Diagnostics of life support systems with limited statistical data on failures

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Abstract. The authors suggest an approach to determine the technical conditions of life support systems of public buildings in conditions of significant uncertainty of statistical information on failures. To improve the re1iabi1ity and increase the resources of life support systems, maintenance and repair strategies are proposed according to the actual state, which implies the availability of objective diagnostic information. The essence of methods for constructing images of system failures based on training procedures is revealed, the latter being founded on the theory of nonparametric statistical analysis. The image is understood as a formalized description of the failure as an element of the system diagnosis model. The solution of image synthesis problem is given when the orthogonal trigonometric basis is applied in the recurrent relations implementing the learning process. The specific case assumes the existence of data on ranges of diagnostic parameter change at all failures of the investigated object. A modification of the training procedure is performed to build images of failures of life support systems of the latest generation when it is possible to find the ranges of changes in diagnostic parameters only in operational state. The modification consists of the formation and application of an orthonormal binary basis in recurrent relations. There is an example of image constructing of one of the ventilation and air conditioning system failures of a public building on the basis of a modified training procedure.

1 Introduction

Life support systems are required for comfortable functioning of public buildings, the former include the systems of heat, energy and water supply as well as ventilation and air conditioning. It is necessary to study carefully the operational properties of life support systems in order to increase their service life and reliability [1-7]. Currently, the operational phase of these systems is dominated by strict maintenance and repair strategies. They are based on the average estimates of changes in the technical condition of the object, so both time and the volume of repair and maintenance works are regulated. These strategies, along with the advantages of easy planning, have significant disadvantages. So, they do not always take into account the features of a particular system, the conditions of its functioning and as a result maintenance and repair work may be carried out untimely. It is necessary to move more actively to flexible strategies which involve varying the time and scope of maintenance work depending on the actual technical condition of the equipment. Studies and practical testing of the results for other types of equipment [8-10] confirm the feasibility of implementing flexible strategies. This transition requires the diagnosis of life-support systems which involves a formalized description of their failures. In the terminology of pattern recognition theory [11] the description of a particular failure is called its image. The totality of all images forms the basis of the diagnostic model.

Theoretical and the applied diagnostic problems were solved in other areas [12-14]. It should be noted that in these works, the modeling of diagnostic processes is based on various mathematical schemes depending on the physical nature of the processes in the equipment. As a result, complex of heterogeneous models appear which is accompanied by difficulties in organizing their interaction with each other and negatively affects the reliability of diagnosis.

The aim of this work is to develop an approach to the diagnosis of life support systems, which provides a common methodology for constructing models, invariant to the physical foundations of the construction and operation of various units in these systems. It gives a possibility to reduce the dimension of models, and as a result – to increase the reliability of diagnostics.

2 Methods

Methods of failure imaging based on training procedures have been developed [11, 15-19]. In a generalized form, these methods are presented as follows.

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If

$$\mathbf{Y}_{<n>} = (y_1, y_2, ..., y_n)^{\mathrm{T}} \quad (1)$$

vector values of physical quantities that characterize the internal state of the system-wear in mating nodes, misalignment in kinematic schemes, deposits from the application of working media on the inner surfaces of pipelines and air ducts, deposits from combustion products in gas paths and others. Vector (1) defines the observed state, and its components $y_j, j = \overline{1, n}$ are diagnostic parameters. In relation to life support systems, these can be temperatures, pressures, costs, levels of various working bodies, parameters of acoustic and vibrational processes.

All kinds of observable States form a set

$$Y = \{\mathbf{Y}_{<n>}\}, \quad (2)$$

on which the structure of the *n*-dimensional Euclidean space is given [20]. Then the subset Y^i of observed States corresponding to the *i*-th failure forms a domain in Euclidean space ($Y^i \subset Y$). Each region is defined by ranges

$$\Delta_{ij} = [y_{ij}^l; y_{ij}^u], \ i = \overline{1, m}, \ j = \overline{1, n} \quad (3)$$

changes in diagnostic parameters (where y_{ij}^l, y_{ij}^u – the lower and upper boundary values of the *j*-th parameter in the state of the system due to the *i*-th failure; *m* – power of the set of failures).

