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CONSTRUCTION OF THE NONLINEAR DYNAMIC OBJECTS DIAGNOSTIC MODEL BASED ON OF MULTIPLE FACTORS VARIANCE ANALYSIS

Abstract. *In this work, the problem of diagnostic models constructing under conditions of description dimension increase in the modern diagnostic objects solves. As a diagnostic objects considers the nonlinear dynamics objects with continuous characteristics and an unknown structure, which can be considered as a "black box". The purpose of the work is to increase the reliability of the diagnosis of nonlinear dynamic objects by forming diagnostic models under conditions of the objects description dimensionality increasing. A review of methods for reducing the dimensionality of the diagnostic features space is given. A method for the construction of diagnostic models of nonlinear dynamic objects with weak nonlinearity on the basis of univariate and multivariate analysis of variance as a filtering stage of signs is proposed. A step-by-step algorithm for the construction of diagnostic models using the proposed method is presented. On the example of the task of technical diagnosis a jet engine, diagnostic models are constructed on the basis of univariate and multivariate analysis of variance of continuous models. A family of diagnostic models of a jet engine is proposed.*

Keywords: *nonlinear dynamic objects; diagnostic models; model reduction; correlation analysis*

Introduction

Until 2010, typical practical data processing tasks were limited by dimensions of several dozen features, usually not more than 40 [1]. The situation changed significantly over the past decade. The global volume of data is more than doubled every two years [2]. At the same time, large volumes of data and significant successes in the field of DataScience and BigData [3-4] provide new opportunities for solving applied diagnostic problems with the features vector dimension of the diagnostic object (DO) of hundreds or even thousands of units [1].

These processes determine the active development of tools and methods of technical diagnostics (TD). Moreover, of great interest are the tasks of indirect monitoring and diagnostics of complex objects of the surrounding world. Ehe basis of such DO are nonlinear dynamic objects with continuous characteristics and an unknown structure, which can be considered as a "black box".

In conditions of rapid growth of the task dimension, the initial diagnostic data (primary diagnostic information) is accompanied by the presence of many redundant variables and a small number of training examples. This factors negatively affect the reliability of diagnosis and the speed of training automated systems of technical diagnostic (ASTD). Therefore, there is a need to review the effectiveness of traditional methods for the formation of diagnostic models of DO.

Due to the large dimension and the volume of accumulated primary diagnostic information, high reliability of diagnosis is ensured, but this leads to increasing computational complexity and decreasing the efficiency of training ASTD.

The solution of this contradiction is a promising and urgent scientific and technical task that can be solved by construction of the diagnostic models of significantly lower dimensions (reduction of primary diagnostic models) [1; 3-8], which provide high reliability of diagnosis, reducing the requirements for measurements and their storage, reducing ASTD training time and the diagnostic process, improving the overall performance of the machine learning algorithm.

The purpose of the work is to increase the reliability of diagnosing nonlinear dynamic objects by construction diagnostic models based on correlation methods for selecting valuable features.

To achieve the goal, the following tasks sets:

– to review methods for reducing the dimension of the DO diagnostic features space with continuous characteristics, to identify promising methods;

– to develop a method for the construction of nonlinear dynamic objects diagnostic models with

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weak nonlinearity on the basis of univariate and multivariate analysis of variance at the stage of features filtering;

– evaluate the effectiveness of the developed method on the example of jet engine technical diagnosis.

Literature review

Traditional approaches to the construction of diagnostic models can be divided into three categories [1; 3; 6]: filtering, wrapping and embedding features.

The construction of diagnostic models based on the features filtering consists in ranking the features on the basis of certain evaluation criteria [1; 6; 7; 9-10]. These methods give fast and effective results. It is important when processing large volumes of data. In addition, the construction of diagnostic models does not depend on the selected algorithm for ASTD training and is performed before its implementation.

Features wrapping methods provide the construction of diagnostic models using the ASTD learning algorithm to evaluate features used in the diagnosis process [1; 6; 9; 11]. The main advantage of the approach is that it allows to take into account the dependencies between the features and to construct the most valuable combination of features for the ASTD learning algorithm. The disadvantage of this approach is the high computational complexity, which increases with an increase with increasing of the DO features number [3; 6; 9].

