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FORMATION OF DIAGNOSTIC MODELS OF CONTINUOUS OBJECTS BASED ON CORRELATION FILTRATION UNDER CONDITIONS OF INTERFERENCE

O.O. Fomin, O.D. Ruban

Odessa National Polytechnic University,
Shevchenko Ave. 1, Odessa, 65044; Ukraine; fomin@opu.ua

The paper solves the problem of constructing diagnostic models for nonlinear dynamics objects with continuous characteristics. The problems of using existing methods of diagnostics of the mentioned objects, including those under conditions of a priori uncertainty, are considered. Interference is caused by the operation of the object in a wide range of external conditions and the presence of a large number of disturbing influences and interferences of the environment. The aim is to improve the reliability and speed of diagnosis of continuous objects under the influence of interference. The aim is achieved by developing a method of model diagnosis based on correlation methods of filtering features. The most significant results: A hybrid method of forming diagnostic models of continuous objects by sequential application of attribute filtering using correlation methods for constructing a diagnostic space and constructing a diagnostic model by rotating method using a total enumeration of diagnostic attributes and method of maximum likelihood is proposed. The step-by-step algorithm of formation of diagnostic models using the proposed method is given. The significance of the results: the application of the proposed method can simultaneously provide high reliability of diagnosis of objects under the influence of noise through the use of continuous information models and to ensure efficiency of the diagnostic procedure due to correlation filtering of attributes. The proposed method is tested on the example of diagnostics of a nonlinear dynamic object with continuous characteristics - a valve-jet engine. Diagnostic models based on the combination of correlation characteristics are constructed. A family of diagnostic models of a valve-jet motor under conditions of disturbing influences and ambient noise is proposed.

Keywords: continuous objects, diagnostic models, model reduction, correlation filtration.

Introduction

With the increasing complexity of modern control objects and their operating conditions in various branches of industry, medicine, economy, the role of automated technical diagnostics systems (ATDS) in tasks of timely and reliable determination of the technical condition of diagnostic objects (DO) on assessment of product quality, minimization of costs during maintenance, etc., is increasing.

These processes lead to the active development of technical diagnostics (TD) tools and methods. In this case, of great interest are the tasks of indirect control and diagnostics of complex objects of the surrounding world with continuous characteristics and unknown structure, which can be considered as a "black box".

Such objects are often accompanied by a priori uncertainty, among the causes of which are considered operation in a wide range of external conditions, presence of a large number of disturbing influences and environmental interferences.

The use of existing ATDS is limited by the action of contradiction between the reliability of diagnostics and the efficiency of ATDS tuning when using diagnostic models of large dimensions. Due to large dimensionality and volumes of accumulated primary diagnostic information high reliability of diagnostics is provided, but it leads to increase of computational complexity and decrease of ATDS tuning efficiency. A decrease in the dimensionality and volume of primary identification information allows increasing the speed of ATDS tuning, but leads to a decrease in the reliability of diagnosis.

Resolution of this contradiction is a promising and urgent scientific and technical task, which can be solved by building diagnostic models with significantly smaller size of diagnostic information (reduction of information models) and ensuring high reliability of diagnosis.

The purpose of the work is to increase reliability and speed of diagnostics of continuous objects under conditions of a priori uncertainty through the development of model diagnostic method based on correlation filtering methods of informative attributes.

Literature review

By 2010, typical practical diagnostic space selection tasks were limited to dimensions of a few dozen attributes, typically no more than 40 [1]. The situation has changed considerably over the past decade. The global volume of data has more than doubled every two years [2]. At the same time, large amounts of data are opening up new opportunities.

The main reasons for this growth are advances in technology and significant advances in Data Science and Big Data [3–5]. New technologies have reduced the cost of creating, collecting, classifying and managing information in dozens of times.

The concepts of the Digital Universe and big data have become one of the driving forces for fundamental changes in social life, technology, science and economics. Such advances stimulate the development of applications with the DO feature vector dimensionality of hundreds or even thousands of units.

An example of a new challenge in the field of modern industrial technology at Industry-4 level is improving the process of the technological process components diagnosis, in particular the electric motors [3, 6] that drive the actuators.

The dimensionality of such task increases, if we take into account that during the years of work the monitoring and control systems the considerable volumes of technical information are accumulated.

