signals, which are typical for objects with different types of defects. The dispersive analysis of the signal spectrum components in the bases of the discrete Hartley transform and the discrete cosine transform is carried out. The analysis of the form of the reconstructed information signal is carried out depending on the number of coefficients of the spectral alignment in Hartley bases and cosine functions. The basis of orthogonal functions of a discrete argument is obtained, which can be used for the spectral transformation of information signals of a flaw detector. A method of simulation of information signals has been developed and experimentally investigated, which allows taking into account the deterministic and random components of the characteristics of real information signals. References 24, figures 13, tables 3.
***Keywords*:** diagnostic, non-destructive testing, information signal, composite material, Hartley transform, dispersion analysis.

Introduction. The system for selecting optimal diagnostic features determines not only the ideology of the recognition algorithm, but also the structure of the construction of the corresponding classifiers. Two approaches are known to assess the diagnostic value of selected features. The first approach is to determine the minimum number of parameters with great information content. It is related to the intuitiveness of the choice and depends on the developer of the diagnostic system. With such an approach, it is impossible to predict how optimal the vector of diagnostic signs will be chosen in comparison with others. The second approach is the formation of a large number of informative parameters, from which, according to the selected criterion, diagnostic signs are selected. Known criteria for evaluating the effectiveness of signs based on methods of mathematical statistics and information theory. There is no general approach to the selection of criteria and the compilation of systems of optimal signs based on them.

Products made of composite materials, in contrast to products made of metals, are formed from primary raw materials simultaneously with the formation of the materials. Due to the complexity of their manufacturing technology, it becomes impossible to build a priori models describing the definitions of informative parameters of controlled objects, and ignorance of the laws of the probability distribution of changes does not allow to form the corresponding decision rule [1, 2].

In tasks of referenceless diagnostics of composite materials, as well as in the case of using neural networks as the core of the classifier, the presence of an adequate simulation model of information signals characteristic of objects with different types of defects or damage's degrees has a great importance, since it allows solving several problems simultaneously [3].

First, the existence of such model allows you to build a library of information signals that characterize possible defects in composites and therefore can be used to train and configure the information and diagnostic system as a whole or in a particular case of a neural network classifier without physically manufacturing such samples [4]. Secondly, a simulation model of the information signal can be used to verify the accuracy of diagnosis and classification, justify the choice of the most successful architecture and type of neural network classifier, select the threshold sensitivity of the system, validate the information and diagnostic system and, if necessary, adjust its parameters, etc [5].

The developed methods and systems for diagnosing products made of composite materials most often use the parameters of information signals as the main diagnostic features, the registration of which causes the least complication, namely amplitude, pulse duration, signal phase, and the like [6, 7]. However, the shape of

ORCID ID: * https://orcid.org/0000-0002-4330-7518 ; ** https://orcid.org/0000-0002-9066-4307 ;
*** https://orcid.org/0000-0002-0704-4116

the information signal, i.e. the function of changing it over time provides much more information about the technical state of the research sample and therefore provides more opportunities for its diagnosis [8].

Analysis of the information signal form allows to get a greater number of diagnostic signs, perform object diagnostics under the condition of a limited amount of information, and provides high noise immunity of the system, and modern computing systems, signal acquisition, and processing devices allow to implement high complexity analysis algorithms, thereby increasing the accuracy of control [9-11].

Since at present there is no single universal physical method for diagnosing composite materials that would identify all possible types of defects, the method of modeling reference signals was studied using a low-speed impact method, which allows determining the largest number of types of possible defects in composites.

Selection of the basis for creating reference diagnostic functions. The information signal of the sensor $X(t)$ will be considered as a function of the discrete argument, that is, a vector which elements are obtained as a result of uniform sampling of the information signal of the sensor:

$$X(Z) = (X_0,\ X_1,\ \ldots,\ X_j), \qquad (1)$$

where $X_j = X(z_j)$, $Z = \{z_0, z_1, \ldots, z_j\}$ are the zone of signal detection $X(Z)$; $j \in \overline{0, N-1}$, N is a number of discrete signal samples $X(Z)$.

The task of synthesizing an information signal model with given parameters is most adequately solved by the representation of a signal in the spectral region. And, if in the case of a continuous periodic signal in many cases, the trigonometric Fourier transform takes precedence, then for pulsed signals the problem of choosing the appropriate spectral basis arises, which provides the minimum number of informative spectral components. In addition to ensuring the minimum number of spectral components during choosing an orthogonal basis, an important aspect is also the choice of such a basis in which the components of the spectrum of the information signal are most dependent on changes in the degree of damage of the test object.