The embedding of features consists in the selection of valuable combinations of diagnostic features simultaneously with the learning process [1; 3; 6]. The computational complexity of embedding methods is less than in wrapper methods, but more than at filtering methods. The main limitation of embedding methods is that the choice of a diagnostic model depends on the hypothesis that the classifier makes and is unsuitable for other classifiers.

Modern information recording subsystems included in ASTD are capable to make hundreds or even thousands of measurements of DO responses per second. This ensures the completeness of primary diagnostic data. Moreover, the measurement results are contain a lot of redundant data.

For fast processing of large volumes of data, it is advisable to use the methods of primary diagnostic features filtering.

Research materials

An effective method for describing the DO nonlinear and dynamic properties in the form of a features vector **x** is to parameterize continuous nonlinear and dynamic OD models $f(t)$. Moreover, the function $f(t)$ is represented by the vector of diagnostic features $\mathbf{x}=(x_1,\ldots, x_n)$. Diagnostic features can be obtained using the preliminary transformation T_j: $C[a, b] \rightarrow R^n$, $(j = 1,\ldots, n)$: $x_j = T_j(f(\tau_1,\ldots, \tau_k))$; where $C[a, b]$ – is the space of real continuous functions $f(t)$ defined on the interval $[a, b]$; a, b – are some real numbers. Orthogonal decompositions and integral transformations of continuous models into vectors of basis functions coefficients can be used as the operator T_j.

In practice, it is customary to use the discretization operator as T_j:

$$x_j = f(t_j), \tag{1}$$

where $t_j = j\Delta t$, Δt — discretization step.

When considering continuous DO models, the obvious fact is the value of different sections of the object responses for the diagnostic procedure (diagnostic value) is different. In [8, 12, 13] shown that, as a rule, the most valuable sections of DO responses are those that carry the highest signal energy. Given the above, the use of a signal discretization operator for consrruction a diagnostic features space is a poorly efficient technique.

In this case, it is advisable, on the basis of the set of primary signs, to form the most valuable subset of the features for the diagnostic process (to filter out features that don’t carry enough information). At this stage, the number of considered features is reduced to several dozens. At the second stage, the choice of the diagnostic features subset delivering maximum reliability performed by the wrapper method – a local search for a subset of features. This approach is highly scalable for data sets consisting of a large number of features.

Features filtering stage use statistical methods to evaluate the relationship between each input variable and the target variable. These estimates are used as the basis for selecting (filtering) those input variables that will be used in the diagnostic model.

When working with continuous DO features, correlation methods for evaluating the diagnostic value of signal samples [1; 12; 14-15], which relate to filtering methods and have all their advantages, can be especially effective.

There are several types of correlation methods for assessing the diagnostic value of features depending on the type of data both input and output variables: numerical or categorical.

The type of output variable usually indicates the type of predictive modeling task. For example, a numerical output variable indicates a problem of predictive modeling with regression, and a categorical output variable indicates a problem of predictive modeling of classification.

In the diagnostic tasks, two options are considered: numerical input and categorical input. A comparison of both cases is given in Table. 1.

Table 1. Comparison of diagnostic tasks with numerical and categorical inputs

Task	Solution method
Classification with numerical input and categorical output	Analysis of variance (ANOVA)
	Kendall Rank Ratio
Classification with categorical input and categorical output	χ^2 criterion (contingency tables)

In the case of classification with numerical input variables and categorical output variables, the criterion determined by the ANOVA method [1] is used in practice to evaluate the diagnostic value of the features. This method has a small computational complexity and allows to take into account the dependencies between the features and construct the most valuable combination of features for the ASTD learning algorithm.

Univariate analysis of variance uses for two or more independent groups, when all groups are combined on one basis. To assess the ratio of intergroup and intragroup variability, the Fisher *F*-test is used:

$$I = \frac{\sum_{i=1}^{n_j}(x_{i,j} - M^2)/J - 1}{\sum_{i=1}^{n_j}(x_{i,j} - M_j^2)/N - J}, \tag{2}$$

where: M – mathematical expectation of the sign; N – the size of the full sample; J – the number of classes.

If the value of criterion (2) exceeds the critical value, then the corresponding feature is not considered as a component of the feature vector **x**.

