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METHOD OF DETECTING ABNORMAL CHANGES IN THE FUNCTIONING OF A TECHNICAL OBJECT USING SINGULAR VALUES DECOMPOSITION OF EXPERIMENTAL DATA MATRIX

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Abstract
The behavior of the dynamic system is characterized by a large set of experimental data, which is well studied for normal conditions of its functioning. The character of this data changed in abnormal case of functioning or in system faults. There are many statistical methods, which allow to detect these changes. The identification of the considerable changes from measurement results almost no using statistical methods is the feature of the article. For this purpose, the experimental data matrix and the singular value decomposition (SVD) method are used to analyze the singular modes of this matrix. The change in singular values occurs as a result of a significant change in the nature of the data. To make a decision regarding the system transition into anomalous mode, the distance in Euclidean space between the set of singular values for normal conditions of system operation and the set of such values for possible anomalous conditions is estimated. If this distance will exceed the given threshold, then a decision is made to transfer the system to abnormal mode. Threshold determination can be carried out using statistical methods.
Key words: measuring information system, singular values decomposition, experimental data matrix, abnormal changing the parameters, distance between sets of singular values.

1. Introduction

Detection of anomalies in the functioning of technically complex objects (TCO) is reduced to identification of experimental results that deviate from standard or expected ones, which makes them incompatible with other data sets. The anomalies of behavior of random processes parameters in the form of amplitude jumps of various duration are dealt with in the article. Detecting jumps or outliers can be difficult because anomalies often do not occur, and the characteristics of normal behavior against which the anomaly parameters are compared can be described by complex dependencies. Automatic identification of sudden changes in the normal behavior of a data set is currently based on artificial intelligence and machine learning. Data anomalies can affect the reliability of decision-making about the state of a dynamic system, leading to false conclusions. Just one powerful outlier can significantly distort the mean of a data set, which is often considered a reference for comparison. In addition, anomalies in the behavior of data can influence the quality of algorithms of machine learning, because they can cause adjustment of model for noise, and not to basic template in the data. Detection and processing of anomalies in measurement data allows to improve their quality, increase the reliability of the decisions making, and also optimize the performance of machine learning.

2. The problem statement

Outliers of random processes parameters or jumps in their amplitude can be of short, medium or long duration. Short-term jumps of not very large amplitude practically do not change the spectrum of the input realization of random processes measured by a multi-channel measurement information system (MIS). If the MIS bandwidth is consistent with the spectrum of the process, then no significant changes in the output of the measuring system are observed, that is, a jump in the amplitude of the process is not registered. To measure such jumps, a system optimal according to the maximum posterior probability density criterion was synthesized in [1], which adjusts its bandwidth to the local time spectrum of the signal with an amplitude jump. At this time, there are no significant difficulties in measuring long-term outliers of the amplitude of a random process realization. The main problem here is to prove that the measured outlier is anomalous. Different approaches may be used for build a system of anomaly detection: the visualization through charts and graphs; the statistical tests, which compare statistical distributions of the received data with templates (tests by Grabs, Kolmogorov, etc.); the machine learning algorithms based on artificial neural networks etc. The methods based on mathematical statistics are used to automatically form a decision about the state of technical objects. The preparatory work for such methods needs to large time-consuming and should be repeated periodically.

An overview of statistical methods used in dynamic systems is given in [2]. Among them, deviations from the average can be distinguished: the parameters of each observation are compared with the average value of the data. The value that differs significantly from the average can be classified as abnormal [3]. In the estimation method [4], the number of standard deviations of each observation from the average is determined. The nearest neighbor method [5] compares the distance of each observation with its nearest points in the data space. If this distance is varies widely from reference, then the measurement can be classified as abnormal. The clustering method [6] groups data based on their similarity, and observations that do not belong to any of the clusters are defined as anomalous. The statistical methods are used widely in the machine learning algorithms. Therefore, in practical terms, to detect abnormal changes in measurement data, it is advisable to reduce the amount of work on statistical data preparation. For this purpose, a different principle of data analysis should be used.

