Intelligent Technology of Nonlinear Dynamics Diagnostics using Volterra Kernels Moments

Oleksandr Fomin, Mohanad Masri, Vitaliy Pavlenko

***Abstract*—**The paper presents the technology of intelligent diagnostic systems construction for improving a reliability of nonlinear dynamic objects fault diagnosing. There genesis of the problem, goals and motivation are presented. It's proposed improving method of model-based diagnostics based on nonparametric identification of systems and parameterization of diagnostic models with using Volterra kernels moments. Effective algorithms of diagnostic models parameterization are offered. Effectiveness of the proposed diagnostic model is investigated on example of switched reluctance motor. The recommendations of using considered technology in the tasks of diagnosing of various parameters of the electric motor are given.

***Keywords*—**Fault detection, efficiency of diagnostics, Volterra kernels, reduction of feature space dimension, switched reluctance motor diagnosing.

I. Introduction

Increasing complexity of control objects, while maintaining the dynamic properties of systems, rising demands to the accuracy and objectivity of decisions leads to the problem of new intelligent computer systems development. These systems will provide the necessary characteristics and automate the process of monitoring for objects with different physical nature. Modern diagnostic systems include both new mathematical techniques and modern resources of intelligent computing [1], [2].

Nowadays, widely developed methods of technical diagnostics, based on the reconstruction of control objects models [3], [4]. It's generally expected that faults only change object's characteristics. However, often defects change object's structure. This fact leads to using nonparametric identifications methods for constructing object's models based on the experimental data "input/output".

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

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

Diagnostic procedure in this case contains determination of Volterra kernels based on "input/output" experiment data in time or in frequency [7], [8] domain. On the base received Volterra kernels formed a set of diagnostic features. In space of these features builds a classifier using statistical recognition methods [8], [9].

As a real significantly nonlinear dynamic object is considered a switched reluctance motor (SRM) [10], [11]. 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 purpose of this work is improving the quality and reliability of diagnosing SRM state with using a model-based diagnostic based on nonparametric identification of objects in the form of Volterra kernels [12], [13].

II. 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:

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

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

High accuracy estimation of the Volterra kernels is achieved with using noise-protected determinate identification methods proposed in [5], [14]. Using recognition theories methods for decision technical diagnostics problems based on the 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 $\mathbf{W}=\{w_k(\tau_1,\dots,\tau_k)\}_{k=1}^N$.

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.

There are different approaches to solving problems of technical diagnostics. They can differ by the way of

O. Fomin, M. Masri, V. Pavlenko are from the Odessa National Polytechnic University, Odessa, 65044 Ukraine (e-mail: aleksandr.fomin@gmail.com).

informative features choice and by the algorithm of building of function $F(\mathbf{W},\mathbf{S})$ [15], [16].

The effectiveness of pattern recognition methods used for diagnostics basically depends on diagnostic value 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 possible defects at such object and their relative small number.

III. Technology of Intelligent Diagnostic Systems Construction

The proposed information technology of nonlinear dynamical objects indirect control and diagnosis based on nonparametric identification of 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 the object's responses on output; definition of Volterra kernels on the basis of experimental data "input-output".

2. Construction of object's diagnostic model. *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. Construction of object's states classifier. *The goal*: construction family of decision rules for optimal classification in the space on informative features.

Stages of implementation: construction of the 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; assigning an object to a certain class (recognition of the object's 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's state recognition.

The problem of objects sampling classification solves by constructing a decision rule by maximum likelihood method [15].

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

Features set value 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 $\mathbf{X}$ ($\mathbf{X}' \subset \mathbf{X}$).

Recognition object's states performed on the basis of secondary diagnostic features obtained by parameterization of the model: $\{w_k(\tau_1,...,\tau_k)\}_{k=1}^{N} \Rightarrow \mathbf{x}=(x_1,\ldots,x_n)'$. 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, $r=\overline{0,3}$) ($\mathbf{M}_k$).

Diagonal sections moments of Volterra kernels. Proposed 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.

