UDC 004.93'11:681.5.015.52

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INTELLIGENT INFORMATION TECHNOLOGY BUILDING SYSTEMS DIAGNOSTICS USING NUCLEAR MOMENTS VOLTERRA

The paper presents the intelligent information technology to increase the efficiency of diagnosing the state of nonlinear dynamical objects of different physical nature with the use of mathematical models in the form of Volterra kernels. Research results on the test object monitoring show that moments of nuclei Volterra 2nd order characterized by the highest stability of the quality of diagnosis (probability of correct recognition) errors in measuring the response of objects of control compared to the data of their classification on the basis of samples of nuclei with a given increment. Figs.: 5. Tabl.: 2. Refs.: 13 titles.

Keywords: intelligent information technology, systems diagnostics, Volterra kernels, mathematical models in the form of Volterra kernels, quality of diagnosis.

Statement of the problem. 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 $w_k(\tau_1,\ldots,\tau_k)$, $k = 1, 2, \ldots$ – Volterra kernels [5], which are invariant to form of input signal.

Using of models on base of Volterra series allows to take into account nonlinear and inertial characteristics of object. It makes the diagnostics procedure more universal and reliable [6].

The diagnostic procedure in this case contains determination of Volterra kernels on base of "input/output" experiment data in time or in frequency [7, 8] 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 [8, 9].

As a diagnostic object it's considered a simulation model of nonlinear dynamic electronic device. It is widely used component in electronics, electric drives, robotics, automated production lines, transportation, aerospace engineering and etc.

The aim of this work is improving the quality and reliability of diagnosing of nonlinear dynamic object's state using a model-based diagnostic nonparametric identification of objects in the form of Volterra kernels.

Forming of features space. For continuous nonlinear dynamic system the relationship between input $u(t)$ and output $y(t)$ signals with zero initial conditions can be represented by Volterra serie:

$$y(t) = w_1(\tau)u(t-\tau)d\tau + \int_0^t\int_0^t\int_0^t w_2(\tau_1,\tau_2)u(t-\tau_1)u(t-\tau_2)d\tau_1 d\tau_2 +$$
$$+\int_0^t\int_0^t\int_0^t w_3(\tau_1,\tau_2,\tau_3)u(t-\tau_1)u(t-\tau_2)u(t-\tau_3)d\tau_1 d\tau_2 d\tau_3 + \ldots, \tag{1}$$

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

High accuracy of Volterra kernels estimation is reached by using of antinoise determinate identification methods, offered in work [10 – 12].

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 **S** with Volterra kernels $\mathbf{W}=\{w_n(\tau_{1,\ldots,}\tau_n)\}^N_{n=1}$.

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 $F(\mathbf{W},\mathbf{S})$ [13].

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.

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

1. 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".

2. 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).

3. 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.

4. 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 [8]. 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 [13]. So, to separate two classes (dichotomy case) it uses discriminant function of the form:

$$d(\boldsymbol{x}) = \frac{1}{2}\boldsymbol{x}'(\boldsymbol{S}_2^{-1} - \boldsymbol{S}_1^{-1})\boldsymbol{x} + (\boldsymbol{S}_1^{-1}\boldsymbol{m}_1 - \boldsymbol{S}_2^{-1}\boldsymbol{m}_2)'\boldsymbol{x} + \\ + \frac{1}{2}(\boldsymbol{m}_1'\boldsymbol{S}_1^{-1}\boldsymbol{m}_1 - \boldsymbol{m}_2'\boldsymbol{S}_2^{-1}\boldsymbol{m}_2 + \ln\frac{|\boldsymbol{S}_2|}{|\boldsymbol{S}_1|}) + \lambda_{\max}, \quad (2)$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n)'$ – features combination; n – features space dimensionality; $\mathbf{S}_i = \mathrm{M}[(\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)']$ – covariance matrix for class i (M[ ] – mathematical expectation operation); $\mathbf{S}_i^{-1}$ – matrix inverse to $\mathbf{S}_i$, $|\mathbf{S}_i|$ – matrix determinant $\mathbf{S}_i$; $\mathbf{m}_i$ – mathematical expectation vector for a features of class i, $i = 1, 2$; $\lambda_{\max}$ – classification threshold that provides the highest classification quality for objects of training sample.