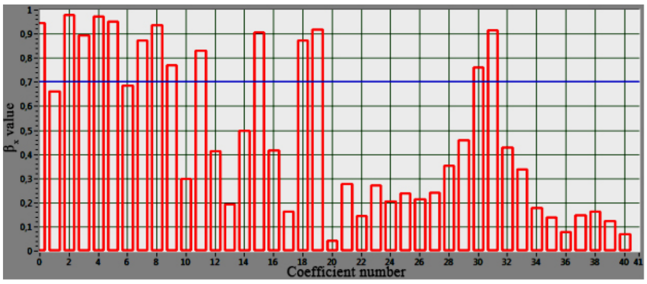


Fig. 1

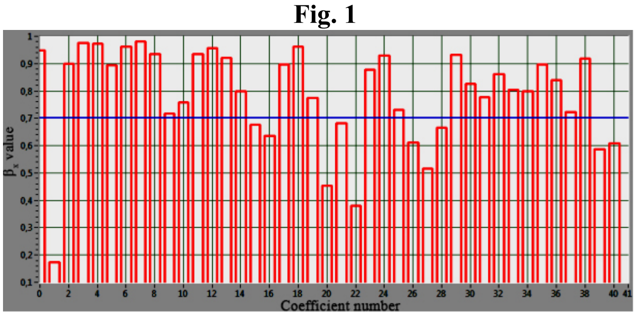


Fig. 2

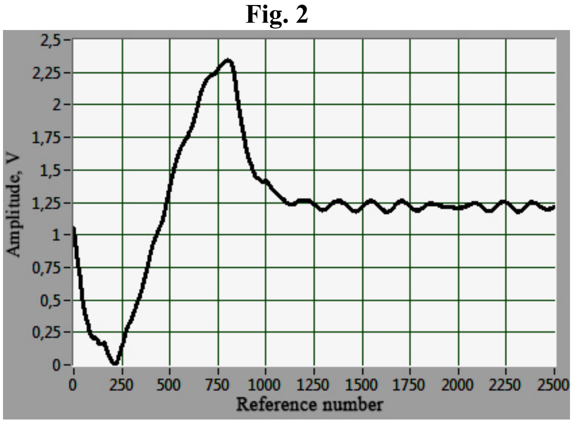


Fig. 3

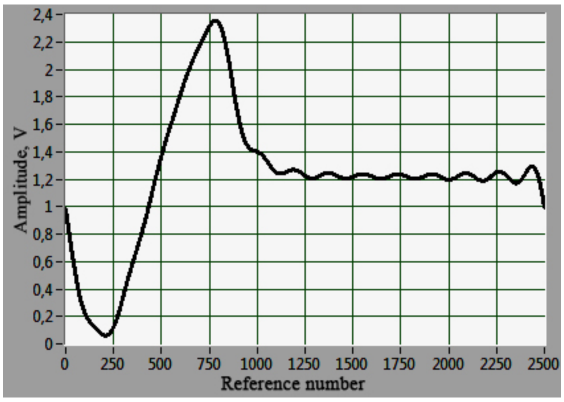
In modern informational diagnostic systems, the results of primary measurements are discrete samples of pulsed analog information S_k, according to which, during further processing, informative parameters are determined, such as the amplitude of pulses, their duration, and shape.

Since the pulse information signals obtained during the diagnostics of products made of composite materials using the low-speed impact method have a complex shape, the application of the most common orthogonal transformations (Fourier, Hartley, Haar, cosine and sine transformations, etc.) is made difficult by the large number of spectral decomposition components, which undergo significant changes when the degree of damage to the controlled object changes [12].

Dispersion analysis showed that the number of coefficients of spectral decomposition, which are characterized by a significance coefficient η_x (describes the degree of dependence of the change of the corresponding coefficient on the damage to the object) with a value of more than 0.7, is from 20 to 36 coefficients depending on the chosen basis. Fig. 1, 2 illustrate the results of analysis of variance in the case of using the discrete Hartley transform (DHT) and discrete cosine transform (DCT) [13, 14] respectively.

Fig. 3-5 illustrate the dependence of the form of the reconstructed information signal on the selected number of spectral decomposition coefficients in Hartley bases and cosine functions. Similar results are characteristic in the case of the use of discrete Fourier transforms, Haar and discrete sine transforms [15, 16]. The spectral alignment is performed by a signal that is obtained by averaging 500 realizations for each of the sample zones studied.

As can be seen from Fig. 3 (information signal from the defect-free zones), Fig. 4 (reconstructed signal from the defect-free zone with 15 spectral decomposition coefficients using DHT (*a*) and DCT (*b*)), Fig. 5 (Reconstructed signal from the defect-free zone with 30 spectral decomposition coefficients using DHT (*a*) and DCT (*b*)) for reliable restoration of signals in the specified bases of orthogonal functions, it is necessary to have at least 30 spectral components, the presence of a smaller number of components leads to significant distortions of the information signal and, as a consequence, the loss of some diagnostic information about the object of study. The need to take into account a large number of components of the spectrum when building an information signal model leads to a significant complication of the simulation algorithm and an increase in computational and time costs.



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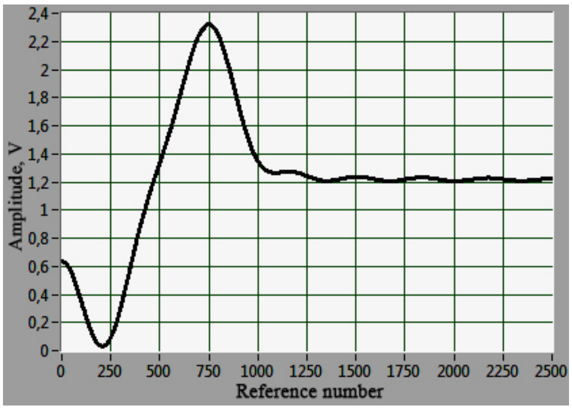

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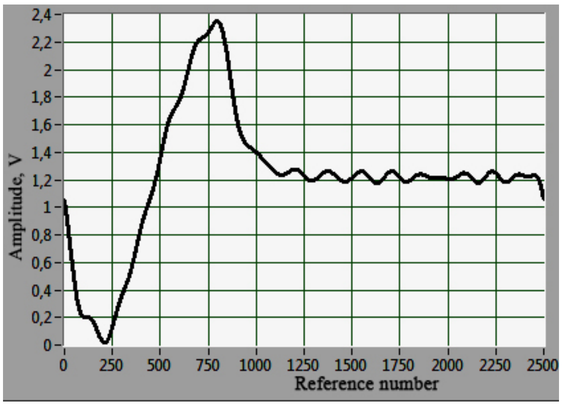
Fig. 4



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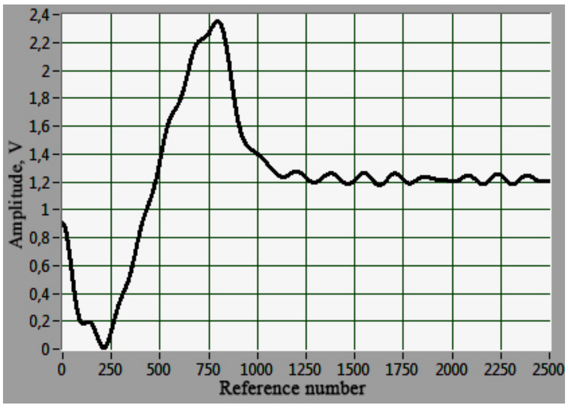

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Fig. 5

Since the set of possible information signals is limited for a specific composite and a physical diagnostic method, the output in such a situation (reduction of the number of spectral components, and hence the dimension of the feature space) is the use of the information signals themselves, obtained by diagnosing this physical method, as the basis [17, 18]. With selecting the necessary set of basic signals, it is possible to build on their own basis an orthogonal basis, which will be used for spectral transformation and restoration of information signals.