With a sharp increase in the dimensionality of tasks, often data accompanied by many redundant variables and a small number of training examples, there is a need to reconsider the effectiveness of traditional methods of forming diagnostic models of DO.

An effective way to solve such problems is the reduction of the primary feature space, a widely used data preprocessing technique in data mining [1, 7, 8].

There are many potential benefits of this approach: easier data visualization and understanding, reduced measurement and storage requirements, shorter training times for the diagnostic system and the diagnostic process, and improved overall performance of the machine learning algorithm.

Main part

The construction of a continuous DO model consists in selecting the type of test influences $x(t)$, measuring the response $y(t)$ and determining the models $w(t_1, t_2, \ldots, t_n)$ on their basis.

The disadvantage of such a model is considered to be the large volume of primary identification information, which leads to a decrease in ATDS tuning speed.

Reducing the amount of primary identification information by using more compact models allows increasing ATDS tuning speed, but leads to a decrease in the reliability of diagnostics.

Thus, there is a contradiction between the reliability of TD and the tuning speed of ATDS when using continuous DO model.

This contradiction can be resolved by developing a new method of secondary identification – construction of diagnostic feature space x with significantly smaller diagnostic information size.

Traditional approaches of feature selection for machine learning can be divided into three categories [1, 7, 9]: feature filtering [1, 7, 10] wrapper methods [1, 9, 11, 12] and feature embedding [1, 7].

When solving practical problems, the application of any method often leads to the desired results. This is primarily due to the a priori ambiguity of the DO. The reasons for priori ambiguity are the complexity of the object (continuous dynamic objects of various physical natures, including those with unambiguous continuous nonlinear characteristics) and insufficient study of the processes occurring in it, as well as the presence of a large number of disturbing influences and environmental interferences are considered.

Currently, many authors are also using hybrid methods consisting of a combination of these approaches, the results of which are also promising. Recently, this is one of the widely used approaches used to form diagnostic models. A hybrid approach combines several methods to take advantage of each to produce satisfactory results. This approach usually provides high diagnostic reliability with low computational complexity.

A hybrid approach to feature selection based on the sequential application of filtering and wrapping methods is a good practice. The first stage involves selecting the most valuable subset of features by filtering – a global feature search. At this stage, the number of considered features is up to several dozen. At the second stage, the optimum (in terms of reliability of diagnosis) subset of features is selected by the wrapping method – local search for the features. The proposed hybrid approach is very scalable for datasets consisting of a large number of features.

Creating a diagnostic feature space based on filtering methods. This paper proposes a hybrid method for constructing diagnostic models based on correlation filtering of features.

A simple method of describing the continuous properties of a DO in the form of a vector of features x is the parameterisation of continuous models of the DO $f(t)$. In this case, the function $f(t)$ is represented by vector $x = (x_1, \ldots, x_n)$. The diagnostic features can be obtained by a prior transformation T_j: $C[a, b] \to R^n$, $(j = 1, \ldots, n)$: $x_j = T_j(f(\tau_1, \ldots, \tau_k))$; where $C[a, b]$ is the space of real continuous functions $f(t)$ given on the interval $[a, b]$; a, b– are some real numbers. Orthogonal decompositions and integral transformations of continuous models into vectors of coefficients of basis functions can be used as operator T_j.

In practice it is accepted to use the discretisation operator as T_j:

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

$t_j = j\Delta t$, where Δt – is a sampling step.

Modern data logging subsystems within ATDS are capable of taking thousands of measurements per second. This ensures completeness of the primary diagnostic data. At the same time, the measurement results are accompanied by a lot of redundant data. Moreover, it is evident that the value of different sections of measured DO output for the diagnostic procedure is different.

It has been shown in [10, 13, 14] that the most valuable parts of the DO responses are usually the parts that carry the highest signal energy. Given the above, the use of signal sampling to form the diagnostic feature space is a poorly effective technique.

When dealing with continuous characteristics of the DO to form the space of diagnostic features, correlation methods of filtering the models samples can be particularly effective [14, 15].The formation of diagnostic models based on feature filtering consists in ranking these features using statistical methods to evaluate the relationship between each input variable and the target variable [10, 14, 16]. These methods provide fast and efficient results especially when processing large amounts of data.

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

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

When dealing with continuous characteristics of the DO to form the space of diagnostic features, correlation methods of filtering the samples of information models can be particularly effective [14, 15, 17].