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

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 $x(t)$:

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

Values

$$\mu_{ij\ldots l}^{(k)}=\int_0^{\infty}\int_0^{\infty}\ldots\int_0^{\infty}\tau_1^i\tau_2^j\ldots\tau_k^l w_k(\tau_1,\tau_2,\ldots,\tau_k)d\tau_1 d\,\tau_2\ldots.d\tau_k\,, \tag{4}$$

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

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

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

IV. Analysis of Features Space Value

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

During long work the rotor of the electric motor has friction against the air and backlash δ (Fig.1) between a stator and rotor in it eventually increases. It is typical for high–speed electric drives. Increasing air backlash leads to a reduction energy parameters and increases the energy losses. But direct measurements of air backlash are impossible. Therefore, engineering of diagnostic system of SRM air backlash using indirect measurements is important today [16], [17].

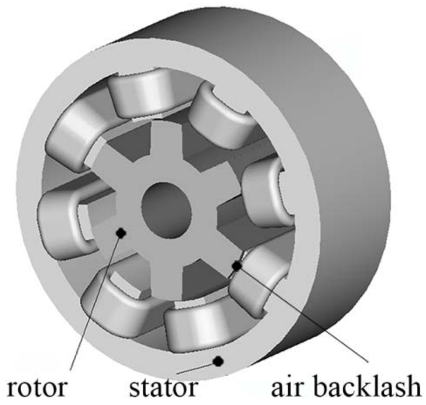

Fig. 1 Air backlash in SRM

In this paper the identification of the SRM as Volterra kernels of the 1st and 2nd orders is realized on a simulation model of the SRM. For the simulation of the SRM it uses a mathematical model as a system of nonlinear differential equations defining the implicit description of the SRM as "input-output" [10] at fixed rotor position:

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

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

Here $U_\phi(t)$ – voltage (input variable); $I_\phi(t)$ – current (measured SRM response); R_ϕ – resistance, Ψ_ϕ – flux linkage; Θ – rotation angle of the rotor relative to the stator.

Function of flux linkage from a current is illustrated on Fig.2.

Expressions (6, 7) are essentially nonlinear. This is determined by the principle of operation and the geometric features of the SRM. Expressions (6, 7) were received for the angle position of the rotor relative to the stator $\Theta = 30^0$ (Fig. 2) and for three air backlashes between the rotor and stator: nominal and increased on 30 % and 60 % from nominal.

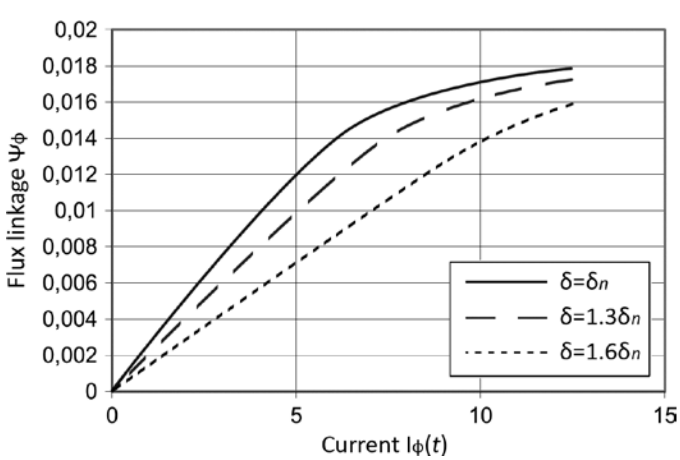

Fig. 2 Function of flux linkage ψ_ϕ from a current $I_\phi(t)$ for $\Theta = 30^0$ for a nominal value of air backlash $\delta=\delta_n$ and for a cases $\delta=1.3\delta_n$ and $\delta=1.6\delta_n$

Numerical calculation of expressions (6, 7) was realized on base of the field mathematical model [18] using the finite element method [19].