Obtaining a proper orthogonal basis, provided that the basis signals are linearly independent, is possible using the Gram-Schmidt algorithm. The construction of its own basis of orthogonal functions of a discrete argument, in this case, is performed by the following recurrence relations:

$$h_1(\mathrm{Z}) = X_1(\mathrm{Z}), \qquad h_2(\mathrm{Z}) = X_2(\mathrm{Z}) - \langle X_2(\mathrm{Z}), g_1(\mathrm{Z})\rangle g_1(\mathrm{Z}),$$
$$h_3(\mathrm{Z}) = X_3(\mathrm{Z}) - \langle X_3(\mathrm{Z}), g_1(\mathrm{Z})\rangle g_1(\mathrm{Z}) - \langle X_3(\mathrm{Z}), g_2(\mathrm{Z})\rangle g_2(\mathrm{Z}), \qquad (2)$$
$$\vdots$$
$$h_n(\mathrm{Z}) = X_n(\mathrm{Z}) - \sum_{k=1}^{n-1} \langle X_n(\mathrm{Z}), g_k(\mathrm{Z})\rangle g_k(\mathrm{Z}),$$

where $X_1(\mathrm{Z}), X_2(\mathrm{Z}), \ldots, X_n(\mathrm{Z})$ are linearly independent vectors (signals) are constructed using the discretization of information signals from the space *U*; *n* is the number of components of the desired basis (the dimension of the subspace U^* of the basis signals enters the space *U*); $h_1(\mathrm{Z}), h_2(\mathrm{Z}), \ldots, h_n(\mathrm{Z})$ is the system of orthogonal vectors (functions of the discrete argument) of the new basis; $g_1(\mathrm{Z}), g_2(\mathrm{Z}), \ldots, g_n(\mathrm{Z})$ is a system of orthonormal vectors (functions of a discrete argument) of a new basis; $\langle X_n(\mathrm{Z}), g_k(\mathrm{Z})\rangle$ is scalar of vectors X_n(Z) and g_k(Z); $Z = \{z_0, z_1, \ldots, z_j\}$ is a signal detection zone; $j \in \overline{0, N-1}$, *N* is the number of samples of a discrete signal.

The system of basic orthonormal vectors is defined as:

$$g_i(\mathrm{Z}) = h_i(\mathrm{Z}) / \|h_i(\mathrm{Z})\|, \qquad (3)$$

where $\|h_i(\mathrm{Z})\|$ is the L_2-norm of a vector in Euclidean space, $\|h_i(Z)\| = \sqrt{\sum_{j=0}^{N-1}\left[h_{i,j}(Z)\right]^2}$.

After performing the described algorithm, a new basis of orthogonal functions of a discrete argument $\{g_1(Z), g_2(Z), \ldots, g_n(Z)\}$ is obtained, which can be used for spectral transformation of information signals of a flaw detector. The number of spectral components of this basis can be minimized, which greatly simplifies the algorithm for processing information signals and building their simulation model.

The spectral conversion of the signal according to this basis is performed according to the equation:

$$a_{i,j} = \langle X_i(\mathrm{Z}), g_j(\mathrm{Z})\rangle, \ i = \overline{1, L}, \ \ j = \overline{1, n}, \qquad (4)$$

where $a_{i,j}$ is the *j*-th coefficient of the spectral decomposition of the *i*-th realization of the information signal; *L* is the dimension of the sample information signals.

Signal recovery is performed as follows:

$$\overset{*}{X}_i(\mathrm{Z}) = \sum_{j=1}^{n} a_{i,j} g_j(\mathrm{Z}), \ i = \overline{1, L}, \qquad (5)$$

where $\overset{*}{X}_i(\mathrm{Z})$ is the restored *i*-th implementation of the information signal of the flaw detector by spectral components $j = \overline{1, n}$.

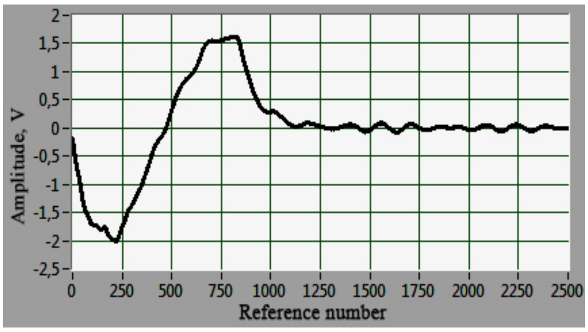
Thus, from a space of dimension *U* (where *U* is the set of all possible signals characteristic of each type of defect), a subspace of dimension U^* is selected (U^* is the set of signals chosen to build its own basis), which makes it possible to approximate with a given accuracy any signal from the *U*-space. Analytically this is described by the expression:

$$\left| X_i(\mathrm{Z}) - \overset{*}{X}_i(\mathrm{Z}) \right| \le \alpha, \qquad (6)$$

where $X_i(\mathrm{Z})$ is the output information signal from the *U*-space; $\overset{*}{X}_i(\mathrm{Z})$ is an approximated signal; *α* is the permissible absolute error (discrepancy) between the signals.

Fig. 6 (output information signals from the defect-free zone (a) and the zone with a damaging impact of 3.24 kJ (*b*)), Fig. 7 (spectral alignment of the information signal from the defect-free area (*a*) and the zone with a damaging impact of 3.24 kJ (*b*)), Fig. 8 (recovered information signals from the defect-free area (*a*) and the zone with a damaging impact of 3.24 kJ (*b*)) show the corresponding realization of spectral schedule of the output information signals, their in the constructed orthogonal basis and the reconstructed signals by the inverse transformation of their spectrum. The values of the coefficients of the spectral decomposition for each type of zone (defect-free or defective) are presented in Table 1 (values of the coefficients of the spectral decomposition of information signals).

Such an approach makes it possible to significantly reduce the number of spectral decomposition coefficients for analyzing and modeling information signals of a flaw detector. In this problem, the dimension of the subspace is reduced to U^* =5.



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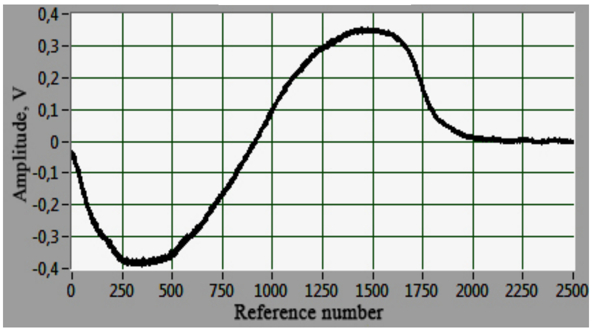

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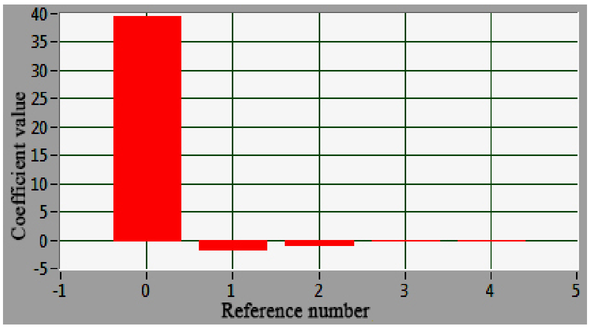
Fig. 6