Areas

$$Y^i, \ i = \overline{1, m}, \quad (4)$$

in space (2) can intersect due to a variety of factors. Therefore, each region must be represented by one element-the image of the *i*-th failure, which is a vector

$$\mathbf{E}_i = (e_{i1}, e_{i2}, ..., e_{in})^{\mathrm{T}}, \ i = \overline{1, m} \quad (5)$$

of the same dimension as (1). Each component e_{ij} of the vector (5) characterizes the similarity of the observed States (1) corresponding to the *i*-th failure by the *j*-th diagnostic parameter.

The whole set of images is further denoted as

$$E = \{\mathbf{E}_i \mid i = \overline{1, m}\}. \quad (6)$$

For the synthesis of images, a training sample of observed States (training images) with a known affiliation of any region is formed (4):

$$\left\{\mathbf{Y}_k^1 \mid k = \overline{1, N^1}\right\} \subset Y^1; \ \left\{\mathbf{Y}_k^2 \mid k = \overline{1, N^2}\right\} \subset Y^2; \cdots; \left\{\mathbf{Y}_k^m \mid k = \overline{1, N^m}\right\} \subset Y^m, \quad (7)$$

where N^i is the number of training images on the *i*-th system failure.

Since the collection of data on system failures is very difficult, the sample (7) is heterogeneous and limited in size. Small, heterogeneous samples are processed by methods of nonparametric statistics, which include the stochastic approximation method [11]. On its basis, various algorithms are proposed, in particular, such a constructive computational scheme as

$$\mathbf{E}_i(k) = \mathbf{E}_i(k-1) - \frac{1}{k}[\mathbf{E}_i(k-1) - G(\mathbf{Y}^i(k))], \ i = \overline{1, m}. \quad (8)$$

Expression (8) represents the recurrence relations in which

$$G(\mathbf{Y}) = (g_1(\mathbf{Y}), g_2(\mathbf{Y}), ..., g_n(\mathbf{Y}))^{\mathrm{T}} - \quad (9)$$

– orthogonal (orthonormal) transformation of the vector **Y**.

Ratios (8) provide synthesis of the image $\mathbf{E}_i(k)$ at the current step through the same image $\mathbf{E}_i(k-1)$ at the previous step and the training image $\mathbf{Y}^i(k)$ from the sample (7).

If in (9) an orthogonal trigonometric basis is used the coordinate functions are given as [15]:

$$g_r(\mathbf{Y}) = \begin{cases} \delta_{rj} \sin k y_j, & k = (j+1)/2, \ j - \text{odd}; \\ \delta_{rj} \cos k y_j, & k = j/2, \quad j - \text{even}; \\ r, j = \overline{1, n}, \end{cases} \quad (10)$$

where $\delta_{rj} = \begin{cases} 1, \text{ if } r = j, \\ 0, \text{ if } r \neq j. \end{cases}$ – Kronecher's simbol. (11)

As the first step of training, an arbitrary sample element (7) is taken, converted on the basis of (9):

$$\mathbf{E}_i(1) = G(\mathbf{Y}^i(1)), \ i = \overline{1, m}, \quad (12)$$

and the next steps are given by the expression (8). By increasing the number of steps ($k \to \infty$) the learning process converges to the optimal image $\mathbf{E}_i^*$:

$$\lim_{k \to \infty} \rho(\mathbf{E}_i(k), \mathbf{E}_i^*) = 0, \quad (13)$$

where $\rho(\mathbf{E}_i(k), \mathbf{E}_i^*)$ is the distance between the vectors $\mathbf{E}_i(k)$ and $\mathbf{E}_i^*$ in Euclidean space $G(Y)$, which is generated from space (2) by the transformation (9).