3. Analysis of recent publications

The analysis of the results of the experiments without extensive use of statistical methods is based on singular values decomposition (SVD) of measured data matrix. The rows of this matrix are the numbers of measuring channels, and the columns of the matrix are numbers of time discrete. The theoretical basis of the method is described in [8]. This method was originally used on hydrodynamics [9], and then began to introduce in other industries [10]. In [11], it forms the basis of the face recognition algorithm. A new approach to speech signal enhancement based on SVD is described in [12]. Decomposition by singular values is also used in the analysis of spectroscopic data due to the qualitative separation of noise from the signal [13]. The possibility of applying SVD for diagnostic tasks is analyzed in [14]. In [15], a compromise between the algorithms of recursive eigendecomposition of the autocorrelation matrix and SVD of measurement data for tasks of adaptive spatio-temporal signal processing is discussed. An improved method of noise removal using SVD not only for periodic signals is described in [16]. It should be noted that in many cases the problem of noise reduction is best provided by the SVD method in signal processing [17, 18]. The matrix filter based on SVD has demonstrated a comparative improvement in the compression ratio, resolution, and signal-to-noise ratio in radars compared to the matched filter under the same conditions [19]. The SVD method is used in both signal and image processing [20]. It is promising to use this method in the diagnosis of technical and other objects [21]. One of the main advantages of SVD is a significant reduction in the dimensionality of the experimental data matrix [22], which simplifies signal processing and increases the performance of real-time systems. The number of scientific works that use SVD is constantly growing and covers different areas of human activity. The article analyzes the possibilities of using this method in the field of diagnostics of technical systems, which is related to the detection of abnormal changes in the measured parameters of random processes.

The article is aimed at developing an effective method for detecting abnormal changes in signal parameters of a technical object using a multi-channel measuring information system without statistical parameter estimation.

The article is illustrative in nature and reveals the stages of using SVD to the experimental data obtained by the authors. Based on these results, the recommendations given by the MIS are formed.

4. The description of the experiment

The structure of the measuring complex is presented in Fig. 1. It contains four digital strain gauges (DSG) for measuring the deformation of the mechanical installation. The external appearance of the measuring channel is shown in Fig. 2. Calibration of the measuring complex was carried out by determining the calibration coefficient for each sensor separately. Amplitudes of mechanical deformations on four sensors in the experiment are shown in Fig. 3.