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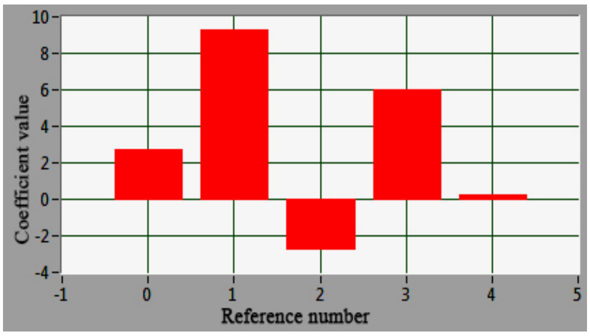

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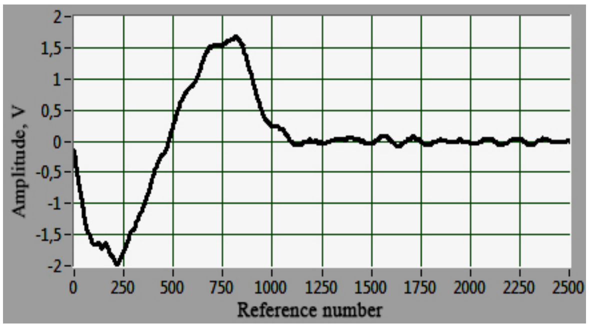
Fig. 7



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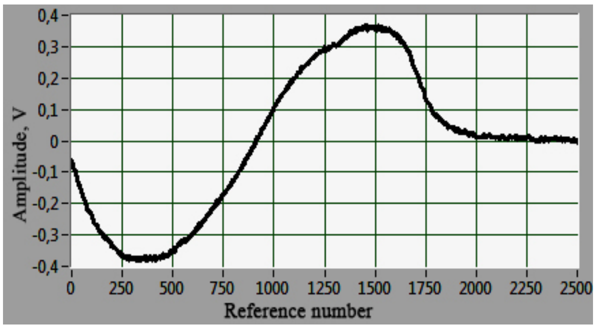

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Fig. 8

Construction and study of approximation equations. To determine the values of the corresponding coefficients, the decomposition characteristic of information signals describing the various defects of the samples under study, it is necessary to obtain a function that approximates the distribution of the values of each of the spectral decomposition coefficients depending on the degree of damage (defectiveness) of the sample under study [19]. Such a function can be determined by interpolating known values of decomposition coefficients, for example, by power polynomials or splines [5]. Further, for each spectral component, it is necessary to select the desired damage degree (defect size) x of the controlled area, determine the value of the spectral components by the established functional dependencies and perform the inverse transformation.

Interpolation using splines is more efficient than interpolation by polynomials [20], since it gives reliable results even for low degrees of interpolation equations, and the Runge phenomenon that occurs when using high-order polynomial interpolation does not occur. The main advantages of spline interpolation are stability and complexity. Systems of linear equations that need to be solved to construct splines are well conditioned, which allows to obtain the coefficients of polynomials with high accuracy. As a result, even for very large N, the computational scheme does not lose stability. Building a table of spline coefficients requires $O(N)$ operations, and calculating the spline value at a given point is $O(\log_2 N)$.

There are many types of interpolation splines [15]. The paper proposes and studies a method for constructing approximations of dependencies of scheduling coefficients on the degree of impact damage using Hermite cubic splines and quadratic splines [21, 22].

Table 1

Zone type	Coefficient number				
	0	1	2	3	4
No defect	37.442	-0.036	0.013	-0.009	-0.006
2.3 kJ energy damage	10.318	14.952	0.007	0.006	-0.005
2.8 kJ energy damage	9.687	12.861	2.311	0.005	-0.004
3.2 kJ energy damage	3.059	9.180	-2.581	5.496	-0.003
5.1 kJ energy damage	-0.140	2.547	-1.659	3.820	4.023

Hermite's cubic spline is defined by the following equation:

$$H_b\left(x\right)=\sum_{j=0}^{b/2}\frac{\left(-1\right)^j}{2^j}\cdot\frac{b!}{j!\left(b-2j\right)!}x^{b-2j}, \tag{7}$$

where b is degree of Hermite polynomial.

Hermite polynomials form a complete orthogonal system on the interval $\left(-\infty,\infty\right)$ with the weight function $e^{-x^2/2}$:

$$\int_{-\infty}^{\infty}H_b\left(x\right)H_m\left(x\right)e^{-x^2/2}dx=b!\sqrt{2\pi}\delta_{bm}, \tag{8}$$

where δ_{bm} is Kronecker symbol.

An important consequence of the orthogonality of Hermite polynomials is the possibility of scheduling various functions in series according to Hermite polynomials. For any integral integer p, the equation is true:

$$\frac{x^p}{p!}=\sum_{k=0}^{k\le p/2}\frac{1}{2^k}\cdot\frac{1}{k!\left(p-2k\right)!}H_{p-2k}\left(x\right). \tag{9}$$

Hermite splines have a continuous first derivative, but the second derivative has a discontinuity in them. This interpolation method uses two control points and two direction vectors. According to this method, the interpolation on the interval $\left(x_k,x_{k+1}\right)$, where $k=\overline{1,Q-1}$ (Q is the number of specified points on the interpolation interval that divide the entire interval into a specified number of segments), is given by the formula:

$$P\left(x\right)=h_{00}\left(t\right)p_0+h_{10}\left(t\right)hq_0+h_{01}\left(t\right)p_1+h_{11}\left(t\right)hq_1, h=x_{k+1}-x_k, t=\left(x-x_k\right)/h, \tag{10}$$

where p_0 is initial point at $t=x_k$; p_1 is final point at $t=x_{k+1}$; q_0 and q_1 are respectively the initial (at $t=x_k$) and final (at $t=x_{k+1}$) vectors; $h_{00}(t)-h_{11}(t)$ are base Hermite polynomials: $h_{00}\left(t\right)=\left(1-t\right)^2\left(1+2t\right)$, $h_{01}\left(t\right)=t^2\left(3-2t\right)$, $h_{10}\left(t\right)=t\left(1-t\right)^2$, $h_{11}\left(t\right)=t^2\left(t-1\right)$.

There are such symmetry properties of polynomials:

- $h_{00}(t)+h_{01}(t)=1$ – symmetry about the y=1/2;
- $h_{00}(t)=h_{01}(1-t)$ – symmetry about the x=1/2;
- $h_{10}(t)=-h_{11}(1-t)$ – symmetry with respect to the point (0, 1/2).

The obtained interpolation functions based on cubic Hermite splines for the first two spectral components, depending on the kinetic energy of the damaging impact, are presented in Fig. 9 (approximation of Hermite's splines for the first (*a*) and second (*b*) components of the spectral decomposition of the information signal).

Interpolation of a set of points $\left(x_k,y_k\right)$ for $k=1,\ldots,Q$ using quadratic splines is carried out for each interval, and the parameters for one point in different intervals are chosen the same. The interpolation spline will be obtained continuously differentiated by (x_1, x_Q). There are several ways to define parameters. The simplest of them is the following.