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 $\mathbf{X}$ ($\mathbf{X}' \subset \mathbf{X}$).

Analysis of a different features combination quality based on averaging of TRP criterion. Quality of selected features combination from considered features set is evaluated by the result of classification on examination sample of data. Classifier builds using decision rules based on discriminant functions constucted during learning process (2) [13].

TRP is calculated for each decision rule. Then the maximum value of the TRP average assessment $\overline{P}_{\max}$ is searched [6]:

$$\overline{P}_{\max} = \max_k \left\{ \frac{1}{m-1} \sum_{i=1}^{m-1} P_{ik} \right\}, \quad (3)$$

where m – classes images count; k – serial number of features combinations in exhaustive search procedure.

So, during the exhaustive search procedure for considered diagnostic features the most valuable combination of two, three, etc. features are determined.

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 kernelssamplesof 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 $u(t)$ 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

$$u(t-\tau)=\sum_{i=0}^{\infty}\frac{(-1)^i}{i!}\frac{d^i u(t)}{d\tau^i}\tau^i . \qquad (4)$$

Steady state signal in the system is determined by a series (4) with $t\to\infty$. If the expression (4) substitute in (1) than obtains expression $u(t)$:

$$y(t)=\sum_{i=0}^{\infty}\frac{(-1)^i}{i!}\frac{d^i u(t)}{d\tau^i}\int_0^{\infty}\tau^i w_1(\tau)d\tau+\sum_{i=0}^{\infty}\sum_{j=0}^{\infty}\frac{(-1)^{i+j}}{i!\,j!}\frac{d^i u(t)}{d\tau^i}\frac{d^j u(t)}{d\tau^j}\times$$
$$\times\int_0^{\infty}\int_0^{\infty}\tau_1^i\tau_2^j w_2(\tau_1,\tau_2)d\tau_1 d\tau_2+\sum_{i=0}^{\infty}\sum_{k=0}^{\infty}\sum_{k=0}^{\infty}\frac{(-1)^{i+j+l}}{i!\,j!\,l!}\frac{d^i u(t)}{d\tau^i}\times \qquad (5)$$
$$\times\frac{d^j u(t)}{d\tau^j}\frac{d^l u(t)}{d\tau^l}\int_0^{\infty}\int_0^{\infty}\int_0^{\infty}\tau_1^i\tau_2^j\tau_3^l w_3(\tau_1,\tau_2,\tau_3)d\tau_1 d\tau_2 d\tau_3+\ldots\ .$$

Values

$$\mu_{ij\ldots l}^{(k)}=\int_0^{\infty}\int_0^{\infty}\ldots\int_0^{\infty}\tau_1^i\tau_2^j\ldots\tau_k^l w_k(\tau_1,\tau_2,\ldots,\tau_k)d\tau_1 d\tau_2\ldots d\tau_k , \qquad (6)$$

where $i, j, \ldots, l$ = 0, 1, 2, … arecalled themomentsof r orderfor kernelof k order, $i+j+\ldots+l=r$ – moments order.

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

$$\mu_r^{(k)}=\int_0^{\infty}t^r w_k(t,t,\ldots,t)dt . \qquad (7)$$

Analysis of features space informativeness. Offered method of building an intelligent computing system for diagnostics is analyzed on example of the nonlinear dynamic object simulation model.

Control object's model. The simulation model of nonlinear dynamic object, represents connection with feedback.It's blocks have characteristics $W_1(t)=e^{-\alpha t}$ and $f(y)=\beta y^2(t)$.

Such object is described by the nonlinear differential equation of the form:

$$\frac{dy(t)}{dt}+\alpha y(t)+\beta y^2(t)=u(t) . \qquad (8)$$

Let the α and β are constant factors (features) inaccessible for direct measurements.

Then, engineering of diagnostic system of nonlinear dynamic objects using indirect measurements becomeswidely impotent today.

The model of object as three members of some Volterra series at zero entry conditions looks like:

$$y(t)=\int_0^t w_1(\tau_1)u(t-\tau_1)d\tau_1+\int_0^t\int_0^t w_2(\tau_1,\tau_2)u(t-\tau_1)u(t-\tau_2)d\tau_1 d\tau_2+$$
$$+\int_0^t\int_0^t\int_0^t w_3(\tau_1,\tau_2,\tau_3)u(t-\tau_1)u(t-\tau_2)\times u(t-\tau_3)d\tau_1 d\tau_2 d\tau_3. \quad (9)$$

Here $u(t)$ *and* $y(t)$ – measured signals accordingly on an input and output of diagnostic object.

