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MODEL-ORIENTED METHOD FOR CONSTRUCTION OF INTELLIGENT INFORMATION SYSTEMS OF DIAGNOSING BASED ON VOLTERRA KERNELS

Abstract. *The method of building an intelligent computing system for diagnostics of nonlinear dynamic objects is offered in this paper. This method is based on integral power Volterra series using as model of objects. The diagnostic features space is built using such models. There are discrete values of first order Volterra kernels and diagonal section of second order Volterra kernels as well as moments of Volterra kernels.*

Estimations of correct recognition probability of objects states base on chosen diagnostic features sets are received using maximum likelihood estimation method.

Second order Volterra kernels sections give more information about diagnostic object than first order Volterra kernels. The possibility and advantages of diagnostic model using for object as a union of first and second order Volterra kernels is shown. These models provide the highest information level about object being diagnosed. The highest informativeness and noise immunity is reached using union of Volterra kernels moments of the first order and Volterra kernels diagonal sections of the second order.

All features set in noiseless conditions usually have several best solutions (features combinations) or several solutions that are in the neighborhood of best solution. The selection of the best features sets should be carried out considering the changes of the diagnostic quality with impact of noise. The numerical experimental results are applied for switched reluctance motor diagnostic model building.

Keywords: *intelligent information systems, faults diagnosis, efficiency of diagnostics, nonlinear dynamic models, Volterra kernels, identification, and reduction of features space dimension*

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МОДЕЛЬНО-ОРИЕНТИРОВАННЫЙ МЕТОД ПОСТРОЕНИЯ ИНТЕЛЛЕКТУАЛЬНЫХ ИНФОРМАЦИОННЫХ СИСТЕМ ДИАГНОСТИРОВАНИЯ НА ОСНОВЕ ЯДЕР ВОЛЬТЕРРА

Аннотация. *Представлен метод построения интеллектуальных информационных систем с целью повышения надежности диагностирования неисправностей нелинейных динамических объектов. Предлагается усовершенствование метода модельной диагностики, основанного на непараметрической идентификации динамических систем и построении диагностических моделей с использованием для параметризации ядер Вольтерра их моментов различных порядков. Эффективность предложенной модели диагностики исследовано на примере вентильно-реактивного двигателя.*

Ключевые слова: *интеллектуальные информационные системы, диагностика неисправностей, эффективность диагностики, нелинейные динамические модели, ядра Вольтерра, идентификация, сокращение размерности пространства признаков*

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МОДЕЛЬНО-ОРІЄНТОВАНИЙ МЕТОД ПОБУДОВИ ІНТЕЛЕКТУАЛЬНИХ ІНФОРМАЦІЙНИХ СИСТЕМ ДІАГНОСТУВАННЯ НА ОСНОВІ ЯДЕР ВОЛЬТЕРРА

Анотація. *Представлено метод побудови інтелектуальних інформаційних систем з метою підвищення надійності діагностування несправностей нелінійних динамічних об'єктів. Пропонується удосконалення методу модельної діагностики, заснованого на непараметричній ідентифікації динамічних систем і побудові діагностичних моделей з використанням для параметризації ядер Вольтерра їх моментів різних порядків. Ефективність запропонованої моделі діагностики досліджено на прикладі вентильно-реактивного двигуна.*

Ключові слова: *інтелектуальні інформаційні системи, діагностика несправностей, ефективність діагностики, нелінійні динамічні моделі, ядра Вольтерра, ідентифікація, скорочення розмірності простору ознак*

1. Introduction. Increase of the control objects complexity while maintaining the dynamic properties of systems, increased requirements for accuracy and objectivity of decisions leads to the problem of the development of new intelligent computing systems. These systems will ensure required characteristics and automate the monitoring process for objects of different physical nature. Modern diagnostic systems include both new mathematical techniques and modern resources of intelligent computing [1 – 2].

At present the methods of technical diagnostics, founded on reconstruction of the control object models [3 – 4], is widely developed. It is usually expected that faults change only object's features. However, often defects change object's structure. This fact leads to using of the nonparametric identifications methods for building of object's models on base of experimental data "input/output".