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$$P_i\left(x\right)=y_i+w_i\left(x-x_i\right)+\frac{w_{i+1}-w_i}{2\left(x_{i+1}-x_i\right)}\left(x-x_i\right)^2. \tag{11}$$

The coefficients of this polynomial can be found by choosing the value of w_0 and using the recurrence relation:

$$w_{i+1} = -w_i + 2\frac{y_{i+1} - y_i}{x_{i+1} - x_i}. \quad (12)$$

The coefficients w_i are determined to an approximate degree. Since only two points are used to calculate the next point of the curve (function) (instead of three), this method is prone to serious oscillation effects when the signal changes abruptly. Due to the presence of such effects, this method may not be used for all tasks.

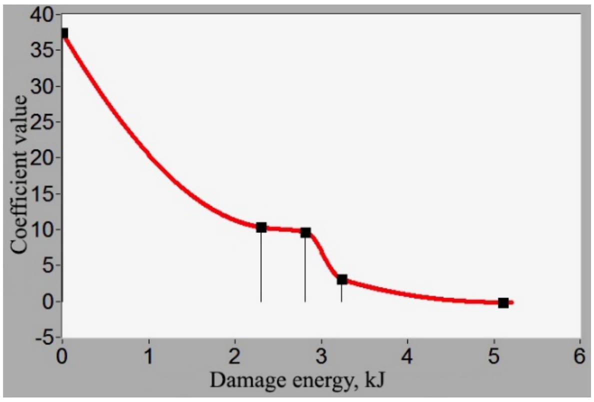

Fig. 9, *a*

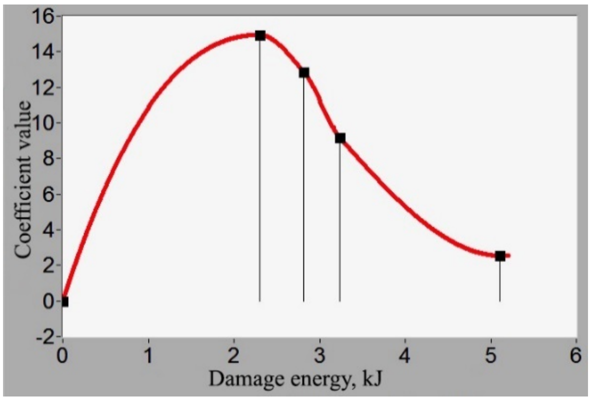

Fig. 9, *b*

The form of the obtained interpolation functions for the first two spectral components depending on the kinetic energy of the damaging impact using quadratic splines is shown in Fig. 10 (approximation by quadratic splines of the first (*a*) and second (*b*) component of the spectral decomposition of the information signal of the flaw detector).

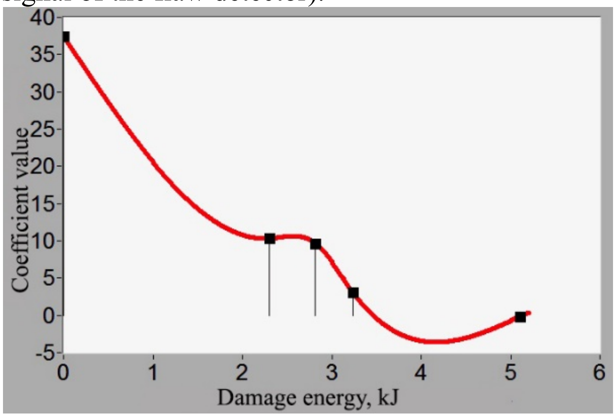

Fig. 10, *a*

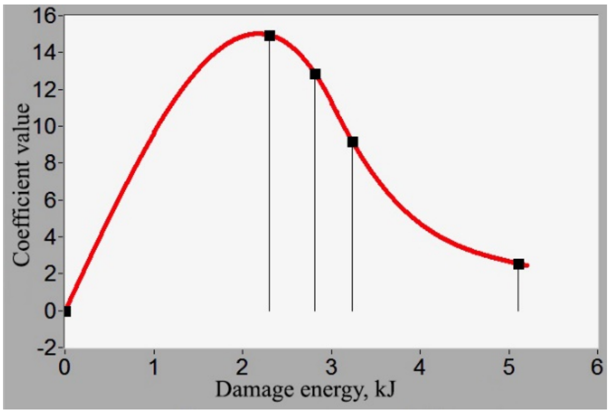

Fig. 10, *b*

To assess the effectiveness of the considered interpolation equations, the information signal received from the site with a damaging impact of 2.81 kJ was compared with the simulated signal corresponds to the same area. Fig. 11 shows the real signals from the damaged area with an energy of 2.81 kJ – curve S_1, as well as the simulated signal using Hermite cubic splines (Fig. 11, *a*) and quadratic splines (Fig. 11, *b*).

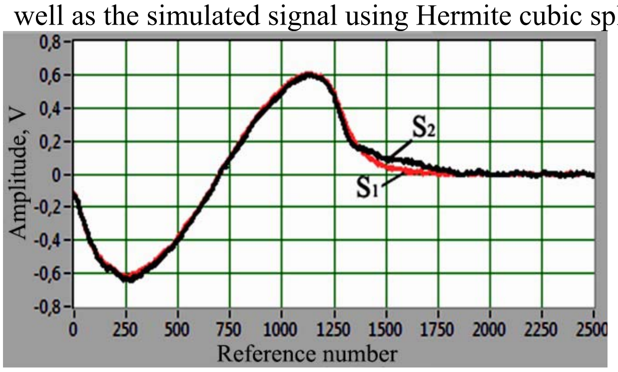

Fig. 11, *a*

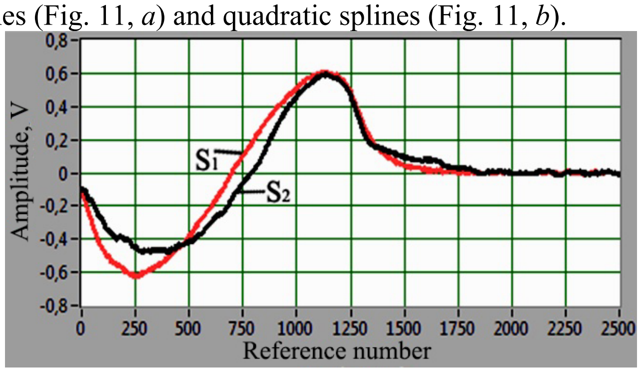

Fig. 11, *b*

The numerical estimate of the disagreement between the simulated and real signals was carried out by calculating the RMSE (root mean square error), the value of which is $2.5 \cdot 10^{-3}$ for Hermite's cubic splines and $4.0 \cdot 10^{-3}$ for quadratic splines.