Using computer calculations of expressions (6, 7), we can find the inverse dependence of flux linkage from the current phase $I_\phi = F(\Psi_\phi, \Theta)$, approximate it by power–mode polynomial and get the model of the motor:

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

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

Block diagram of the simulation model is presented on Fig. 3.

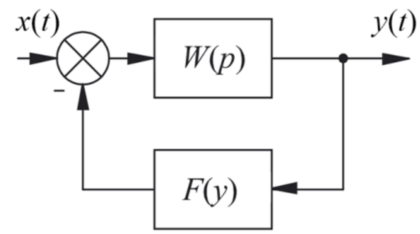

Fig. 3 Block diagram of the SRM simulation model.

Here

$$W(p) = \frac{1}{p+\alpha}, \ F(y) = \beta y^2, \quad (9)$$

where $\alpha = a_1 R_\phi$, $\beta = a_2 R_\phi$.

As a result of transformation we obtain the model of the motor in the form of ordinary nonlinear differential equation of the first order:

$$\frac{d\psi_\phi}{dt} + \alpha\psi_\phi + \beta\psi_\phi^2 = U_\phi. \quad (10)$$

From equation (10) we can obtain the analytical expressions for Volterra kernel of first order and diagonal sections for Volterra kernels of second orders [11]:

$$w_1(t) = e^{-\alpha t}, \ w_2(t,t) = \frac{\beta}{\alpha}(e^{-2\alpha t} - e^{-\alpha t}). \quad (11)$$

Based on of expressions (11) functions for Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t,t)$ are plotted (Fig. 4).

Expressions correspond to SRM with characteristics: rated torque – 0.05 Nm, rated voltage – 24 V, maximum speed – 4500 rpm at different values of air gap – 0.15 mm (nominal), 0.195 mm and, 0.24 mm, corresponding to cases $\delta=1.3\delta_n$ and $\delta=1.6\delta_n$.

Implementations of expressions (11) for different values of the air backlash and the corresponding values of the parameters α and β are then used in the formation of the test sets of diagnostic features.

Training samples are received for different states of SRM and are divided to 3 classes (100 items in each class) for air backlash $\delta \in [\delta_n, 1.3\delta_n]$ (normal mode – class **A**); $\delta \in (1.3\delta_n, 1.6\delta_n]$ (fault mode – class **B**) and $\delta > 1.6\delta_n$ (emergency mode – class **C**).