Condition (13) reflects the theoretical learning outcome. For a real system, it is only possible to obtain an approximately optimal image due to the small sample size (7). Since the given volume for each failure is equal to the N^i elements, the image at the final step is considered optimal:

$$\mathbf{E}_i^* = \mathbf{E}_i(N^i), \ i = \overline{1, m}. \quad (14)$$

In the future, additional information may appear and the training sample is replenished. Then the images are refined in the learning process. For example, additional training $\bar{N}^i$ images are obtained, resulting in refined images based on (8):

$$\mathbf{E}_i^* = \mathbf{E}_i(N^i + \bar{N}^i), \ i = \overline{1, m}.$$

Example. The observed state of the system includes 5 diagnostic parameters:

$$\mathbf{Y} = (y_1, y_2, y_3, y_4, y_5)^{\mathrm{T}}.$$

A training sample on the *i*-th system failure was formed ($N^i = 9$):

$$\mathbf{Y}_1^i = (5, \ 6, \ 1, \ 1.8, \ 2.5)^{\mathrm{T}}; \quad \mathbf{Y}_2^i = (5.5, \ 6, \ 1.2, \ 2.1, \ 2.7)^{\mathrm{T}}; \quad \mathbf{Y}_3^i = (5.3, \ 6.5, \ 0.9, \ 1.6, \ 2.8)^{\mathrm{T}};$$

$$\mathbf{Y}_4^i = (4.9, \ 5.5, \ 1.4, \ 1.7, \ 2.6)^{\mathrm{T}}; \quad \mathbf{Y}_5^i = (5.2, \ 6.3, \ 1.3, \ 1.7, \ 2.7)^{\mathrm{T}}; \quad \mathbf{Y}_6^i = (5.1, \ 6, \ 1.1, \ 2, \ 2.5)^{\mathrm{T}};$$

$$\mathbf{Y}_7^i = (5.4, \ 6.2, \ 1, \ 2.2, \ 2.4)^{\mathrm{T}}; \quad \mathbf{Y}_8^i = (5.3, \ 6.2, \ 1.2, \ 1.6, \ 2.5)^{\mathrm{T}}; \quad \mathbf{Y}_9^i = (5, \ 6.1, \ 1.1, \ 2.1, \ 2.7)^{\mathrm{T}}.$$

You want to build an image of the *i*-th failure.

From expressions (9) – (12) the first step of training is obvious:

$$\mathbf{E}_i(1) = G(\mathbf{Y}^i(1)) = \begin{pmatrix} \sin 5 \\ \cos 6 \\ \sin 2 \\ \cos 3.6 \\ \sin 7.5 \end{pmatrix} = \begin{pmatrix} -0.96 \\ 0.96 \\ 0.91 \\ -0.90 \\ 0.94 \end{pmatrix}.$$

The second step covers the orthogonal transformation of the next sample element and the derivation of the approximation $\mathbf{E}_i(2)$:

$$G(\mathbf{Y}^i(2)) = \begin{pmatrix} \sin 5.5 \\ \cos 6 \\ \sin 2.4 \\ \cos 4.2 \\ \sin 8.1 \end{pmatrix} = \begin{pmatrix} -0.71 \\ 0.96 \\ 0.68 \\ -0.49 \\ 0.97 \end{pmatrix};$$

from (8) follows

$$\mathbf{E}_i(2) = \mathbf{E}_i(1) - \frac{1}{2}\left[\mathbf{E}_i(1) - G(\mathbf{Y}^i(2))\right] = \begin{pmatrix} -0.96 \\ 0.96 \\ 0.91 \\ -0.90 \\ 0.94 \end{pmatrix} - \frac{1}{2}\left[\begin{pmatrix} -0.96 \\ 0.96 \\ 0.91 \\ -0.90 \\ 0.94 \end{pmatrix} - \begin{pmatrix} -0.71 \\ 0.96 \\ 0.68 \\ -0.49 \\ 0.97 \end{pmatrix}\right] = \begin{pmatrix} -0.83 \\ 0.96 \\ 0.79 \\ -0.69 \\ 0.95 \end{pmatrix}.$$

Similarly, the other steps of the learning process are performed and in accordance with the condition (14), the optimal image is taken

$\mathbf{E}_i^* = \mathbf{E}_i(9) = (-0.87,\ 0.95,\ 0.70,\ -0.78,\ 0.93)^{\mathrm{T}}$.