The case of numerical input and categorical output is considered in the task of diagnosing continuous DO. In this case, Fisher's F-criterion is used to estimate the relationship between inter- and intra-group variability:

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

where M is the mathematical expectation of the signs, L is the full sample size, P is the number of classes.
For comparison, the results of this method are compared with the results of the method for calculating the diagnostic value I of the primary signs of OD, determined by the information method [10] according to the expression:

$$H(x) = -\sum_{i=1}^{n} p_i \log_2 p_i \, , \tag{3}$$

The evaluation of the reliability of diagnosis in the work is based on solving the problem of classification of examination sample by the method of maximum likelihood. The reliability of various combinations of features is indicated by the probability of correct recognition P [17]:

$$P = \sum_{i=1}^{m} L_i \left(\sum_{i=1}^{m} N_i\right)^{-1} , \tag{4}$$

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

The maximum likelihood method allows constructing the best solution when the distribution of features in the training sample is normal. To improve the quality of classification in the case of non-normal distribution of a random variable, it is proposed to perform transformations aimed at removing the relationship between the variance and the mathematical expectation. Thus, the variance becomes constant with respect to the mean. Such stabilization is proposed to be carried out by applying power transformations, in particular by logarithm the values of a random variable:

$$x_j^0 = \log_a(x_j + b) , \tag{5}$$

where a–base of the logarithm's –stabilizing coefficient.

This paper proposes a method for constructing a diagnostic features space based on continuous information models, followed by their discretisation and filtering of features using an assessment of their correlation.

Hybrid method for constructing the diagnostic feature space of continuous objects. The proposed method of constructing the diagnostic feature space based on continuous models of nonlinear dynamic DO is reduced to the identification of the information model of the object in the form of multidimensional weight functions (MWF) by the "input-output" experimental data [18, 19]. The space of attributes is built on the basis of discrete samples of the obtained continuous models. Diagnostic models are built in the obtained space by filtering of attributes based on assessment of their correlation.

The stages of the method of the diagnostic features space constructing based on integral dynamic models are shown in Table 1. The development of this method consists in adding step 3 (power transformations of training sample data for distribution of features in classes different from normal for stabilization of variance of random variables) and steps 4 and 5 to the well-known procedure of model-based diagnostics for preliminary features evaluation.

Creating a diagnostic model of a valve-jet engine

Table 1.

Stages of the method of the diagnostic feature space constructing based on integral dynamic models

Stage		Description
No	Title	
1.	DO identification	*Purpose*: DO model generation. *Input*: test input signal $x(t)$ *Model*: continuous function (functional series) *Output*: DO continuous model
2.	Continuous model sampling	*Purpose*: discrete DO model generation *Input*: DO continuous model $w(t_1, t_2, \ldots, t_n)$ *Model*: sampling operator (1) *Output*: features vector $\mathbf{x}$
3.	Stabilization of model sampling variance	*Purpose*: stabilization of variance of vector $\mathbf{x}$ *Input*: features vector $\mathbf{x}$ *Model*: power transformations, logarithmic transformations *Output*: features vector $\mathbf{x}^0$
4.	Features evaluation	*Purpose*: get the value of each feature in vector $\mathbf{x}^0$ *Input*: features vector$\mathbf{x}^0$ *Model*: Fisher's F-criterion (2) *Output*: features vector$\mathbf{x}^1$, ranked by value I
5.	Features filtering	*Purpose*: get a space of diagnostic features *Input*: vector of ranked features $\mathbf{x}^1$ *Model*: $\mathbf{x}^2 = (x_1, \ldots, x_p)' \in \mathbf{x}$, $p<n$ *Output*: diagnostic features vector $\mathbf{x}^2 = \left(x_1, \ldots, x_p\right)'$ with maximum values I
6.	Evaluation of the noise immunity of the diagnostic model	*Purpose*: get an interference-free diagnostic feature space *Input*: diagnostic features vector $\mathbf{x}^2 = \left(x_1, \ldots, x_p\right)'$ with maximum values I *Model*: probability of correct recognition P(4) *Output*: value of probability of correctly recognizing P

Approbation of diagnostic futures space building method of continuous models is made on an example of valve-jet engine – object with non-linear dynamic characteristics.

In the process of long-term operation the rotor of valve-jet engine has friction in the air and with the time the air gap δbetween rotor and stator in engine increases (fig.1), and consequently, its power performances decrease. Therefore, it is necessary to periodically monitor the value δ [20] during the operation of the engine. Direct measurements are unacceptable, as they are lab our-intensive and require the removal of the engine from operation to be monitored.