This paper uses a non-parametric nonlinear dynamic models based on integro-power Volterra series. They consist of the sequence of multidimensional weight functions $w_k(\tau_1,\ldots,\tau_k)$, k=1,2,…– Volterra kernels [5], which are invariant to form of input signal.

Using of models on base of Volterra series allows taking into account nonlinear and inertial characteristics of object. It makes the diagnostics procedure more universal and reliable [8].

The diagnostic procedure in this case contains determination of Volterra kernels on base of "input/output" experiment data in time or in frequency [9 – 10] domain. On base of taken Volterra kernels a set of diagnostic features is formed. In space of these features builds a classifier using statistical recognition methods [10 –11].

As a real significantly nonlinear dynamic object is considered switched reluctance motor (SRM) [6]. It's fast developing scientific and technical direction. The electric motor is widely used in machine-tool construction and robotics, automated production lines, transportation, aerospace engineering and etc.

The aim of this work is improving the quality and reliability of diagnosing of the SRM state using a model-based diagnostic nonparametric identification of objects in the form of Volterra kernels [6].

2. Forming of features space and data compression. For continuous nonlinear dynamic system the relationship between input and output signals with zero initial conditions $x(t)$ can be represented by Volterra series:

$$\begin{gathered} y(t) = w_1(\tau)x(t-\tau)d\tau + \\ + \int_0^t\int_0^t\int_0^t w_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2 + \\ + \int_0^t\int_0^t\int_0^t w_3(\tau_1,\tau_2,\tau_3)x(t-\tau_1)x(t-\tau_2)\times \\ \times x(t-\tau_3)d\tau_1 d\tau_2 d\tau_3 + \ldots \end{gathered} \quad , \quad (1)$$

where $w_1(\tau_1)$, $w_2(\tau_1,\tau_2)$, $w_3(\tau_1,\tau_2,\tau_3)$ – Volterra kernels of 1st, 2nd and 3rd orders; t – current time.

High accuracy of Volterra kernels estimation is reached by using of antinoise determinate identification methods, offered in work [5].

Using of recognition theories methods for decision of the technical diagnostics problems on base of nonparametric dynamic object's models in the form of Volterra series is founded on the following supposition:

1. It exists objective (but implicit) relationship between multidimensional Volterra kernels, which describe the object's structure, and technical condition of object, i.e. it exists a certain function $F(\mathbf{W},\mathbf{S})$, linking object's condition $\mathbf{S}$ with Volterra kernels $\mathbf{W}=\{w_n(\tau_1,\ldots,\tau_n)\}_{n=1}^{N}$.
2. Function $F(\mathbf{W},\mathbf{S})$, built on base of Volterra kernels of explored object's, can be extrapolated on objects with an unknown characteristic.
3. Object's structure can be adequately presented in form of Volterra kernels.

Different approaches to decision of the problems of the technical diagnostics are possible. They can differ by the way of informative features choice and by the algorithm of building of function $F(\mathbf{W},\mathbf{S})$ [3; 5].

The effectiveness of pattern recognition methods used for diagnostics basically depends on self–descriptiveness of used set of features.

If features well characterize internal structure of the object, than most of objects, identical by internal structure, will display in space of these features in form of compact set of points. The objects with a fault structure will display to the points, deviating from this compact set and located more seldom considering variety of defects at such object and their relative small number.

3. Technology of intelligent diagnostic systems building. The proposed information technology of nonlinear dynamical objects indirect control and diagnosis bases on nonparametric identification of objects using Volterra kernels. It consists of following tasks.

Object identification. *The goal*: to obtain an information model of the object in the form of Volterra kernels.

Stages of implementation: supplying of test signals to the object's inputs; measuring of object's responses on output; definition of Volterra kernels on the basis of experimental data "input-output".

Objects diagnostic model building

The goal: to form the feature space.

Stages of implementation: parameterization of Volterra kernels (diagnostic information compression), evaluation of features diagnostic values; selection of the most informative features set (reduction of the diagnostic model).

Building an object's states classifier

The goal: construction of decision rules family for optimal classification in the space of informative features.

Stages of implementation: construction of decision rules (training); evaluation of the classification reliability (examination); optimization of the diagnostic model.

Object's diagnosis

The goal: Control object's state assessment.