The analytical expressions for Volterra kernel of 1st order and diagonal sections for Volterra kernels of 2nd and 3rd order are:

$$w_1(\tau_1)=e^{-\alpha\tau_1}, \quad (10)$$

$$w_1(\tau_1,\tau_2)=\frac{\beta}{\alpha}(e^{-\alpha\tau_1}e^{-\alpha\tau_2}-\ e^{-\alpha\tau_2}),\ \tau_1\le\tau_2, \quad (11)$$

$$w_3(\tau_1,\tau_2,\tau_3)=\frac{2}{3}\left(\frac{\beta}{\alpha}\right)^2(e^{\alpha(\tau_1-\tau_2-\tau_3)}+3e^{-a(\tau_1+\tau_2+\tau_3)}-$$
$$-4e^{-\alpha(\tau_2+\tau_3)}-2e^{-\alpha(\tau_1+\tau_3)}+2e^{-\alpha\tau_3}),\ \tau_1\le\tau_2\le\tau_3. \quad (12)$$

Diagonal sections of Volterra kernelsof 2nd and 3rd order (11) – (12) at $t_1=t_2=t_3=t$ has the form:

$$w_2(t,t)=\frac{\beta}{\alpha}(e^{-2\alpha t}-e^{-\alpha t}),$$
$$w_3(t,t,t)=2\left(\frac{\beta}{\alpha}\right)^2(e^{-3at}-2e^{-2\alpha t}+e^{-\alpha t}). \quad (13)$$

For diagnostics of the object's states Volterra kernels of 1st order $w_1(t)$ and diagonal sections of Volterra kernels of 2nd $w_2(t,t)$ and 3rd order $w_3(t,t,t)$ are used.

Training and examination samples are received for objects of four classes (100 objects in each class) depending on the α and β values. The first class forms by objects with features $\alpha\in[0.95\alpha n,\ 1.05\alpha n]$ and $\beta\in[0.95\beta n,\ 1.05\beta n]$, where αn and βn – nominal values (normal mode – class A).The second class forms by objects with features $\alpha\in(0.9\alpha n,\ 0.95\alpha n)\cup(1.05\alpha n,\ 1.1\alpha n)$ and

$\beta \in [0.95\beta n,\ 1.05\beta n]$ (fault modes – class B). The third class forms by objects with features $\alpha \in [0.95\alpha n,\ 1.05\alpha n]$ and $\beta \in (0.9\beta n,\ 0.95\beta n) \cup (1.05\beta n,\ 1.1\beta n)$ (fault modes – class C). The forth class forms by objects with features $\alpha \in (0.9\alpha n,\ 0.95\alpha n) \cup (1.05\alpha n,\ 1.1\alpha n)$ and $\beta \in (0.9\beta n,\ 0.95\beta n) \cup (1.05\beta n,\ 1.1\beta n)$ (fault and emergency modes – class D).

The estimations of Volterra kernels of 1st order $w_1(t)$ and diagonal sections of Volterra kernels of 2nd $w_2(t, t)$ and 3rd order $w_3(t, t, t)$ for described four classes are taken by the results of the simulation (Fig. 1).

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

On base of training sets of data for an object's classes **A**, **B**, **C** and **D** there successively calculates three discriminant functions $d1(x)$, $d2(x)$ and $d3(x)$. The function $d1(x)$ separates the objects of the first class A from the objects of second, third and fourth classes $B \cup C \cup D$; $d2(x)$ – separates the objects of the second class B from the objects of third and fourth classes $C \cup D$; $d2(x)$ – separates the objects of the third class C from the objects of fourth class D.

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

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 $\boldsymbol{V}_1$) and diagonal sections of Volterra kernels of the second (feature set $\boldsymbol{V}_2$).

Diagnostic spaces form by selection of all features combination. Quality of a features combination estimates by solving the problem of statistical classification [13].

The best results of features sets selection among $\boldsymbol{V}_1$, $\boldsymbol{V}_2$ and $\boldsymbol{V}_3$ are shown in a tabular mode (Table 1) and in a chart mode (Fig. 2).