3 Results and Discussion

Life-support systems of the latest generation are in use not so long so statistical information may not be sufficient to estimate ranges (3). You can define only ranges

$$\Delta_{0j} = [y_{0j}^l; y_{0j}^u],\ j = \overline{1,n}, \tag{15}$$

changes in diagnostic parameters in the operational state of the system (where y_{0j}^l, y_{0j}^u – the lower and upper permissible values of the *j*-th parameter). In this situation, the training procedure (section 2) is proposed to be modified as follows.

The components of the observed state (1) are represented in binary form

$$z_j = \begin{cases} 1, \text{ if } & y_j \in \Delta_{0j}; \\ -1, \text{ if } & y_j \notin \Delta_{0j}. \end{cases} \tag{16}$$

The expression (16) is an orthonormal transformation (9) in which coordinate functions are defined as

$$g_r(\mathbf{Y}) = z_j \delta_{rj}, \quad r, j = \overline{1,n}, \tag{17}$$

where δ_{rj} is the Kronecker symbol (11).

Given (17), the observed state in binary form is written by the vector

$$G(\mathbf{Y}) = (z_1,\ z_2, ..., z_n)^{\mathrm{T}} = \mathbf{Z}. \tag{18}$$

On the set of vectors (18) is the structure of the Euclidean space *Z*. Then gets the binary form and the sample (7). The recurrence relations (8) take the form

$$\mathbf{S}_i(k) = \mathbf{S}_i(k-1) - \frac{1}{k}[\mathbf{S}_i(k-1) - \mathbf{Z}^i(k))],\ \ i = \overline{1,m}. \tag{19}$$

By analogy with the (12) image in the first step $\mathbf{S}_i(1) = \mathbf{Z}^i(1),\ i = \overline{1,m}$. Relations (19) are applied from the second step. The binary transformation (16) gives a physical meaning to the image components: a positive value s_{ij} indicates the predominance in the sample by the *i*-th failure of such elements in which the values of the *j*-th diagnostic parameter do not exceed the range (15), and Vice versa at a negative value. This greatly simplifies the analysis of the images.

However, binary transformation leads to some coarsening of statistical information. So, regardless of the value of the diagnostic parameter within the range of Δ_{0j} binary feature is the same $z_j = 1$. If the parameter exceeds the allowed range ($y_j \notin \Delta_{0j}$), it is not taken into account on which side – to the left or to the right of Δ_{0j} its value. The binary trait is still $z_j = -1$.

Despite the above mentioned facts, the advantage of the presented approach is that it allows you to build a model of diagnosis in conditions of extreme limitation of data on failures. In the future, with the accumulation of information, the procedure of additional training is implemented, the essence of which is disclosed above. When the required amount of data is reached, it is possible to find ranges (3), which provides a transition to image synthesis based on the approach described in section 2. Thus, the construction of images based on the binary representation of parameters is considered not as an alternative to the known approaches, but as an extension. This makes it possible to diagnose modern life support systems at the initial stages of operation, when the level of knowledge of changes in the technical condition is very low.

An example of the application of the modified training.

21 diagnostic parameters were measured in the ventilation and air conditioning system of the public

building with Central air conditioning. Below are 7 parameters:

$$\mathbf{Y}_{<7>} = \left(y_1, y_2, y_3, y_4, y_5, y_6, y_7\right)^{\mathrm{T}},$$

where y_1 – air pressure in the supply line; y_2 - power consumption by the supply fan; y_3, y_4, y_5 – vibration speed, vibration acceleration and temperature of the supply fan bearings, respectively; y_6, y_7 – air temperature difference on the recuperator of the supply and exhaust lines.