The task of valve-jet engine diagnosis is to build a diagnostic model of the drive using indirect measurements of the air gap between the rotor and stator of the engine.

The task of valve-jet engine diagnosis is complicated by the following significant factors:

– the motor is a dynamic object with non-linear characteristics;

– the motor works under conditions of a priori uncertainty: in a wide range of external conditions, in the presence of a large number of disturbing influences and environmental noise;

– under operating conditions it is necessary to provide reliable and efficient diagnostics of the motor condition.

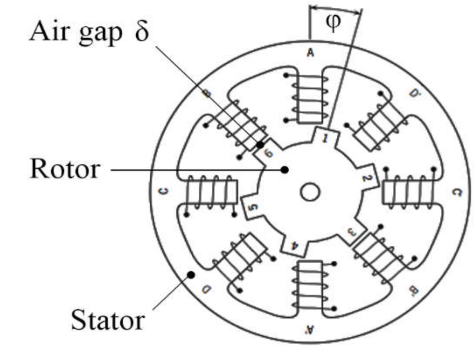

Fig.1. Air gap δ between the rotor and stator of the valve-jet engine.

For evaluation of air gap between rotor and stator of valve-jet engine in [20] it is suggested to use data of side measurements "input-output" on the basis of which the model in the form of multidimensional weight functions $w_k(\tau_1,\ldots,\tau_k)$ is constructed. The structural scheme of the input-output experiment organization in the valve-jet engine diagnostics task is shown in Fig. 2. The input signal $x(t)$ (input voltage U_φ) is set by the diagnostic signal generator DSG, the output signal $y(t)$ (phase current I_φ, by which the air gap δbetween the rotor and the stator is estimated) is measured by the recording device RD.

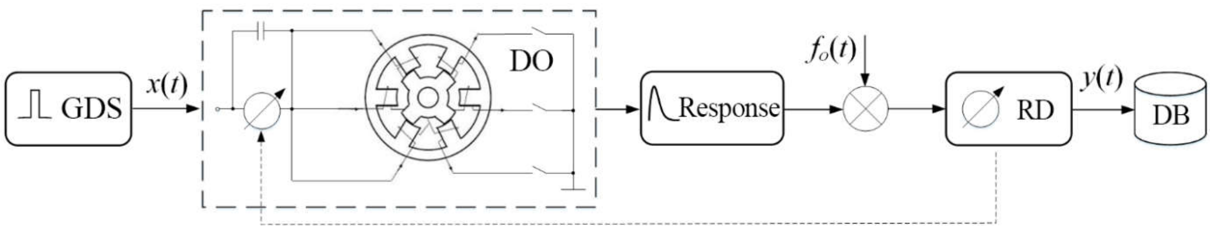

Fig. 2. Flowchart of side-measurement organisation in the valve-jet engine diagnostic task.

The valve-jet engine identification in the form of MWF is carried out using the simulation model of the VREP-57-005 engine (nominal torque – 0.04 Nm, nominal voltage – 24 V, maximum speed – 4000 rpm).

Analytical expressions for MWF of the first $w_1(t)$ order and diagonal relations of MWF of the second order $w_2(t,t)$:

$$w_1(t)=e^{-\alpha t},w_2(t,t)=\frac{\beta}{\alpha}\left(e^{-2\alpha t}-e^{-2\alpha t}\right) \tag{6}$$

The training sample in the form of first-order MWF $w_1(t)$ (Fig. 3, a) and diagonal sections of second-order MWF$w_2(t,t)$ (Fig. 3, b) at various values of air gap δ are obtained for various states of valve-jet engine and divided into 3 classes on 100 elements in each class: for

δ_ε [δ_n, 1.3δ_n] (normal mode – class *A*), δ_ε (1.3δ_n, 1.6δ_n) (failure mode – class *B*), $\delta>\delta_n$ (emergency mode – class *C*), δ_n–nominal value of air gap δ.