The most informative description of objects from considered features sets gives the collection $\boldsymbol{V}_2$.

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 $\boldsymbol{V}_1$ there are $x_i = w_1(t_i)$, $i = \overline{1,\ 4}$; for the set $\boldsymbol{V}_2 - x_i = w_2(t_i, t_i)$, $i = \overline{1,\ 4}$.

Volterra kernels moments. The training sample creates on base of four Volterra kernels moments (5) of Volterra kernels of first order (M_1) and diagonal sections of Volterra kernels of the second order (M_2) and third order (M_3).

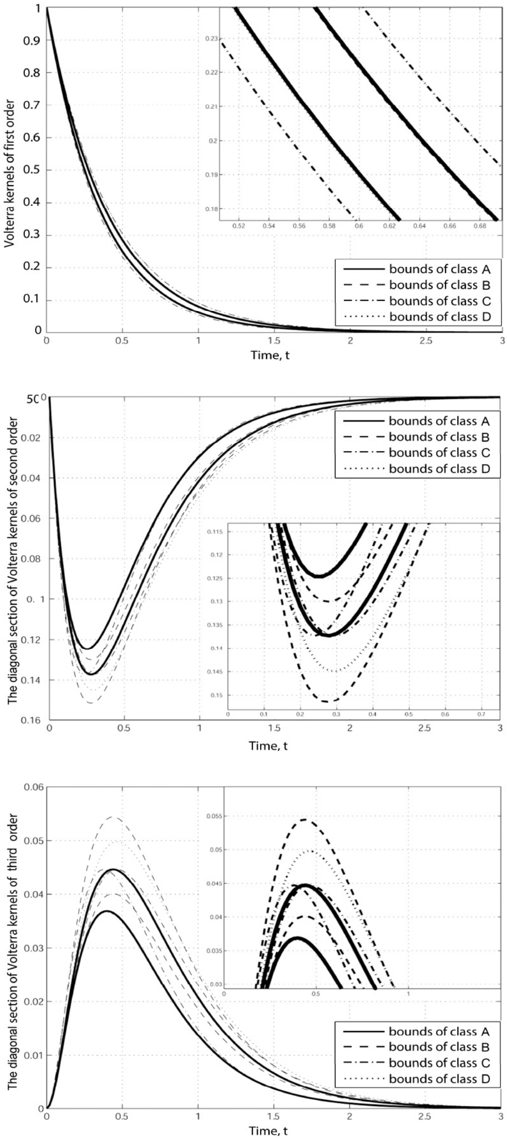

Fig 1. Volterra kernels of first order $w_1(t)$ and the diagonal sections of Volterra kernels of second $w_2(t, t)$ and third order $w_3(t, t, t)$ for objects of 4 classes

The best results of features sets selection among $\boldsymbol{M}_1$, $\boldsymbol{M}_2$ and $\boldsymbol{M}_3$ are shown in a tabular mode (Table 1) and in a chart mode (Fig. 2).

The most informative moments correspond to order $r = 0, 1, 2, 3$. For the set $\boldsymbol{M}_1$ there are $x_{r+1} = \mu_r^1$; for the set $\boldsymbol{M}_2$ there are $x_{r+1} = \mu_r^2$; for the set $\boldsymbol{M}_3$ there are $x_{r+1} = \mu_r^3$

The most informative description of motor's states gives the feature set $\boldsymbol{V}_2$ or $\boldsymbol{M}_2$ (Table 1).

Table 1

Averaged values of TRP for features sets $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, $\boldsymbol{V}_3$, $\boldsymbol{M}_1$, $\boldsymbol{M}_2$, $\boldsymbol{M}_3$

Features set	Informative features	TRP
$\boldsymbol{V}_1$	x_1, x_2, x_3, x_7	0.84
$\boldsymbol{M}_1$	x_1, x_2, x_3, x_4	0.83
$\boldsymbol{V}_2$	x_1, x_2, x_3, x_4	0.95
$\boldsymbol{M}_2$	x_1, x_2, x_3, x_4	0.95
$\boldsymbol{V}_3$	x_1, x_2, x_3, x_4	0.95
$\boldsymbol{M}_3$	x_1, x_2, x_3, x_4	0.94