Thus, using interpolation functions, it is possible to obtain the values of spectral components for a given level of damage to the sample zone, and using the inverse transform to obtain a simulated information signal [23, 24].

Creating a simulation model of the information signal. Information signals are characterized by a deterministic and random component. The random component describes such factors as the presence of noise in the measuring channels, random errors of the primary transducers, spatial heterogeneity of the composites, the state of the surface of the product, and the like. So, to build an adequate simulation model of information signals, it is necessary to take into account both components.

Existing physical models that describe the transformation of information signals depending on the defectiveness of the product have a number of significant drawbacks that do not allow them to be used in the calculations and the formation of the space of diagnostic signs. These disadvantages include the dependence of the flexibility of the defective region and its mechanical impedance on the physical characteristics of the edge sections of the defects and their shape, the inability to take into account the effect of the entire nomenclature of defects of composite materials on their mechanical characteristics, and considerable difficulties in calculating the frequency-dependent mechanical impedances of sections with real defects. Therefore, it is advisable to construct stochastic simulation models of information signals, taking into account their random changes in time.

A simulation model of the information signal of a flaw detector can be represented by the following equation:

$$S_i(Z)=\sum_{j=1}^{n}\left[a_{i,j}+\eta_j\right]g_j(Z), \qquad i=\overline{0,L-1}, \tag{13}$$

where $a_{i,j}$ is the deterministic component of the signal, is found according to the algorithm described previously through the distribution function of the values of the coefficients of spectral decomposition, depending on the degree of damage to the test object; η_j is a random component based on the eigenvalues and eigenvectors of the covariance matrix of the information signal; $g_j(Z)$ is the basis of the orthogonal functions of the discrete argument; L is the volume of the generated sample of information signals; n is the number of components in the signal spectrum.

The determined component of the signal is as follows. It is necessary to consider a vector $X(Z)=(X_0,X_1,...X_i)$, whose elements are obtained as a result of uniform sampling of the information signal of the sensor $X(t)$. Then we can find the vector $Y(Z)=(Y_0,Y_1,...Y_i)$ $Y_i=M[X_i]$, $i=\overline{0,N-1}$ is the mathematical expectation of the vector $X(Z)$, N is the dimension of this vector (the dimension of the space of diagnostic signs). After which it is determined:

$$a_{i,j}=\left\langle Y(Z),g(Z)\right\rangle,\ i=\overline{1,L},\quad j=\overline{1,n}, \tag{14}$$

where $a_{i,j}$ is the j-th coefficient of spectral decomposition of the i-th implementation of the information signal; L is the dimension of the sample of information signals; n is the number of spectral components; $g_j(Z)$ is the basis of the orthogonal functions of the discrete argument.

Based on the studies of information signals, the first set of diagnostic features of the model is formed of five components of the schedule (n_1=5) of the signal by the constructed basis of the orthogonal functions of the discrete argument (the orthogonalization interval $t_{ort}\in[0,Z]$, the number of samples N=2500 of the discrete signal $X(Z)$). Modeling a certain degree of damage to the sample occurs by changing the values of the necessary components of the signal spectrum to values characteristic of the area with the corresponding degree of damage.

The second set of diagnostic features characterizing the random component of the model is determined based on the Karunen-Loev transform. The Karunen-Loev transformation is of fundamental importance, since it leads to the construction of uncorrelated features. Thus, there is an expression:

$$\eta_j=\sum_{k=0}^{n-1}\xi_k\phi_k(j), \qquad \mathrm{j}=\overline{0,n-1}, \tag{15}$$

where $\xi_k=\sum_{j=0}^{n-1}\eta_j\phi_k(j)$ are the expansion coefficients, which are independent Gaussian random variables with variances $D_{\xi_k}=\sigma_k^2,\ k=\overline{0,n-1};\ \{\phi_k(j),\ j=\overline{0,n-1}\}$ is the orthogonal basis whose elements $\phi_k(j)$ are eigenvectors of the covariance matrix R of the real signal.

Elements of the matrix R are found by the expression:

$$r_{i,j} = (n-1)^{-1}\sum_{k=0}^{n-1}(v_{k,i} - m_i)(v_{k,j} - m_j), \tag{16}$$

where $v_{i,j}$ are the elements of the matrix V of the coefficients of the spectral decomposition of information signals $X(Z)$; m_i are the elements of the matrix M of the mathematical expectation of each coefficient of spectral decomposition of the flaw detector signals.

Matrices V and M are formed as follows:

$$V = \begin{pmatrix} v_{0,0} & v_{0,1} & \cdots & v_{0,n-1} \\ v_{1,0} & v_{1,1} & \cdots & v_{1,n-1} \\ \vdots & \vdots & \vdots & \vdots \\ v_{B-1,0} & v_{B-1,1} & \cdots & v_{B-1,n-1} \end{pmatrix}, \qquad M = \{m_0, m_1, \ldots m_{n-1}\}, \tag{17}$$

where B is the number of implementations of information signals; n is the number of spectral decomposition coefficients of one implementation, $m_i = \sum_{k=0}^{B-1} v_{k,i} / B$.

The total energy of the vector $\eta = \{\eta_0, \eta_1, \ldots, \eta_{n-1}\}$, is defined as:

$$\sum_{i=0}^{n-1} R_{ii} = \sum_{k=0}^{n-1} \lambda_k. \tag{18}$$

The set of eigenvalues λ_k and eigenvectors $\varphi_k(j)$ uniquely characterize the covariance matrix R (and hence the vector η), therefore, it would be advisable to choose as the second set of signs n_2=n_1=5 eigenvalues and the corresponding eigenvectors of the covariance matrix of η.

Thus, for the simulation of information signals in the framework of the considered types of defects and the applied physical diagnostic method, it can be selected:

- 5 coefficients of orthogonal decomposition of the information signal in the constructed basis of orthogonal functions of the discrete argument $g_j(Z)$;
- 5 eigenvalues and the corresponding eigenvectors of the covariance matrix R of the vector η, characterizing the random component of the simulated signal.

The algorithm for modeling the information signal is shown in Fig. 12.