Stages of implementation: object's identification; evaluation of diagnostic features; referring an object to a particular class (recognition of states).

Application of the proposed model diagnostics method entails the need of parameterization of Volterra kernels functions [14]. Diagnostic features sets selection has a decisive influence on the accuracy of the diagnostic model and, as a consequence, on the reliability of the object state recognition.

In this paper, the informativeness of the selected features combinations assessed by the results of the classification problem solving. The problem of objects sampling classification solves by constructing a decision rule by maximum likelihood estimation method [15].

Features combinations for which the quality of recognition is insufficient are discarded. In summary, features combination for which the addition of any new feature does not increase its informative value is selected.

Features set informativeness is determined on the base of the maximum of true recognition probability (TRP) criteria $P_{\max}$, implemented on a subset $\mathbf{X}'$ of a given signs set $\mathbf{X}$ ($\mathbf{X}' \subset \mathbf{X}$).

Object's states recognition performed on the basis of secondary diagnostic features obtained by parameterization of the model: $\{w_k(t_1,t_2,\ldots,t_k)\}_{k=1,2,\ldots,N} \Rightarrow \mathbf{x}=(x_1,x_2,\ldots,x_n)'$. The paper considers the system of secondary features obtained as the Volterra kernels samples of order k (k = 1,2) with a specified discreteness ($\mathbf{V}_k$) and moments of Volterra kernels $\mu_r^{(k)}$ of different orders r ($r=\overline{0,3}$) ($\mathbf{M}_k$).

Moments of Volterra kernels diagonal sections. It is offered the universal approach to forming a of diagnostic features sets, which consists in using of Volterra kernels moments.

Let a signal $x(t)$ in form of analytic function acts on input of stationary system, represented by the model in the form of Volterra kernels. Let's decompose it in a neighborhood of point t in a Taylor series.

$$x(t-\tau)=\sum_{i=0}^{\infty}\frac{(-1)^i}{i!}\frac{d^i x(t)}{d\tau^i}\tau^i . \quad (2)$$

Steady state signal in the system is determined by a series (2) with $t \to \infty$. If the expression (2) substitute in (1) than obtains expression $x(t)$:

$$\begin{aligned} y(t) &= \sum_{i=0}^{\infty}\frac{(-1)^i}{i!}\frac{d^i x(t)}{d\tau^i}\int_0^{\infty}\tau^i w_1(\tau)d\tau + \\ &+\sum_{i=0}^{\infty}\sum_{j=0}^{\infty}\frac{(-1)^{i+j}}{i!\,j!}\frac{d^i x(t)}{d\tau^i}\frac{d^j x(t)}{d\tau^j}\times \\ &\times\int_0^{\infty}\int_0^{\infty}\tau_1^i\tau_2^j w_2(\tau_1,\tau_2)d\tau_1 d\tau_2 + \\ &+\sum_{i=0}^{\infty}\sum_{k=0}^{\infty}\sum_{k=0}^{\infty}\frac{(-1)^{i+j+l}}{i!\,j!\,l!}\frac{d^i x(t)}{d\tau^i}\frac{d^j x(t)}{d\tau^j}\frac{d^l x(t)}{d\tau^l}\times \\ &\times\int_0^{\infty}\int_0^{\infty}\int_0^{\infty}\tau_1^i\tau_2^j\tau_3^l w_3(\tau_1,\tau_2,\tau_3)d\tau_1 d\tau_2 d\tau_3 + \ldots \end{aligned} \quad (3)$$

Values

$$\begin{aligned} \mu_{ij\ldots l}^{(k)} &= \int_0^{\infty}\int_0^{\infty}\ldots\int_0^{\infty}\tau_1^i\tau_2^j\ldots\tau_k^l\times \\ &\times w_k(\tau_1,\tau_2,\ldots,\tau_k)d\tau_1 d\tau_2\ldots d\tau_k \end{aligned} . \quad (4)$$

where $i, j,..., l$=0, 1, 2, … are called the moments of r order for kernel of k order, $i+j+...+l=r$ – moments order.