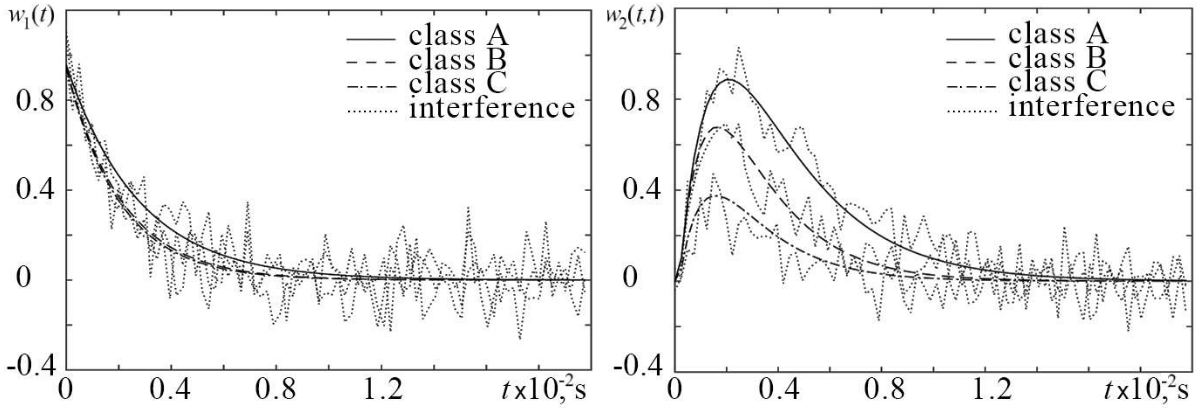

Fig. 3. On the left are first-order MWF $w_1(t)$; on the right are diagonal sections of second-order MWF $w_2(t,t)$ at different values of the air gap δ (classes *A*, *B*, *C*).

Information model sampling.

The MWF samples and their sections obtained with step Δt= 2.5 ms were used for experimental investigations.

The space of diagnostic features $\mathbf{x}=(x_1,\ldots,x_l)'$ in the form of samples of MWF diagonal sections $w_k(t-\tau_1,\ldots,t-\tau_k)$ of order k = 1, 2 with dimension l = 81 samples was formed.

Evaluation of the features.

Calculation of the primary DO model diagnostic value *I*: WMF samples $w_1(t)$ (Fig. 4, a) and WMF diagonal sections of the second order $w_2(t,t)$ (Fig. 4, b) is carried out using criterion (2).

As a result, the resulting vectors of features $\mathbf{x}^1=(x_1,\ldots,x_1)'$, ranked by value *I*.

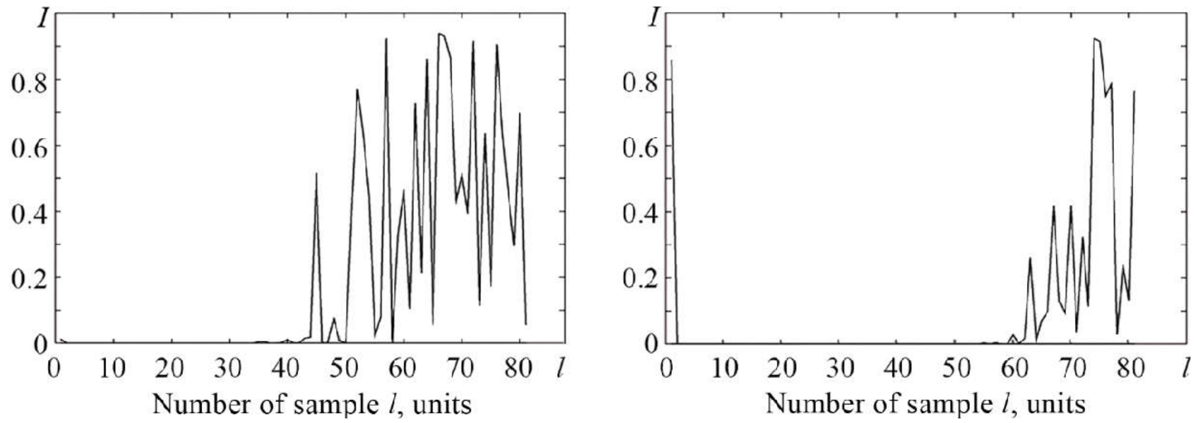

Fig. 4. Diagnostic value *I* of samples according to criterion (3): on the left –the first-order MWF $w_1(t)$; on the right– the second-order WMF diagonal section $w_2(t,t)$.

Feature filtering.