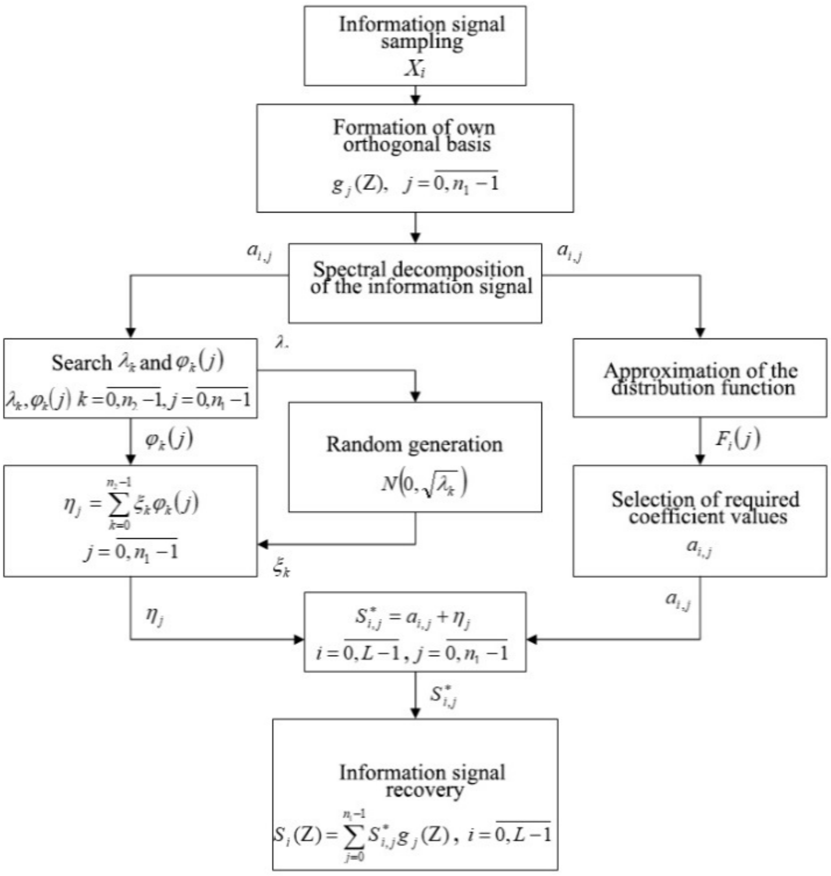

Fig. 12

The selection of the coefficients of orthogonal decomposition a_{k_1}, $k_1 = \overline{0, n_{1-1}}$, eigenvalues λ_{k_2} and eigenvectors $\phi_{k_2}(j)$, $k_2 = \overline{0, n_2 - 1}$, $j = \overline{0, n-1}$ was carried out using realizations of the estimates of these characteristics obtained in the analysis of real information signals in the diagnosis of composite materials.

Since each component (coefficient) of the spectral decomposition is characterized by a different scattering value depending on the defect or the degree of damage to the sample and serial number, therefore, in the simulation

simulation scheme, for each coefficient, respectively, there are different eigenvalues λ_k and eigenvectors $\phi_k(j)$. Therefore, each of the spectral components will, to varying degrees, experience the influence of random factors on its deterministic component, which happens in the analysis ealnyh information signals obtained when diagnosing articles made of composite materials. So, it can be noted that the described approach allows you to build an adequate simulation model of a real information signal, taking into account both its deterministic and its random components.

Study the adequacy of the developed simulation model. To assess the adequacy of the information signal simulation models constructed using the proposed algorithm, the statistical characteristics of the obtained values of the spectral decomposition coefficients were evaluated.

Table 2

Zone type	Defect-free	Defect 1	Defect 2	Defect 3	Defect 4
Coefficient No 0					
Expected value	35.442	10.318	9.687	3.059	-0.14
Standard error	4.181	1.582	2.003	0.551	0.079
Median	36.636	10.030	8.730	3.007	-0.141
χ^2	3.07	3.08	3.19	3.35	3.16
Coefficient No 1					
Expected value	-0.036	14.951	12.861	9.18	2.547
Standard error	1.371	2.566	3.445	1.666	0.352
Median	0.175	13.817	10.996	8.998	2.539
χ^2	3.29	3.12	2.99	3.13	2.94
Coefficient No 2					
Expected value	0.012	0.007	2.311	-2.581	-1.659
Standard error	0.879	0.310	0.377	0.449	0.227
Median	0.191	-0.041	2.155	-2.534	-1.671
χ^2	3.39	3.27	3.11	3.45	3.11
Coefficient No 3					
Expected value	0.029	0.006	0.005	5.496	3.821
Standard error	0.142	0.162	0.063	0.956	0.511
Median	0.042	-0.040	-0.005	5.408	3.866
χ^2	3.21	3.05	2.95	3.12	3.34
Coefficient No 4					
Expected value	-0.006	-0.005	-0.004	-0.003	4.023
Standard error	0.067	0.031	0.031	0.074	0.516
Median	0.005	0.007	-0.015	-0.014	4.103
χ^2	3.37	3.01	3.35	3.40	3.18

Hypotheses regarding the Gaussian law of the distribution of the values of the coefficients of spectral decomposition in the obtained basis were tested using the Pearson χ^2-test. The results of calculating the sample characteristics of estimates and χ^2-statistics for one-dimensional distributions with 7 degrees of freedom are presented in Table 2. For one-dimensional distributions with 7 degrees of freedom with a significance level of α = 0.99, χ^2 = 3.49.

According to the data presented, it can be concluded that the hypothesis of the Gaussian law of the distribution of the values of the coefficients of spectral decomposition does not contradict the available data, therefore they are completely characterized by their own mathematical expectations and the correlation function. So, it is obvious that the diagnostic parameters for constructing an information model of information signals should be selected based on the analysis of these characteristics.

Using the developed method, information signal implementations were obtained for each of the sections of a real sample (250 implementations for each of the 5 sections). Fig. 13 presents real and simulated signals characteristic of a defect-free zone and a zone with a different degree of damage; curve S_1 is the real signal that was obtained in the diagnosis of cell panels with shock damage using the low-speed impact method, and curve S_2 is the simulated signal. Fig. 13 presents signal from a zone without damage (a) and zones with damage 2.3 kJ (*b*), 2.8 kJ (*c*), 3.2 kJ (*d*), 5.1 kJ (*e*).

Analyzing the received signals, the average discrepancy of the averaged simulated signals from the real ones was determined. The corresponding values are given in Table 3 (values of the standard error of the modeling of the information signal).

The obtained simulation models correspond in parameters and characteristics to real information signals, and can be used later in the formation of a training sample to configure the system, as well as to generate a control sample to verify the validity of the classifier and its validation. This is especially true for systems designed for non-standard diagnostics of objects; artificial neural networks are used as the classifier core.

The results of the study confirm the adequacy of the obtained simulation models of information signals and the effectiveness of the proposed method for obtaining reference signals.

The disadvantage of the discrete argument basis of the orthogonal functions created by the described algorithm is its specialization for a certain specific type of information signals. For the spectral conversion of signals of another type, it is necessary to re-execute the procedure for constructing an own basis of the orthogonal functions of the discrete argument, a new type of information signals will be specified.