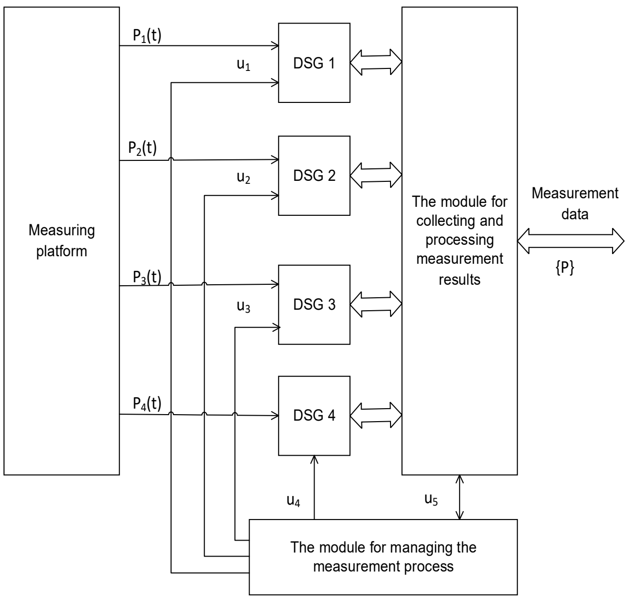


Fig. 1. The structure of the measuring complex

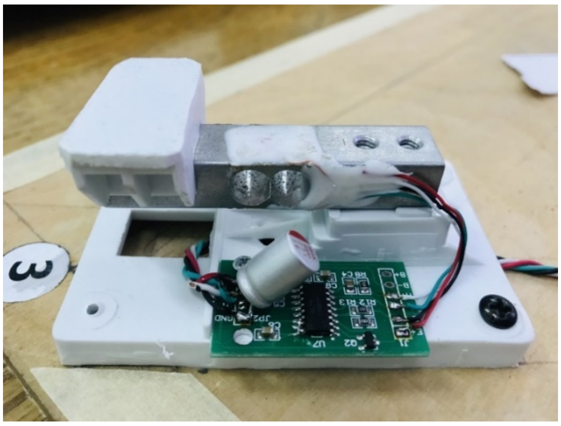


Fig. 2. Appearance of the measuring channel

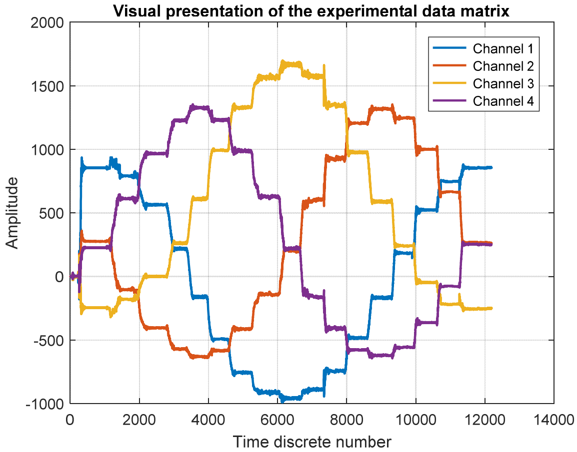


Fig. 3. The time distributions of deformations on four channels of measuring system for normal operating conditions

Fig. 3 is obtained for normal operating conditions of the technical object. The method of detecting anomalous changes in parameters is based on the comparison of the averaged dependence of the parameters of the random process in each measuring channel during regular system operation modes and the current dependence, which is directly measured at the selected time interval.

This interval for the specified object can be metrological normalized. The averaged dependence is recorded in the computer memory and periodically updated during the operation of the technical object. The periodicity of updating the average dependence is determined by the requirements of metrological support. The results of many experiments for the normal conditions of the functioning of the dynamic system are entered into the database, and further statistical processing of the data is carried out in order to determine the average dependence. This method cannot completely reject the statistical methods. The time distributions of deformations along the four channels of the measuring system (Fig. 3) are close to the averaged ones. The SVD method significantly reduces the scope of the application of statistical data processing at the stage of current measurement of physical quantities.

5. The result of SVD application for normal operation conditions of the object

The SVD method is used to non-symmetric matrices and is analog of square matrices diagonalization. The matrix of experimental data L can be expressed as

$$L = U\Sigma V^T, \qquad (1)$$

where Σ is the matrix of singular values; the matrix U and V contain, respectively, left and right orthonormal singular vectors for which $U^TU = I$ and V^TV=I, when I - identity matrix. For this experiment data matrix L has dimensions 4×12193, though, matrix dimensions U is 4×4,and matrix V - 12193×12193. The matrix dimensions Σ coincide with dimensions L. In the article, for the purpose of the research, the main attention is paid to the matrix Σ, which contains singular values placed diagonally in descending order. Decomposition of singular values is carried out in the Matlab package using the svd operator. The results of the decomposition of the L matrix are shown in Figs. 4 and 5.

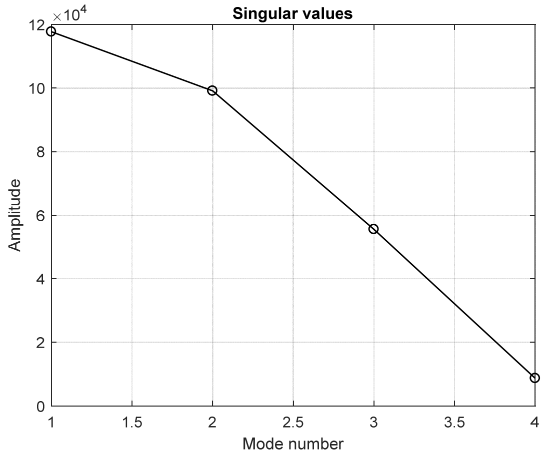


Fig. 4. Dependence of the singular values of the matrix on the mode number for normal conditions

Singular values of matrix Σ for four modes are shown in Fig. 4. The nature of the graph is descending for all experiments. The distribution of modes according to their relative energy characteristics is shown in Fig. 5. There are actually four modes, but in practice it may be reasonable to use three, since the fourth mode has much lower energy. This, however, depends on the tasks that the researcher solves and the dynamic characteristics of the technical object.