From the elements of the diagnostic features vector $\mathbf{x}^1$ a subspace $\mathbf{x}^2=(x_1,\ldots,x_p)'$ is formed by filtering the features with the maximum value index *I*. The dimension *p* of the space $\mathbf{x}^2$ is chosen so as to ensure a given reliability of diagnosis. In this paper, the reliability is estimated by solving the problem of classifying the objects of the examination sample by the maximum likelihood method [10].

To form a reduced space of diagnostic features, 2 methods are compared: by means of model samples according to expression (1) and by means of correlation coefficients.

The calculation of diagnostic value I of DO features –samples of MWF of the first order $w_1(t)$ (Fig. 5, a) and diagonal samples of MWF of the second order $w_2(t,t)$ (Fig. 5, b) are presented in Fig. 5.

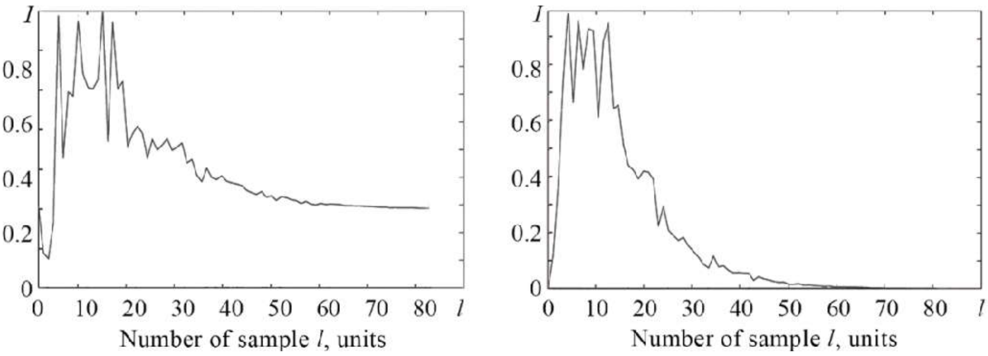

Fig. 5. Correlation coefficient of samples (ANOVA method): on the left –MWF of the first order $w_1(t)$; on the right – diagonal sections of MWF of the second order $w_2(t,t)$

In this task, at p = 5, the diagnostic model of valve-jet engine, constructed using the correlation filtering of features $\mathbf{x}^1$, provides a given level of diagnostic reliability P = 0.99.

For comparison, the value of each feature I of space $\mathbf{x}$ was determined by estimating the diagnostic reliability P for each count of the first-order MWF (Fig. 5, a) and the diagonal links of the second-order MWF (Fig. 5, b).

The comparison of the values of the corresponding MWF models samples (Fig. 4-5) shows that the diagnostic attributes obtained by filtering based on correlation significantly coincide with the attributes selected by the classification of the examination sample objects using the maximum likelihood decisive rule. The computational complexity of obtaining the result by filtering based on correlation is 6-8 times less than that based on classification results.

Research of the valve-jet engine diagnostic model under conditions of interference.

The reliability index P (probability of correct recognition) of forming diagnostic features spaces is studied: samples $x_k=f(t_k)$, $t_k=k\Delta t$, k=1, 10of the first order MWF $w_1(t)$ (diagnostic space $\mathbf{Y}_1$) and diagonal sections of the second order MWF $w_2(t,t)$ (diagnostic space $\mathbf{Y}_2$). The results of research of diagnostic models reliability P depending on different measurement errors and interferences of the system response: 0, 3, 5 and 10% are presented in Fig. 6.

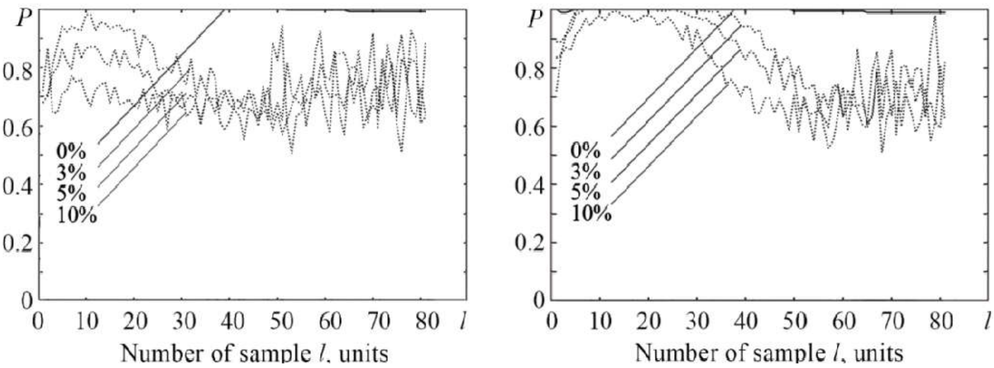

Fig. 6. Reliability P of samples: on the left– first-order MWF $w_1(t)$; on the right– diagonally sections of second-order MWF $w_2(t,t)$.