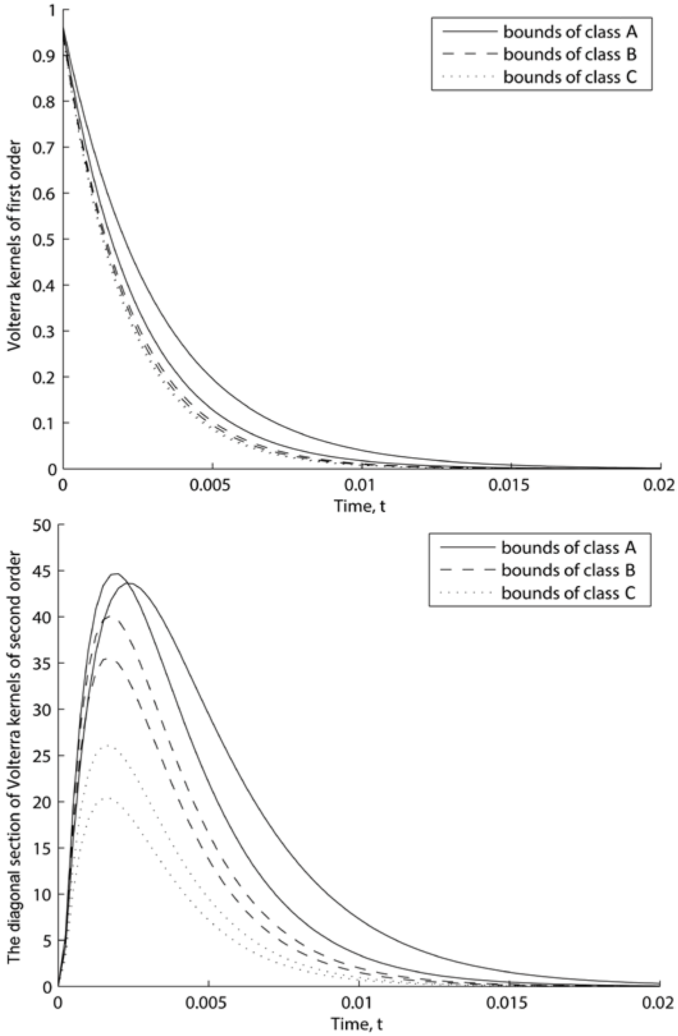

Fig. 4 Volterra kernels of first order $w_1(t)$ and the diagonal section of Volterra kernels of second order $w_2(t,t)$ for $\delta=\delta_n$, $\delta=1.3\delta_n$, $\delta=1.6\delta_n$

The deterministic approach for classification in this case is impossible, because obtained models for all classes forms the overlaying areas (Fig. 4). In this case, the methods of object's states recognition are used.

The effectiveness of recognition methods is largely dependent on diagnostic quality of used sets of features. If a selected features adequately characterize the internal structure of the diagnosing 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.

On base of training sets of data for an object's classes **A**, **B** and **C** there successively calculate two discriminant functions $d_1(\mathbf{x})$ and $d_2(\mathbf{x})$. The function $d_1(\mathbf{x})$ separates the objects of the first class **A** from the objects of second and third classes **B**U**C**; $d_2(\mathbf{x})$ – separates the objects of the second class **B** from the objects of third classes **C**. To separate two classes (dichotomy case) it uses discriminant function [15] of the form:

$$d(\mathbf{x}) = \frac{1}{2}\mathbf{x}'(\mathbf{S}_2^{-1} - \mathbf{S}_1^{-1})\mathbf{x} + (\mathbf{S}_1^{-1}\mathbf{m}_1 - \mathbf{S}_2^{-1}\mathbf{m}_2)'\mathbf{x} + \\ + \frac{1}{2}(\mathbf{m}_1'\mathbf{S}_1^{-1}\mathbf{m}_1 - \mathbf{m}_2'\mathbf{S}_2^{-1}\mathbf{m}_2 + \ln\frac{|\mathbf{S}_2|}{|\mathbf{S}_1|}) + \lambda_{\max}, \quad (12)$$

where $\mathbf{x}=(x_1,x_2,\dots,x_n)'$ – features combination, n – features space dimensionality, $\mathbf{S}_i=\mathrm{M}[(\mathbf{x}\text{-}\mathbf{m}_i)(\mathbf{x}\text{-}\mathbf{m}_i)']$ – 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 TRP for objects of training sample.

Analysis of a different features combination quality bases 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 constructed during learning process (12) [6].

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

$$\overline{P}_{\max} = \max_k \left\{ \frac{1}{m-1} \sum_{i=1}^{m-1} P_{ik} \right\}. \quad (13)$$

where m – classes images count, m=3; k – serial number of features combinations in exhaustive search procedure.

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

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

A. *Discrete values of Volterra kernels*

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

Diagnostic spaces form by selection of all features combination. Quality of a features combination estimates by solving the problem of statistical classification [15].

The best results of features sets selection among $\mathbf{V}_1$, $\mathbf{V}_2$ are shown in a tabular mode (Table I) and in a chart mode (Fig. 5).

Collection $\mathbf{V}_2$ gives the most informative description of objects from considered features sets.

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 $x_i = w_1(t_i)$, $i=\overline{1,4}$; for the set $\mathbf{V}_2$: $x_i = w_2(t_i,t_i)$, $i=\overline{1,4}$.