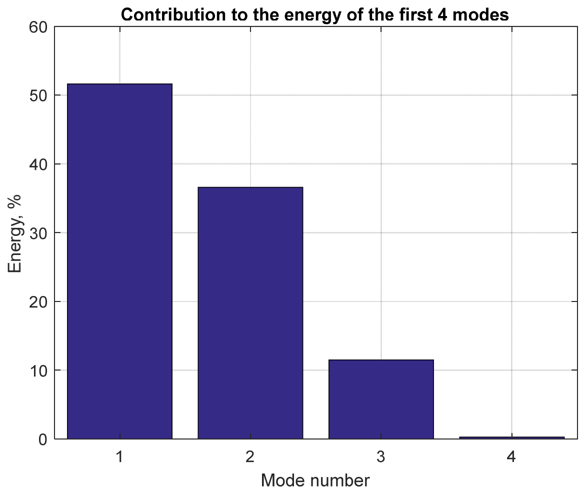


Fig. 5. The relative energy characteristics of modes for normal conditions

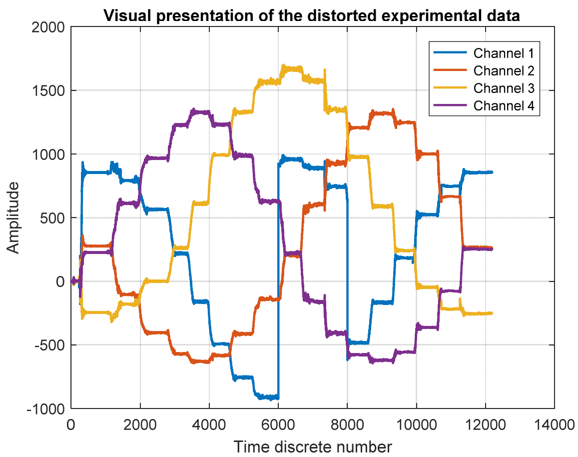
Matrix L describes the average distribution of parameter values measured by sensors. It is logical to assume that under abnormal conditions, for example, in case of a faulty sensor or malfunctions in the technical object operation, the nature of the singular values distribution will change.

6. The result of SVD application for abnormal conditions of considered object

Let us consider the results of SVD application for anomalous conditions, which will be formed by changing the *L* matrix. For example, in the range of column numbers from 6000 to 8000 for the first row (first sensor), we replace the measured values on their modules. As a result, the *L* matrix is changed to the *B* matrix. The time distributions of measured data for four channels of the system are presented in Fig. 6. In contrast to Fig. 3, here the distribution of data in the first channel has changed in the range of time samples from 6000 to 8000.

For anomalous operating conditions, the nature of the singular values distribution and their energy characteristics has changed significantly (Figs. 7, 8). First of all, the relative contribution to the total energy of the first mode decreased, and all other modes increased. Even the fourth mode cannot be neglected.

Comparison of Figs. 5 and 8 shows that the energy characteristics of the first mode under abnormal conditions significantly decreased, and they became almost the same for the first and second modes, and



Figc. 6. The time distributions of deformations on four channels of measuring system for abnormal operating conditions

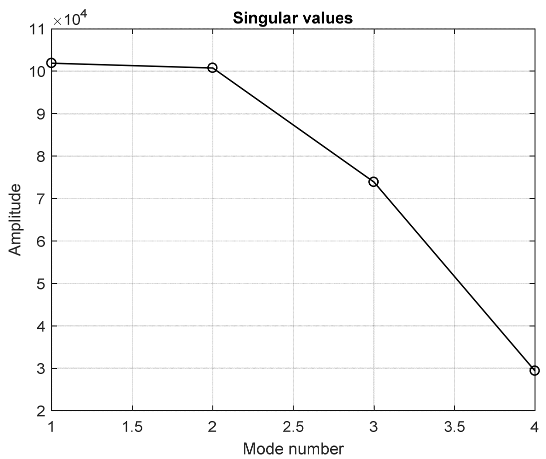


Fig. 7. Dependence of the singular values of the matrix on the mode number for abnormal conditions

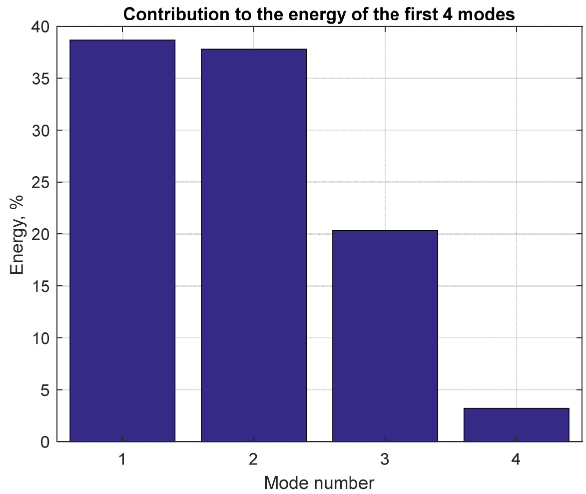


Fig. 8. The relative energy characteristics of modes for abnormal conditions

increased for the third mode. A significant increase in the energy characteristics of the fourth mode can be considered the main feature. Therefore, this example shows that abnormal operating conditions of a technical object change the magnitude and distribution of singular values of the matrix of experimental data, which creates an opportunity to detect these conditions.