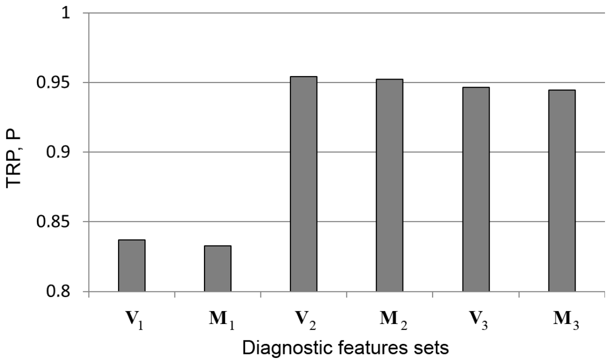

Fig. 2. Averaged values of TRP for features sets $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, $\boldsymbol{V}_3$, $\boldsymbol{M}_1$, $\boldsymbol{M}_2$, $\boldsymbol{M}_3$

Stability of features space informativeness to estimation of noisy Volterra kernels. It was analyzed a stability of informativeness for features sets $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, $\boldsymbol{V}_3$, $\boldsymbol{M}_1$, $\boldsymbol{M}_2$, $\boldsymbol{M}_3$. It was created 4 training sample on base of noisy Volterra kernels of first order and diagonal sections of Volterra kernels of the second and third order with noise rate accordingly 1%, 3%, 5%, 10% of Volterra kernels extremum. The best results of stability analysis are shown in Fig. 3 and Table 2.

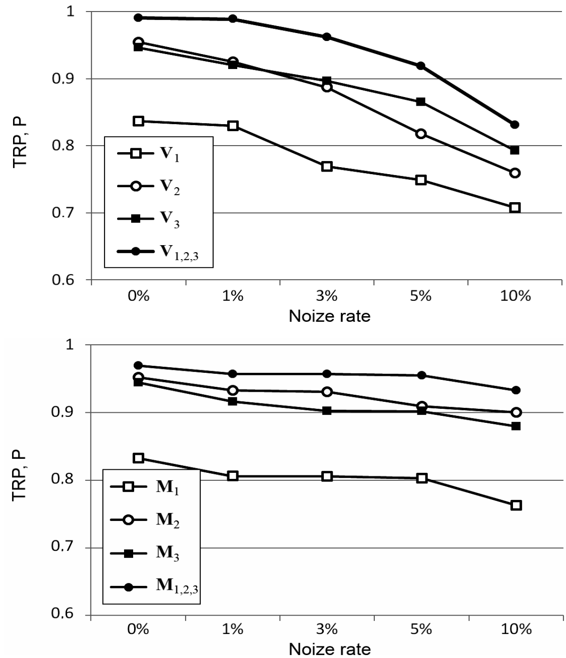

Fig. 3. Informativeness for features sets $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, $\boldsymbol{V}_3$, $\boldsymbol{V}_{1,2,3}$, $\boldsymbol{M}_1$, $\boldsymbol{M}_2$, $\boldsymbol{M}_3$, $\boldsymbol{M}_{1,2,3}$ under the influence of noise for Volterra kernels estimations

The most noise immunity features sets are received on the base ofdiagonal sections of Volterra kernels of the second and third order $\boldsymbol{V}_3$, $\boldsymbol{M}_2$. Herewith, features set $\boldsymbol{M}_2$ unlike $\boldsymbol{V}_3$ save a stability as on small as on big noise rates.

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

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 ($\boldsymbol{V}_1$) and diagonal sections of Volterra kernels of the second ($\boldsymbol{V}_2$) and third ($\boldsymbol{V}_3$) order $\boldsymbol{V}_{1,2,3} = \boldsymbol{V}_1 \cup \boldsymbol{V}_2 \cup \boldsymbol{V}_3$ – $x_i = w_1(t_i)$, $x_i+1 = w_2(t_i, t_i)$, $i = \overline{1,10}$. Similarly we consider a features set, combining a features on the basis of Volterra kernels moments of Volterra kernels of first order ($\boldsymbol{M}_1$) and diagonal sections of Volterra kernels of the second and third order ($\boldsymbol{M}_2$, $\boldsymbol{M}_3$) $\boldsymbol{M}_{1,2,3} = \boldsymbol{M}_1 \cup \mathbf{M}_2 \cup \boldsymbol{M}_3$ – $x_{r+1} = \mu_r^{(1)}$, $x_{r+4} = \mu_r^{(2)}$, $r = \overline{0,\ 3}$.