As the *i*-th failure is considered the wear of the supply fan bearings, training sample for this failure:

$$\mathbf{Z}_1^i = (-1, -1, -1, -1, -1,\ 1,\ 1)^{\mathrm{T}}; \quad \mathbf{Z}_2^i = (-1,\ 1, -1, -1, -1,\ 1, -1)^{\mathrm{T}}; \quad \mathbf{Z}_3^i = (-1, -1, -1, -1, -1, -1, -1)^{\mathrm{T}};$$

$$\mathbf{Z}_4^i = (1,\ -1,\ 1, -1, -1,\ 1,\ 1)^{\mathrm{T}}; \quad \mathbf{Z}_5^i = (-1,\ -1, -1, -1, -1,\ 1, -1)^{\mathrm{T}}; \quad \mathbf{Z}_6^i = (1,\ -1, -1, -1, -1,\ 1, -1)^{\mathrm{T}};$$

$$\mathbf{Z}_7^i = (-1,\ -1, -1, -1, -1,\ 1, -1)^{\mathrm{T}}; \quad \mathbf{Z}_8^i = (-1,\ -1, -1, -1,\ 1,\ 1, -1)^{\mathrm{T}}.$$

You want to build an image . The training results are summarized in table 1.

Table 1. The sequence of steps of the modified training procedure

$\mathbf{Z}^i(1)$	$\mathbf{S}_i(1)$	$\mathbf{Z}^i(2)$	$\mathbf{S}_i(2)$	$\mathbf{Z}^i(3)$	$\mathbf{S}_i(3)$	$\mathbf{Z}^i(4)$	$\mathbf{S}_i(4)$
–1	–1	–1	–1	–1	–1	1	–0.50
–1	–1	1	0	–1	–0.33	–1	–0.50
–1	–1	–1	–1	–1	–1	1	–0.49
–1	–1	–1	–1	–1	–1	–1	–1
–1	–1	–1	–1	–1	–1	–1	–1
1	1	1	1	–1	0.33	1	0.48
1	1	–1	0	–1	–0.33	1	0
$\mathbf{Z}^i(5)$	$\mathbf{S}_i(5)$	$\mathbf{Z}^i(6)$	$\mathbf{S}_i(6)$	$\mathbf{Z}^i(7)$	$\mathbf{S}_i(7)$	$\mathbf{Z}^i(8)$	$\mathbf{S}_i(8)$
–1	–0.60	1	–0.33	–1	–0.43	–1	–0.51
–1	–0.60	–1	–0.67	–1	–0.72	–1	–0.76
–1	–0.59	–1	–0.66	–1	–0.71	–1	–0.75
–1	–1	–1	–1	–1	–1	–1	–1
–1	–1	–1	–1	–1	–1	1	–0.77
1	0.58	1	0.66	1	0.70	1	0.74
–1	–0.20	–1	–0.33	1	–0.14	–1	–0.24

The image is taken as the optimal one $\mathbf{S}_i^* = \mathbf{S}_i(8)$.

Indeed, here the invariance of models to the physical nature of diagnostic parameters is achieved (hence, to the physical foundations of the construction of certain aggregates of life-support systems). Whatever this nature, the parameters are represented in binary form and all subsequent formalization is based on this representation. This is an effective means of identifying quantitative patterns of change in the technical condition. The totality of all images provides diagnostics of systems based on metric ratios in Euclidean spaces, which makes it possible to switch to maintenance and repair according to the actual state.

The proposed approach to determining the technical condition of life support systems can be applied for the integrated solution of other tasks related to the organization of the required air exchange in buildings. For example, tasks to ensure the tightness of buildings [21] or to simulate ventilated facades [22-24], modeling of energy-efficient buildings and energy saving processes in life support systems [25, 26].

4 Conclusions

1. The expediency of transition to flexible strategies for maintenance and repair in life-support systems is established, the perfection of the ways of obtaining diagnostic information being required.
2. A well-known approach to the formation of images of life support systems by means of training procedures developed on the basis of stochastic approximation is presented in a generalized form. The approach to diagnosing life support systems provides a common methodology for model constructing which is invariant to the physical foundations of the structure and functioning of various aggregates in these systems.
3. A modification of the learning process in the construction of images of failures of life support systems at the initial stages of operation is proposed, which is a new approach in relation to the known results.
4. An example of image synthesis based on modified training for a specific failure of the ventilation and air conditioning system of a public building with Central air conditioning is considered.

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