7. The criteria of normal and abnormal operating conditions comparison for the object

So, for normal and abnormal conditions there are two sets consisting of four modes (K = 4) or singular values of matrix Σ. The number K is not known in advance, but it is known for the matrix of reference averaged dependences of the parameter in the channels for normal conditions. The singular values for these conditions let denote as σ_{L_k}, and for abnormal conditions - σ_{B_k}. Then, the distance d (metric) in Euclidean space between these sets is determined by the known ratio:

$$d = \sqrt{\Sigma_{k=1}^{K} (\sigma_{L_k} - \sigma_{B_k})^2}. \quad (2)$$

This formula provides a single number, that is, the distance between two sets. To assess the behavior of the distance d for different anomalous situations, we will create four model cases. In all cases, the measurement data changes only in the first channel, and in the range of time samples from 6000 to 8000. In the first case, the modular values of the amplitudes for this range are multiplied by 0.5, in the second - by 1, in the third - by 1.5, and in the fourth - by 2. Then the obtained 4 valuesof the distance between sets of singular values are illustrated in Fig. 9.

The reduction of the distance for the second case is due to the equality of the singular modular values with the reference set of experimental data in the first channel. This special case does not happen often. In general, for physical reasons, a regularity should be observed: the greater the deviations in experimental data, the greater the distance between singular values. If, instead of the distance d, the cosine of the angle θ between the matrices L and B, is used, then a similar relationship can be obtained:

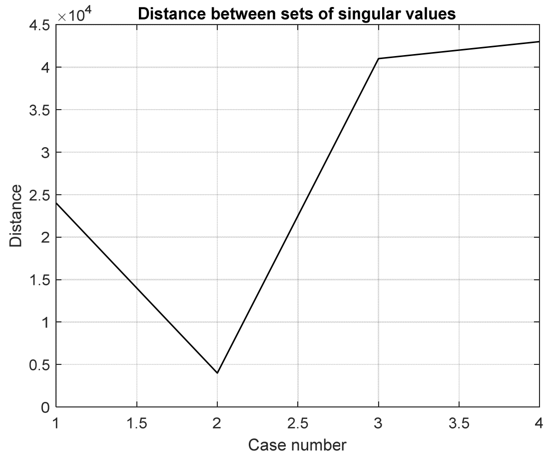


Fig 9. Distance between sets of singular values for four model cases

$$\cos\theta = \frac{\langle L,B\rangle}{\|L\|\cdot\|B\|}, \quad (3)$$

when $\langle L, B\rangle$ is the scalar product of matrices L and B, which is determined by the formula: $\langle L, B\rangle = Sp(L^T B)$. Here Sp means the trace of the product of the matrices in parentheses, that is, the sum of the values of the elements of the main diagonal. Norms of matrices L and B are determined by similar formulas: $\|L\| = \sqrt{\langle L, L\rangle}$, $\|B\| = \sqrt{\langle B, B\rangle}$. The values of the cosine of the angle between the matrices describing the experimental data for normal and abnormal conditions are shown in Fig. 10. If the angle θ=0°, and cos θ=1, then the matrices coincide and, on the contrary, at θ=90° and cos θ=0 the matrices completely lose their similarity.