Moments of Volterra kernels diagonal sections ($\mathbf{M}_k$), considered in this work, calculated by the formula

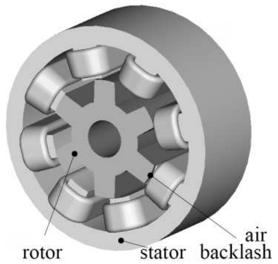
$$\mu_r^{(k)} = \int_0^\infty t^r w_k(t,t,...,t)dt. \quad (5)$$

4. Analysis of features space in formativeness

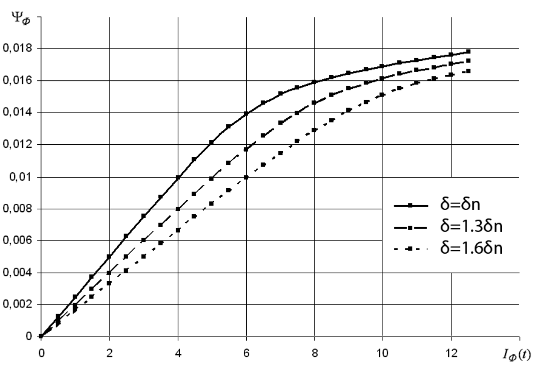
Offered method of building an intelligent computing system for diagnostics is analyzed on example of the SRM.

During long work the rotor of the electric motor has air friction and an air backlash δ (Fig. 1, *a*) between a stator and rotor in it eventually increases. It is typical for high-speed electric drives. An air backlash increasing leads to power parameters decreasing and increasing of energy losses. But direct measurements of air backlash are impossible.

Therefore, engineering of diagnostic system of SRM air backlash using indirect measurements is impotent today.



a



b

Fig. 1. Air backlash in SRM (*a*); function of flux linkage from a current for Θ=30º for a nominal value of air backlash $\delta=\delta_n$ and for a cases $\delta=1{,}3\delta_n$ and $\delta=1{,}6\delta_n$ (*b*)

Training samples are received for different states of SRM and are divided to 3 classes (100 items in each class) for air backlash $\delta=\delta_n$ (normal mode); $\delta=1.3\delta_n$ (fault modes) and $\delta=1.6\delta_n$ (fault and emergency modes).

The electric motor is described by the system of nonlinear differential equations [5]:

$$U_\Phi = I_\Phi R_\Phi + \frac{d\Psi_\Phi}{dt}. \quad (6)$$

$$\Psi_\Phi = f_1(I_\Phi, \Theta), \quad (7)$$

here $U_\Phi(t)$ – voltage (entrance variable); $I_\Phi(t)$ – current (measured response); R_Φ – resistance, Ψ_Φ – flux linkage; Θ – rotor angle. Function of flux linkage from a current is illustrated on Fig.1, *b*.

Find the inverse dependence flux linkage of the current phase $I_\phi = F(\Psi_\phi, \Theta)$ and approximated by its power-mode polynomial – we can get the model of the motor:

$$\frac{d\psi_\phi}{dt} + F(\Psi_\phi, \Theta) \cdot R_\phi = U_\phi, \quad (8)$$

where $F(\Psi_\phi, \Theta) = (a_1\psi_\phi + a_2\psi_\phi^2 + a_3\psi_\phi^3 + ...)$.

As a result of transformation we obtained the model of the motor in the form of nonlinear differential equation:

$$\frac{d\psi_\phi}{dt} + a_1\psi_\phi + a_2\psi_\phi^2 + a_3\psi_\phi^3 + ... = U_\phi. \quad (9)$$

From equation (9) we can obtain the analytical expressions for Volterra kernel of first-order and diagonal sections for Volterra kernels of second orders [11]:

$$w_1(t) = e^{-a_1 t},\ w_2(t,t) = \frac{a_2}{a_1}(e^{-2a_1 t} - e^{-a_1 t}). \quad (10)$$

For diagnostics of the SRM states Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t,t)$ are used. The estimations of Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t,t)$ for a cases $\delta=\delta_n$, $\delta=1{,}3\delta_n$ and $\delta=1{,}6\delta_n$ are taken by the results of the simulation (Fig. 2).

The deterministic approach for classification is impossible, because obtained models for all 3 classes forms the overlaying areas (Fig. 2). In this case, the methods of object's states recognition are used.