Conclusions

The paper successfully solved the problem of increasing the reliability and speed of diagnosis of nonlinear dynamic objects by forming diagnostic models while increasing the dimensionality of describing objects of diagnosis and under conditions of interference.

To achieve the goal a review of diagnostic models building methods. It was found that filtering methods are computationally more effective.

Analysis of existing methods and recent trends in building diagnostic models allowed solving the problem of improving the reliability and speed of diagnosis of nonlinear dynamic objects in the primary space features of large dimensionality from a pragmatic point of view – to develop a hybrid method of building of diagnostic models. Under such conditions, application of filtering methods does not provide a given reliability of diagnosis, and it is difficult to apply wrapping methods because of significant growth of computational complexity of the problem (the curse of dimensionality).

The method of building a diagnostic features space of nonlinear dynamic objects based on information models in the form of MWF by applying single-factor and multifactor correlation analysis as a stage of filtering of features with subsequent enumeration of combinations of features provides maximum reliability of diagnosis. The use of this approach can simultaneously provide high reliability of diagnosing objects under a priori uncertainty through the use of primary information models based on MWF and rapid diagnostic procedure due to filtering based on a correlation analysis of the diagnostic space. A stepwise algorithm of the method with the representation of the incoming, outgoing information and the data model used at each step is given.

The proposed method is tested on the real data of the task of diagnosing a nonlinear dynamic object – a valve-jet engine. The method demonstrates greater noise immunity of reliability value than existing methods of constructing diagnostic feature spaces based on the primary diagnostic model.

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ФОРМУВАННЯ ДІАГНОСТИЧНИХ МОДЕЛЕЙ ОБ'ЄКТІВ З НЕПЕРЕРВНИМИ ХАРАКТЕРИСТИКАМИ НА ОСНОВІ КОРЕЛЯЦІЙНОЇ ФІЛЬТРАЦІЇ В УМОВАХ ДІЇ ЗАВАД

О.О. Фомін, О.Д. Рубан

Одеський національний політехнічний університет,
просп. Шевченка, 1, Одеса, 65044; Україна; fomin@opu.ua

В роботі вирішується задача побудови діагностичних моделей для об'єктів нелінійної динаміки з неперервними характеристиками. Розглянуто проблеми використання існуючих методів діагностики означених об'єктів, в тому числі, в умовах апріорної невизначеності. Завади обумовлені експлуатацією об'єкта в широкому діапазоні зовнішніх умов і наявності великої кількості збурюючих впливів і перешкод навколишнього середовища. Метою роботи є підвищення достовірності і швидкодії діагностування неперервних об'єктів в умовах дії завад. Поставлена мета досягається шляхом розвитку методу модельної діагностики на основі кореляційних методів фільтрації ознак. Найбільш вагомі результати: запропоновано гібридний метод формування діагностичних моделей неперервних об'єктів шляхом послідовного застосування фільтрації ознак за допомогою кореляційних методів для побудови діагностичного простору та побудови діагностичної моделі методом обертання з використанням повного перебору діагностичних ознак та методу найбільшої правдоподібності. Наведено покроковий алгоритм формування діагностичних моделей за допомогою запропонованого методу. Значення отриманих результатів: застосування запропонованого методу дозволяє одночасно забезпечити високу достовірність діагностування об'єктів в умовах дії завад завдяки використанню безперервних інформаційних моделей і забезпечити оперативність діагностичної процедури завдяки кореляційній фільтрації ознак. Запропонований метод апробовано на прикладі діагностування нелінійного динамічного об'єкту з неперервними характеристиками – вентильно-реактивного двигуна. Побудовано діагностичні моделі на основі комбінування кореляційних характеристик. Запропоновано сімейство діагностичних моделей вентильно-реактивного двигуна в умовах збурюючих впливів і перешкод навколишнього середовища.

Ключові слова: неперервні об'єкти, діагностичні моделі, редукція моделей, кореляційна фільтрація.