However, methods for assessing the diagnostic value of individual features have a significant drawback: features that have low diagnostic value separately (useless for diagnosis) in combination with other features can not only become useful, but also provide an error-free classification [8].

To overcome this drawback, it is necessary to evaluate the diagnostic value of the combination of features. This procedure allows you to perform multivariate analysis of variance.

Multivariate analysis of variance allows to check the influence of several features on the dependent variable. Unlike the one-feature model, where there is one intergroup sum of squares, the multivariate analysis model includes the sum of squares for each factor separately and the sum of squares of all interactions between them. In the course of the analysis, several hypotheses of the influence of each trait are checked using the Fisher criterion (2).

So, at the first stage, on the basis of analysis of variance constructs a subset of features, which provide the greatest value for the diagnostic process. At the second stage, a selection of the features subset, providing the best reliability of diagnostics, performed by the wrapper method – a local search for a features subset. The reliability of diagnosis is assessed using the ASTD learning algorithm, used in the diagnosis process [16-18].

In this paper, a quantitative determination of the reliability of features is made on the basis of solving the task of examination sample objects classification by the maximum likelihood method. The reliability indicator of various combinations of features is the probability of correct recognition of P [19]:

$$P = \sum_{i=1}^{m} L_i \cdot \left(\sum_{i=1}^{m} N_i\right)^{-1}, \tag{3}$$

where: L_i – the number of objects of the i-th class mistakenly assigned to another class k ($k \neq i$); N_i – the number of elements of the i-th class in the examination sample; i=1, 2, …, m; m – the number of DO state classes.

Building a diagnostic model of a jet engine

During long-term operation, the rotor of a valve-jet engine (VJE) have a friction in the air and over time, the air gap δ between the rotor and the stator in the engine increases. The energy performance of VJE decreases. Therefore, during the operation of the VJE, it is necessary to periodically monitor the value of δ [10; 20]. Direct measurements of δ are unacceptable, because they are laborious and require to remove the VJE from the operation mode for the control.

The task of diagnosing the VJE is to build a diagnostic model of the electric drive according to indirect measurements of the air gap δ between the motor rotor and stator.

To estimate the air gap δ between the rotor and stator of the VJE in [20] it is proposed to use the data of side measurements “input-output”. Based on this measurements it can be constructed the model in the form of multidimensional weight functions $w_k(\tau_1, \ldots, \tau_k)$.

Analytical expressions for multidimensional weight functions of the first $w_1(t)$ order and diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$ [20]:

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$$w_1(t)=e^{-\alpha t}, \quad w_2(t,t)=\frac{\beta}{\alpha}\left(e^{-2\alpha t}-e^{-\alpha t}\right). \tag{4}$$

A training sample in the form of multidimensional first-order weight functions $w_1(t)$ (Fig. 1a) and diagonal sections of multidimensional second-order weight functions $w_2(t,t)$ (Fig. 1b) for various values of the air gap δ obtained for some VJE states and divided into 3 classes of 100 elements in each class: for $\delta \epsilon [\delta_n, 1.3\delta_n]$ (normal mode – class A), $\delta \epsilon (1.3\delta_n, 1.6\delta_n]$ (fault mode – class B), $\delta > \delta_n$ (emergency mode – class C), δ_n = 0.15 mm – nominal value of the air gap δ.

The diagnostic model of DO constructed using k samples of the obtained models – is the vector $\mathbf{x}=(x_i)$, $i=pl/k$, l – the number of samples of the model, $p=0,\dots,k-1$. For the task of diagnosing VJE, the number of samples of multidimensional weight functions and their sections l=81. For k=5, the diagnostic model of the VJE constructed using the samples of the obtained functions $\mathbf{x}^1=(x_1, x_{21}, x_{41}, x_{61}, x_{81})$. The resulting solution is compared with the reduced space obtained using one-way analysis of variance (2).

In Fig. 2 it shows the calculation of the diagnostic value I of the primary features of DO – samples of multidimensional weight functions of the first order $w_1(t)$ (Fig. 2, left) and diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$ (Fig. 2, right) using criterion (2).

The Fig. 2 shows that the number of informative samples decreases to the interval $[x_3, x_{30}]$. VJE diagnostic model constructed using the criterion (2) is $\mathbf{x}^2=(x_3, x_9, x_{15}, x_{21}, x_{27})$.