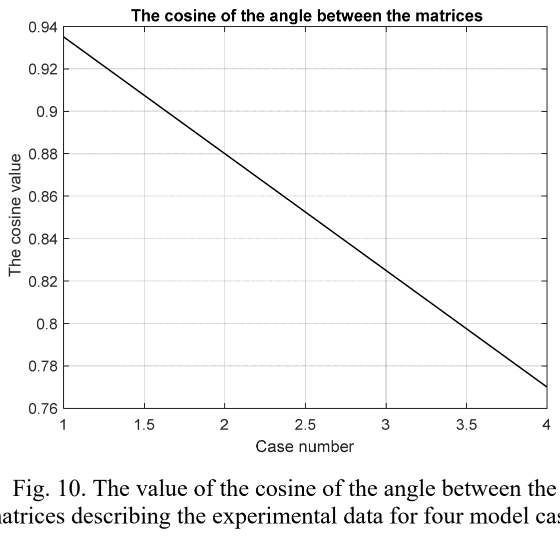


Fig. 10. The value of the cosine of the angle between the matrices describing the experimental data for four model cases

Fig. 10 shows that for selected cases, with an increase in the amplitude of the data in the first channel in the previously specified time interval, the cosine of the angle between the matrices decreases almost linearly. There are no violations of the monotonicity of the graph here, as can be seen in Fig. 9. This is an advantage of the approach compared to determining the distance between sets of singular values. However, in Fig. 10, in the range of considered cases, the value of the cosine of the angle changes by approximately 20%, while in Fig. 9, it changes several times. In addition, matrices of a large dimension were used to obtain Fig. 10, and matrices of a smaller dimension, which was commensurate with the rank of large dimension matrix, were used for Fig. 9. Therefore, for practical needs, the method of determining the distance between sets of singular values of the matrix of averaged experimental data for normal conditions and the same set of the matrix of current data is more suitable. A combination of these approaches is also possible. Since the singular values for the modes are related to the variances of the measured values, the first modes contain the most information that is important for practice.

8. The main stages of the method of detecting abnormal operating conditions of a technical object

Therefore, the method of classifying the experimental values of the multi-channel measuring information system as abnormal includes the following stages:

1) formation of a database for experimental values obtained under normal operating conditions and determination of averaged distributions across all channels, as well as other statistical characteristics, if they are required;

2) obtaining similar data for abnormal conditions based on modeling, and if possible, experimentally;

3) determination of the criterion for identifying abnormal conditions and justification of the threshold, which indicates the transition of the measurement information system to such conditions;

4) obtaining a set of singular values for the matrix of averaged experimental data and the matrix of current data obtained by the measurement information system; the specified matrices must have the same size;

5) estimating the distance between two sets of singular values; if this distance exceeds the previously determined threshold, then a decision is made to classify the received data as abnormal.

9. Conclusions

The article proposes a method of detecting abnormal operating conditions of a technical object based on the use of data from a multi-channel measurement information system. The results of the authors' experimental research were used to illustrate the method. The method of estimating the singular values of the data matrix can be used without restrictions for the results of other measurements. It is advisable to use the method for technical objects in which the time dependences of the parameters in the measuring channels have stable statistical characteristics over a period of time, that is, the object performs the same work. The proposed method is also suitable for recognizing the operating conditions of the object. A significant advantage of the SVD method is the ability to process large data sets, as they can be described by several modes. The left and right singular vectors of the data matrix characterizing the spatial and temporal modes are not considered in the article, but they can also be useful in the processing of measurement information. Determining the distance threshold between two sets of singular values requires separate studies for each technical object. The effectiveness of recognizing abnormal operating conditions of a technical object can be increased with the complex application of other known methods.

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Метод виявлення аномальних змін у функціонуванні технічного об'єкту з використанням декомпозиції сингулярних значень матриці експериментальних даних

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Анотація

Поведінка динамічної системи характеризується великим набором експериментальних даних, який для нормальних умов її функціонування є добре вивченим. При несправності системи або аномальних умовах функціонування характер цих даних змінюється. Існує багато статистичних методів, які дозволяють виявити ці зміни. Особливістю статті є виявлення істотних змін в результатах вимірювання майже без використання статистичних методів. Для цього використовується матриця експериментальних даних і з допомогою методу декомпозиції сингулярних значень здійснюється аналіз сингулярних мод цієї матриці. При істотній зміні характеру даних відбувається змінювання сингулярних значень. Для прийняття рішення щодо переходу системи в аномальний режим оцінюється відстань у евклідовому просторі між множиною сингулярних значень для нормальних умов функціонування системи і множиною таких значень для можливих аномальних умов. Якщо ця відстань буде перевищувати наперед встановлений поріг, то приймається рішення щодо переходу системи в аномальний режим. Визначення порогу може здійснюватися статистичними методами.

Ключові слова: вимірювальна інформаційна система, декомпозиція сингулярних значень, матриця експериментальних даних, аномальні змінювання параметрів, відстань між множинами сингулярних значень