The effectiveness of recognition methods is largely dependent on informativeness of used sets of features. If selected features adequately characterize the internal structure of the diagnosis object, the objects being identical in structure, appear in the space of these features in the form of a dense set of points. Objects with structural fault will correspond to the points that deviate from this dense set.

Further, the informativeness of different diagnostic features sets (discrete values of Volterra kernels and the moments (5)) are analyzed.

The most informative description of objects from considered features sets gives the collection V_2.

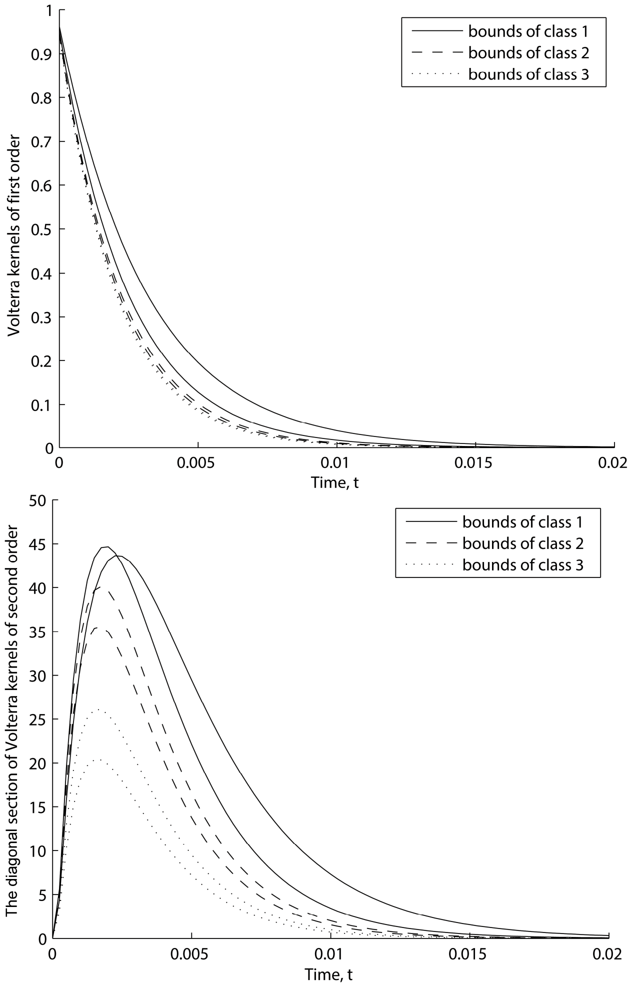


Fig. 2. Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t,t)$ for $\delta=\delta_n$, $\delta=1{,}3\delta_n$, $\delta=1{,}6\delta_n$

Discrete values of Volterra kernels

The training sample creates on base of ten discrete values (with uniform step on interval (0, T], where T – simulation time) of Volterra kernels of first order (feature set $\mathbf{V}_1$) and diagonal sections of Volterra kernels of the second order (feature set $\mathbf{V}_2$).

Diagnostic spaces form by selection of all features combination. Informativeness estimates as averaged value of TRP among all classes. The best results of features sets selection among $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$ are shown in Fig. 3.

The most informative part of functions of Volterra kernels of first order and the diagonal sections of Volterra kernels of second order is the initial area, corresponding to first four discrete values. For the set $\mathbf{V}_1$ there are $x_i = w_1(t_i)$; for the set $\mathbf{V}_2$ – $x_i = w_2(t_i,t_i)$; for the set $\mathbf{V}_{1,2}=\mathbf{V}_1 \cup \mathbf{V}_2$ – $x_i = w_1(t_i)$, $x_{i+1} = w_2(t_i,t_i)$, $i=\overline{1,10}$.

Volterra kernels moments

The training sample creates on base of four Volterra kernels moments (5) of Volterra kernels of first order (feature set $\mathbf{M}_1$) and diagonal sections of Volterra kernels of the second order (feature set $\mathbf{M}_2$).

The best results of features sets selection are shown in a tabular mode (Table 1) and in a chart mode (Fig. 3).