In order to compare the diagnostic models $\mathbf{x}^1$ and $\mathbf{x}^2$, the reliability of the diagnosis evaluates by the selected sets of features based on the results of solving the classification problem of the examination sample objects using the decision rule constructed by the maximum likelihood method.

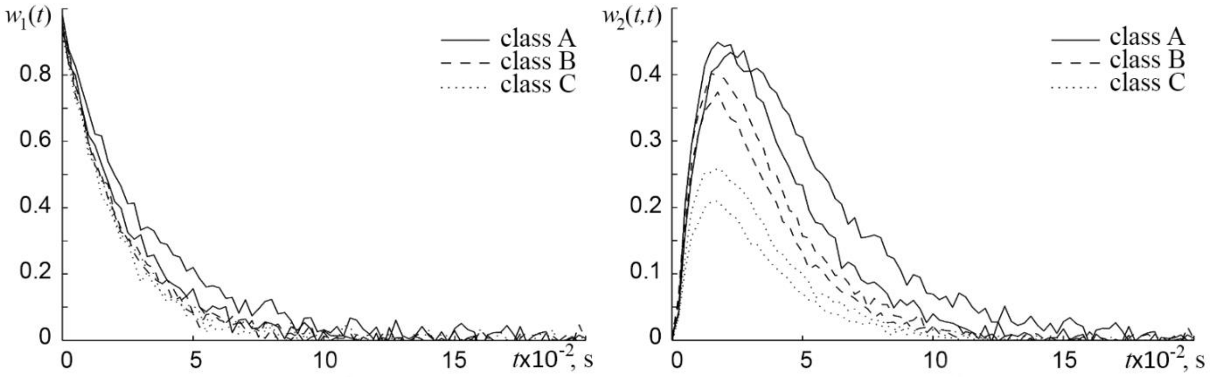

Fig. 1. On the left are multidimensional weight functions of the first order $w_1(t)$;
on the right are the diagonal sections of the multidimensional weight functions of the second order $w_2(t,t)$ for various values of the air gap δ

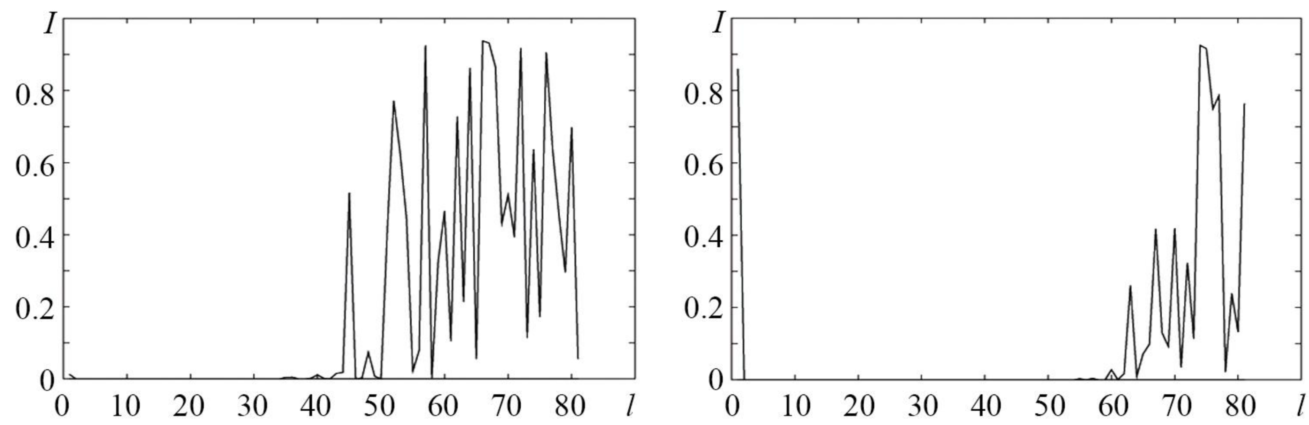

Fig. 2. The diagnostic value of responses according to criterion (2):
on the left, for the multidimensional weight functions of the first order $w_1(t)$;
on the right, diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$

In Fig. 3 it presents the calculation of the reliability of diagnosis P for each sample of multidimensional first-order weight functions $w_1(t)$ (Fig. 3, left) and diagonal sections of multidimensional second-order weight functions $w_2(t,t)$ (Fig. 3, right) using the criterion (3).