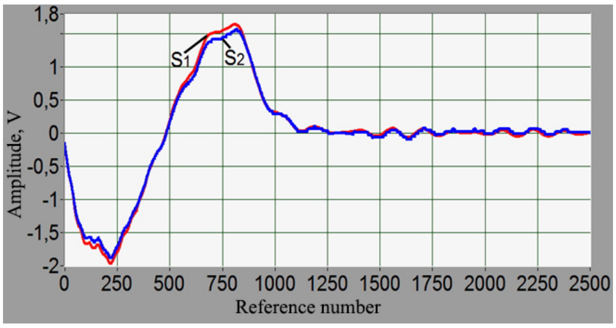

Fig. 13, *a*

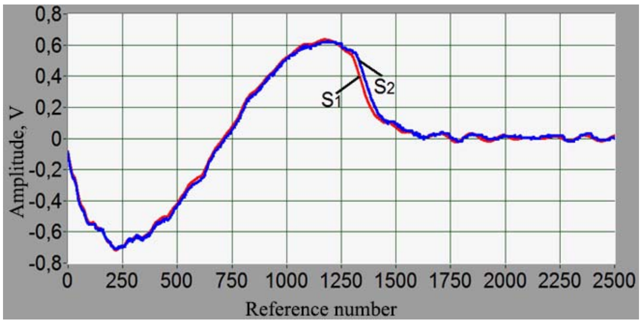

Fig. 13, *b*

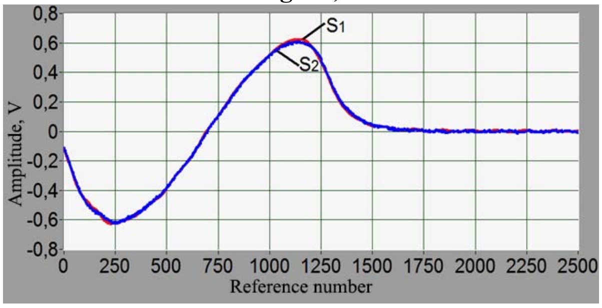

Fig. 13, *c*

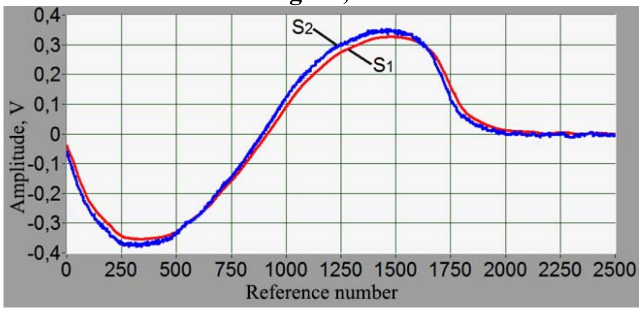

Fig. 13, *d*

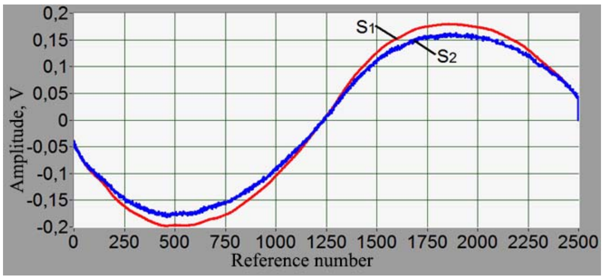

Fig. 13, *e*

Table 3

Type of zone	Standard error of recovery
Defect-free	$3.6 \cdot 10^{-3}$
With damage energy 2.30 kJ	$2.4 \cdot 10^{-3}$
With damage energy 2.81 kJ	$2.0 \cdot 10^{-3}$
With damage energy 3.24 kJ	$2.6 \cdot 10^{-3}$
With damage energy 5.11 kJ	$1.8 \cdot 10^{-3}$

Conclusions. Based on the obtained experimental signals for non-destructive testing of products made of composite materials, approaches are developed to construct a simulation model of signals, which takes into account the deterministic and random components of real signals.

The method of simulation modeling of signals obtained while controlling cellular panels using the low-speed impact method using orthogonal and orthonormal transformations is investigated. On its basis, a series of computer simulation experiments on the simulation of these signals was carried out. The obtained results can be applied during testing and training diagnostic systems for recognizing the technical condition of products made of composite materials about the possible range of defects of a particular material and the nature of their development and allow to analyze the transformation of information signals in real technical systems.

A method for simulating information signals has been developed and experimentally investigated, which allows one to take into account the deterministic and random components of the characteristics of real information signals, which made it possible to model information signals corresponding to various types and sizes of defects, the degree of damage to the material, and optimize the space of diagnostic signs depending on the type of material and characteristics defects of composites, synthesize a training set for training and customizing diagnostic system parameters and reduce the amount needed for this procedure actual reference samples with models defects.

Conducted experimental studies to determine the adequacy of the proposed simulation models, the obtained value of the standard error of the simulation does not exceed $3.6 \cdot 10^{-3}$.

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МЕТОД СТВОРЕННЯ ЕТАЛОННИХ СИГНАЛІВ ПРИ НЕРУЙНІВНОМУ КОНТРОЛІ НА ОСНОВІ НИЗЬКОШВИДКІСНОГО УДАРУ

В.С. Еременко[1], В.П. Бабак[2], А.О. Запорожець[2]
[1] НТУ України «КПІ ім. І. Сикорського»
пр. Перемоги, 37, Київ, 03056, Україна,
e-mail: nau_307@ukr.net
Інститут технічної теплофізики НАН України,
вул. Марії Капніст, 2а, 03057, Україна
e-mail: vdoe@ukr.net; a.o.zaporozhets@nas.gov.ua

Описано підхід до формування імітаційної моделі інформаційних сигналів, характерних для об'єктів з різними типами дефектів. Проведено дисперсійний аналіз компонентів сигнального спектра в базах дискретного перетворення Хартлі та дискретного косинусного перетворення. Аналіз форми реконструйованого інформаційного сигналу проводиться залежно від кількості коефіцієнтів спектрального розкладу в базах Хартлі та косинусних функцій. Отримано основу ортогональних функцій дискретного аргументу, яку можна використовувати для спектрального перетворення інформаційних сигналів дефектоскопа. Розроблено та експериментально досліджено метод моделювання інформаційних сигналів, що дозволяє враховувати детерміновану та випадкову складові характеристик реальних інформаційних сигналів. Бібл. 24, рис. 13, табл. 3.

Ключові слова: діагностика, неруйнівний контроль, інформаційний сигнал, композиційний матеріал, перетворення Хартлі, дисперсійний аналіз.

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