1. Averaged values of TRP for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$.

FEATURES SET	INFORMATIVE FEATURES	TRP
$\mathbf{V}_1$	x_1, x_2, x_3, x_4	0,993
$\mathbf{M}_1$	x_1, x_2, x_3	0,994
$\mathbf{V}_2$	x_1, x_2, x_3, x_4	1,0
$\mathbf{M}_2$	x_1, x_2, x_3	1,0

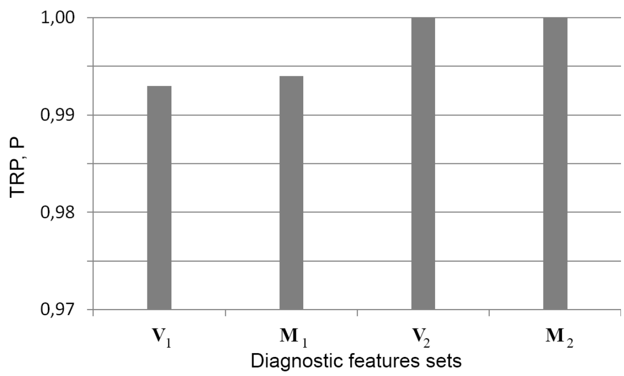


Fig. 3. Averaged values of TRP for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$

The most informative moments correspond to order r=0, 1, 2. For the set $\mathbf{M}_1$ there are $x_{r+1} = \mu_r^{(1)}$; for the set $\mathbf{M}_2$ there are $x_{r+1} = \mu_r^{(2)}$;

for the set $\mathbf{M}_{1,2} = \mathbf{M}_1 \cup \mathbf{M}_2$ there are $x_{r+1} = \mu_r^{(1)}$, $x_{r+4} = \mu_r^{(2)}$.

The most informative description of motor's states gives the feature set $\mathbf{V}_2$.

5. Stability of features space informativeness to estimation of noisy Volterra kernels

It was analyzed a stability of informativeness for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$. It was created 4 training sample on base of noisy Volterra kernels of first order and diagonal sections of Volterra kernels of the second order with noise rate (Fig. 4) accordingly 1 %, 3 %, 5 %, 10 % of Volterra kernels extremum. The best results of stability analysis are shown in Table 2 and Fig. 5.

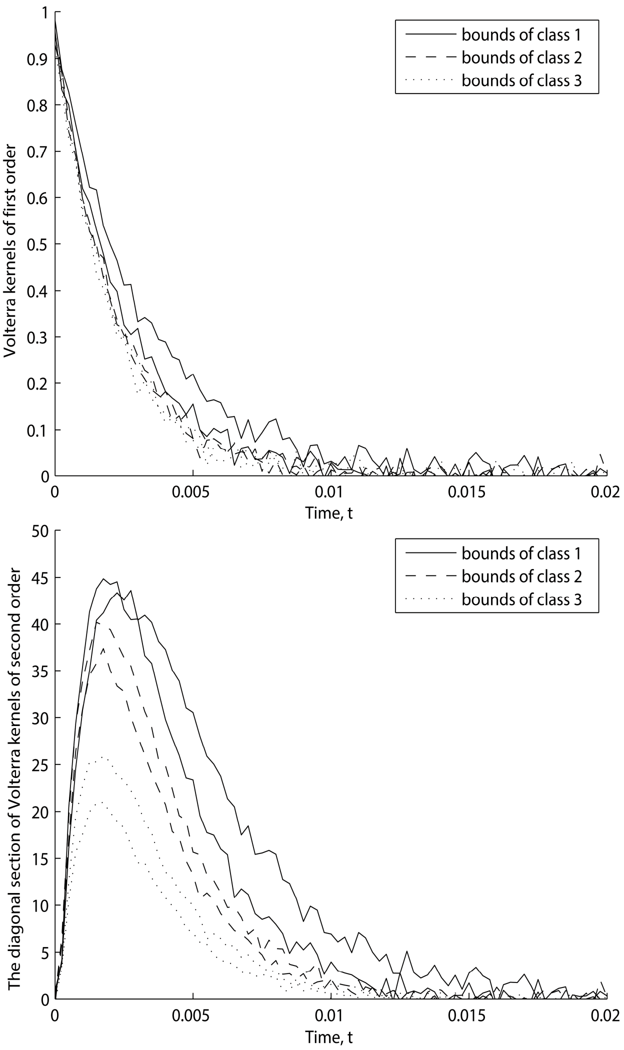


Fig. 4. Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t, t)$ for $\delta=\delta_n$, $\delta=1{,}3\delta_n$, $\delta=1{,}6\delta_n$ at noise acting