Fig. 3 shows that the components of the $\mathbf{x}^2$ feature space have greater diagnostic value than the components of the $\mathbf{x}^1$ space.

To assess the diagnostic value of the features in combination with other features, a research performed using multivariate analysis of variance. In Fig. 4 it shows the calculation of the diagnostic value of I pairwise combinations of the primary features of DO – samples of multidimensional first-order weight functions $w_1(t)$ (Fig. 4, left) and diagonal sections of multidimensional second-order weight functions $w_2(t,t)$ (Fig. 4, right).

Here, the most valuable combinations of diagnostic features correspond to the minimum values of the criterion (2). In Fig. 5 presents in the form of contour images the most valuable region for diagnosing in the space of two DO features – samples of multidimensional first-order weight functions $w_1(t)$ (Fig. 5, left) and diagonal sections of multidimensional second-order weight functions $w_2(t,t)$ (Fig. 5, on the right). Here, the bright areas correspond to the most valuable combinations of the considered features.

In order to compare the diagnostic models $\mathbf{x}^1$ and $\mathbf{x}^2$, the reliability of diagnosing on pairwise combinations of features estimates by the results of solving the classification problem of objects of the examination sample using the decision rule constructed by the maximum likelihood method.

In Fig. 6 it presents the calculation of the reliability P for pairwise combinations of features – samples of multidimensional first-order weight functions $w_1(t)$ (Fig. 6, left) and diagonal sections of multidimensional second-order weight functions $w_2(t,t)$ (Fig. 6, right) using criterion (3).

The Fig. 4, Fig. 5 and Fig. 6 show that combinations of diagnostic features obtained by multivariate discriminant analysis close to combinations of features selected on the base of the solving the classification task on the examination sample using the decision rule constructed by the maximum likelihood method. Moreover, the computational complexity of the result obtaining by multivariate discriminant analysis with a pairwise combination of features is less in 6-8 times according to the results of solving the classification problem.

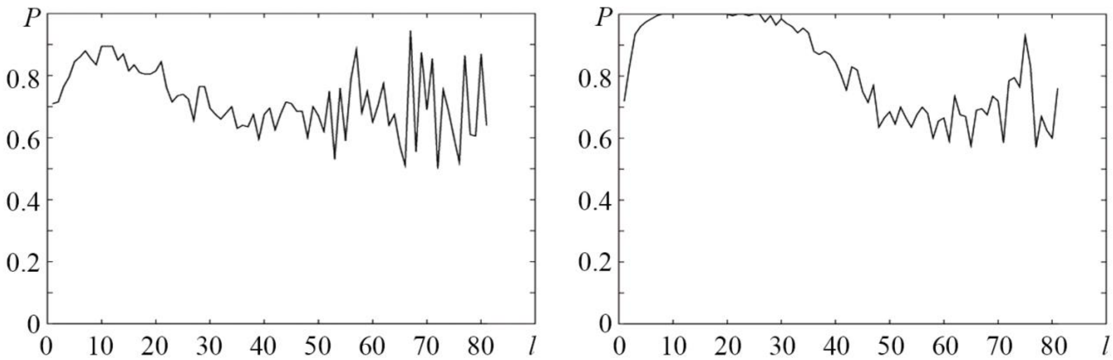

Fig. 3. Reliability P of samples:
on the left – multidimensional weight functions of the first order $w_1(t)$;
on the right – diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$