The best results of stability analysis for the features sets $V_{1,2,3}$ and $M_{1,2,3}$ also are shown in Table 2 and Fig. 4. The both features sets $V_{1,2,3}$ and $M_{1,2,3}$ have better noise immunity than features sets V_1, V_2, V_3, M_1, M_2, M_3. The features set $M_{1,2,3}$ have the belter noise immunity over $\mathbf{V}_{1,2,3}$ on a high noise rate.

According to the data in Table 2 the functions of TRP deviation depending on noise rates are build (Fig. 3).

Table 2

Averaged values of TRP for features sets V_1, V_2, V_3, M_1, M_2, M_3, $V_{1,2,3}$, $M_{1,2,3}$ at different noise rates of Volterra kernels sections

Features sets	**Informative features**	**Noise rate, %**				
		0	**1**	**3**	**5**	**10**
V_1	x_1, x_2, x_3, x_7	0.84	0.83	0.77	0.75	0.71
M_1	x_1, x_2, x_3, x_4	0.83	0.80	0.80	0.80	0.76
V_2	x_1, x_2, x_3, x_4	0.95	0.93	0.89	0.82	0.76
M_2	x_1, x_2, x_3, x_4	0.95	0.93	0.93	0.91	0.90
V_3	x_1, x_2, x_3, x_4	0.95	0.92	0.90	0.87	0.79
M_3	x_1, x_2, x_3, x_4	0.94	0.93	0.92	0.91	0.89
$V_{1,2,3}$	$x_{12}, x_{14}, x_{22}, x_{24}$	0.99	0.96	0.93	0.90	0.81
$V_{1,2,3}$	x_1, x_4, x_{11}, x_{21}*	0.98	0.91	0.74	0.70	0.68
$M_{1,2,3}$	x_5, x_9, x_{10}, x_{11}	0.98	0.92	0.92	0.91	0.89

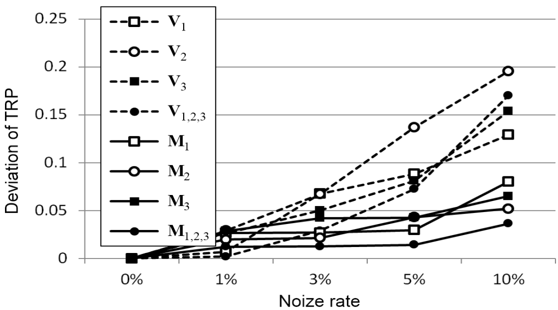

Fig. 4. TRP deviation for features sets V_1, V_2, V_3, $V_{1,2,3}$, M_1, M_2, M_3, $M_{1,2,3}$ under the in fluence of noise for Volterra kernels estimations.

Graph clearly demonstrates the change reliability of diagnosis at different noise rates for considered diagnostic features sets.

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 $\{x_1, x_4, x_{11}, x_{21}\}$*. 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. 5).

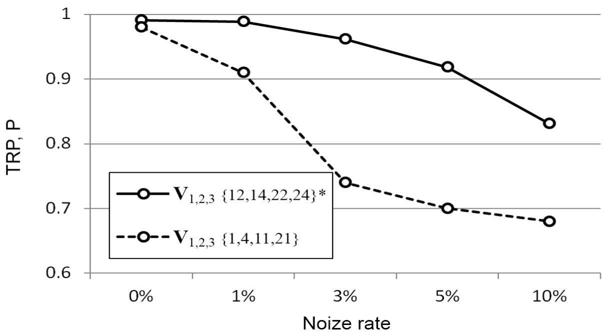

Fig. 5. Informativeness for different combinations of features set $V_{1,2,3}$ under the influence of noise

Conclusion. In this work the method of building an intelligent diagnostics system 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 and third order 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 and third 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, second and third orders. These models provide the highest information about diagnostic object.

The highest informativeness and noise immunity is reached by union of moments ofVolterra kernels of the first order and Volterra kernels diagonal sections of the second and third 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 nonlinear dynamic object 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 diagnostic system builds.

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Надійшла (received) 20.09.2015

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