The most noise immunity features sets are received on the base of diagonal sections of Volterra kernels of the second order ($\mathbf{V}_2$, $\mathbf{M}_2$). Herewith, features set $\mathbf{M}_2$ unlike $\mathbf{V}_2$ save stability as on small as on big noise rates.

However, the TRP decrease even in features set $\mathbf{M}_2$ with increasing noise rate may become critical, so that the features set will not be suitable for use in conditions of noise.

2. Averaged values of TRP for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{V}_{1,2}$, $\mathbf{M}_{1,2}$ at different noise rates of Volterra kernels sections

Features sets	Informative features	Noise rate, %				
		0	1	3	5	10
$\mathbf{V}_1$	x_1, x_2, x_3, x_4	0,993	0,981	0,936	0,885	0,825
$\mathbf{M}_1$	x_1, x_2, x_3	0,994	0,988	0,98	0,954	0,927
$\mathbf{V}_2$	x_1, x_2, x_3, x_4	1,0	1,0	0,998	0,983	0,979
$\mathbf{M}_2$	x_1, x_2, x_3	1,0	0,998	0,997	0,996	0,995
$\mathbf{V}_{1,2}$	x_1, x_4, x_6, x_{14}	1,0	1,0	1,0	0,998	0,998
$\mathbf{V}_{1,2}$	x_1, x_2, x_{10}, x_{17} *	1,0	0,966	0,93	0,906	0,828
$\mathbf{M}_{1,2}$	x_1, x_3, x_5, x_6	1,0	1,0	1,0	1,0	0,998

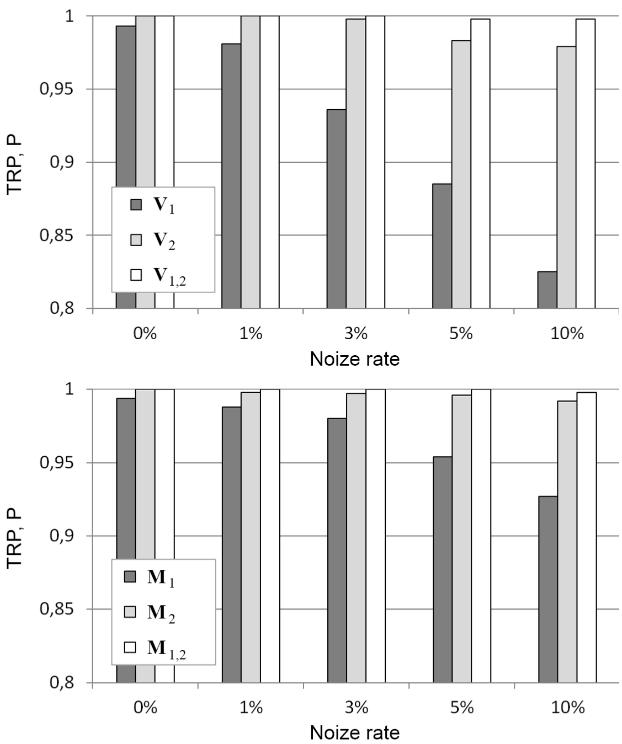


Fig. 5. Informativeness for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{V}_{1,2}$, $\mathbf{M}_{1,2}$ under the influence of noise for Volterra kernels estimations

For noise immunity solution in this case we consider a sets, combining a features on the basis of discrete values of Volterra kernels of first order (**V**$_1$) and diagonal sections of Volterra kernels of the second order (**V**$_2$) **V**$_{1,2}$=**V**$_1$U**V**$_2$. Similarly we consider a features set, combining a features on the basis of Volterra kernels moments of Volterra kernels of first order (**M**$_1$) and diagonal sections of Volterra kernels of the second order (**M**$_2$) **M**$_{1,2}$= **M**$_1$U**M**$_2$.