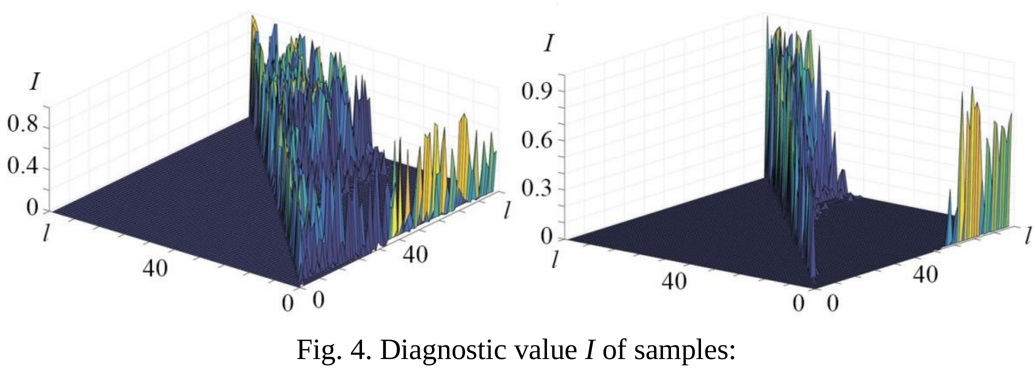

Fig. 4. Diagnostic value I of samples:
on the left, multidimensional weight functions of the first order $w_1(t)$;
on the right – diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$

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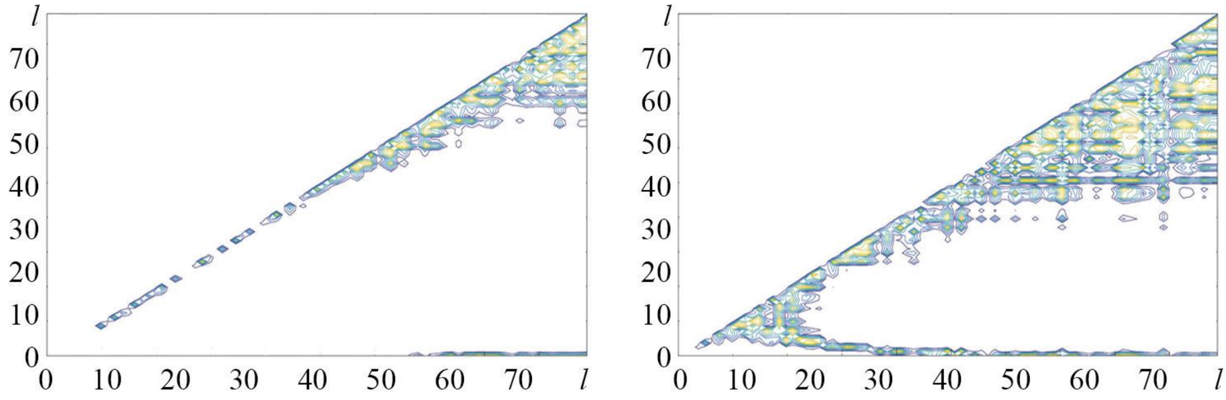

Fig. 5. Contour presentation of the diagnostic value *I* of samples:
on the left, multidimensional weight functions of the first order $w_1(t)$;
on the right – diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$

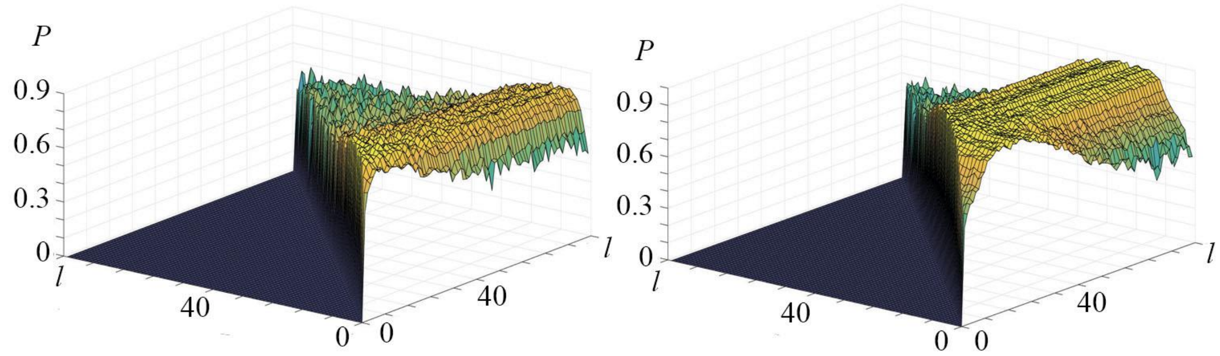

Fig. 6. Reliability *P* of samples pairwise combinations:
on the left – multidimensional weight functions of the first order $w_1(t)$;
on the right – diagonal sections of multidimensional weight functions of the second order $w_2(t,t)$

Conclusions

The work successfully solved the problem of increasing the reliability of diagnosing nonlinear dynamic objects by construction diagnostic models based on correlation methods for selecting valuable features.

It shown that the filtering methods are computationally more efficient than wrapping and embedding methods.

It developed the method for the diagnosis of nonlinear dynamic objects with weak nonlinearity. It consist in using univariate and multivariate analysis of variance to evaluate the diagnostic value of primary features as a first stage of filtering signs with subsequent enumeration of combinations of features that ensure the maximum reliability of diagnosisas a second stage.

The proposed method tested on the diagnosing data of the nonlinear dynamic object – a valve-jet engine. The method demonstrates a reduction in computational complexity by a factor of 6–8 when constructing a diagnostic model compared to a method based on samples with a uniform step while saving a given diagnostic reliability.

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ПОБУДОВА ДІАГНОСТИЧНИХ МОДЕЛЕЙ НЕЛІНІЙНИХ ДИНАМІЧНИХ ОБ'ЄКТІВ НА ОСНОВІ БАГАТОФАКТОРНОГО ДИСПЕРСІЙНОГО АНАЛІЗУ

Анотація. *В роботі вирішується задача побудови діагностичних моделей для об'єктів нелінійної динаміки в умовах збільшення розмірності їх опису. Метою роботи є підвищення достовірності діагностування нелінійних динамічних об'єктів шляхом формування діагностичних моделей в умовах збільшення розмірності опису об'єктів діагностування. Наведено огляд методів зниження розмірності простору діагностичних ознак, в тому числі, для нелінійних динамічних об'єктів з безперервними характеристиками і невідомої структурою, які можна розглядати як «чорний ящик». Запропоновано метод формування діагностичних моделей нелінійних динамічних об'єктів зі слабкою нелінійністю на основі однофакторного і багатофакторного дисперсійного аналізу в якості етапу фільтрації ознак з подальшим перебором сполучень ознак, що забезпечують максимальну достовірність діагностування. Наведено покроковий алгоритм формування діагностичних моделей за допомогою запропонованого методу. На прикладі задачі технічного діагностування вентильно-реактивного двигуна побудовано діагностичні моделі на основі однофакторного і багатофакторного дисперсійного аналізу безперервних моделей. Запропоновано сімейство діагностичних моделей вентильно-реактивного двигуна.*

Ключові слова: *нелінійні динамічні об'єкти; діагностичні моделі; редукція моделей; кореляційний аналіз*

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ПОСТРОЕНИЕ ДИАГНОСТИЧЕСКИХ МОДЕЛЕЙ НЕЛИНЕЙНЫХ ДИНАМИЧЕСКИХ ОБЪЕКТОВ НА ОСНОВЕ МНОГОФАКТОРНОГО ДИСПЕРСИОННОГО АНАЛИЗА

Аннотация. *В работе решается задача построения диагностических моделей для объектов нелинейной динамики в условиях увеличения размерности описания современных объектов диагностирования. Целью работы является повышение достоверности диагностирования нелинейных динамических объектов путем формирования диагностических моделей в условиях увеличения размерности описания объектов диагностирования. Приведены обзор методов снижения размерности* *пространства диагностических признаков, в том числе, для нелинейных динамических объектов с непрерывными характеристиками и неизвестной структурой, которые можно рассматривать как «черный ящик». Предложен метод формирования диагностических моделей нелинейных динамических объектов со слабой нелинейностью на основе однофакторного и многофакторного дисперсионного анализа в качестве этапа фильтрации признаков с последующим перебором сочетаний признаков, обеспечивающих максимальную достоверность диагностирования. Приведены пошаговый алгоритм формирования диагностических моделей с помощью предложенного метода. На примере задачи технического диагностирования вентильно-реактивного двигателя построено диагностические модели на основе однофакторного и многофакторного дисперсионного анализа непрерывных моделей. Предложено семейство диагностических моделей вентильно-реактивного двигателя.*

Ключевые слова: *нелинейные динамические объекты, диагностические модели, редукция моделей, корреляционный анализ.*

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