The best results of stability analysis for the features sets **V**$_{1,2}$ and **M**$_{1,2}$ also are shown in Table 2 and Fig. 5. The both features sets **V**$_{1,2}$ and **M**$_{1,2}$ have better noise immunity than features sets **V**$_1$, **V**$_2$, **M**$_1$, **M**$_2$. The features set **M**$_{1,2}$ have the belter noise immunity over **V**$_{1,2}$ on a high noise rate.

According to the data in Table 2 the functions of TRP deviation depending on noise rates are build (Fig. 6). Graph clearly demonstrates the change reliability of diagnosis at different noise rates for considered diagnostic features sets.

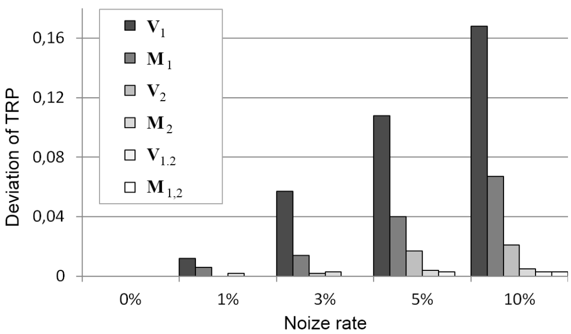


Fig. 6. TRP deviation for features sets **V**$_1$, **V**$_2$, **M**$_1$, **M**$_2$, **V**$_{1,2}$, **M**$_{1,2}$ under the influence of noise for Volterra kernels estimations

Each features set in the conditions of noise absence usually has several best solutions (combinations of features), or several solutions that are in the neighborhood of best solution.

In this case, when the noise acts the some solutions remain quite reliable (in terms of diagnostics quality), while others lose in diagnostic quality.

As an example, in Table 2 for the features set **V**$_{1,2}$ it is given a combination of features {x_1, x_2, x_{10}, x_{17}}*. At zero-noise rate it provides maximum diagnostic quality. But when the noise rate increases the diagnostics quality of the features combination is reduced considerably (Fig. 7).

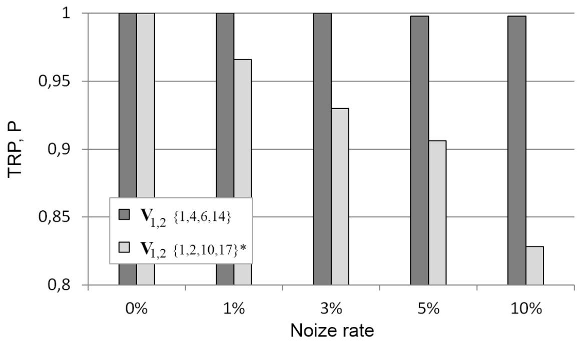


Fig. 7. Informativeness for different combinations of features set **V**$_{1,2}$ under the influence of noise

6. Conclusion. In this work the method of building an intelligent computing system for diagnostics of nonlinear dynamic objects is offered. The method founds on using integro–power Volterra series as object's models. On base of such models the diagnostic features space builds. There are discrete values of Volterra kernels of first order and diagonal sections of Volterra kernels of the second orders as well as moments of Volterra kernels.

Estimations of true recognition probability of object's states on base of taken diagnostic features sets received using maximum likelihood estimation method.

Volterra kernels sections of second order give more information about diagnostic object than Volterra kernels of first order. It is shown a possibility and advantages to use diagnostic model of object as a union of Volterra kernels of first and second orders. These models provide the highest information about diagnostic object.

The highest informativeness and noise immunity is reached by union of moments of Volterra kernels of the first order and Volterra kernels diagonal sections of the second order.

Each features set in the conditions of noise absence usually has several best solutions (combinations of features), or several solutions that are in the neighborhood of best solution.

The selection of the best features sets should be carried out taking into account the changes of the diagnostic quality at the noise action.

The results of numerical experiments with switched reluctance motor allow making a conclusion about high efficiency of nonparametric dynamic models on base of integro–power Volterra series. The features set on base of Volterra kernels moments is most preferred when intelligent computing system for diagnostics of complex nonlinear dynamic objects builds.

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