Table I: 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

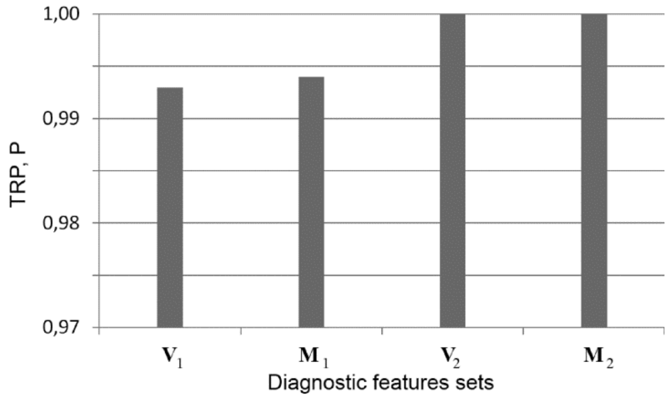

Fig. 5 Averaged values of TRP for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$

Mapping of all classes in the feature space of discrete values of Volterra kernels $\{x_1, x_2\}$ shown in Fig. 6.

B. *Volterra kernels moments*

The training sample creates on base of four Volterra kernels moments (5) of Volterra kernels of the 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 among , $\mathbf{M}_1$, $\mathbf{M}_2$ are shown in a tabular mode (Table I) and in a chart mode (Fig. 5).

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 $x_{r+1} = \mu_r^{(2)}$.

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

Mapping of all classes in the feature space of Volterra kernels moments $\{x_1, x_2\}$ shown in Fig. 7.

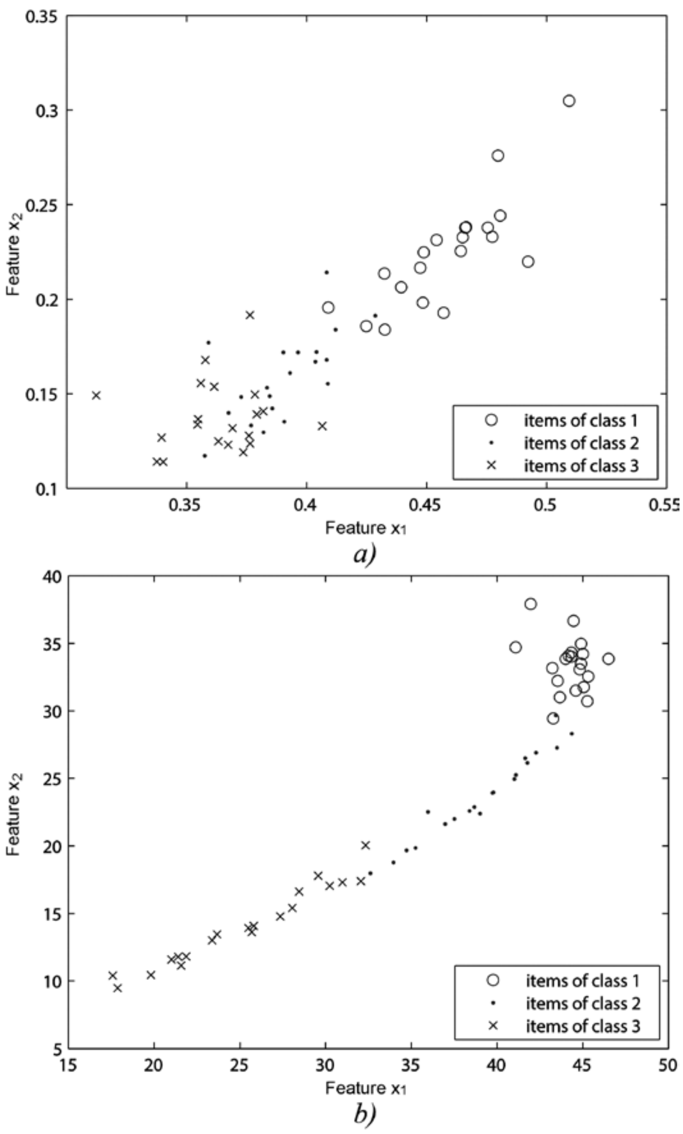

Fig. 6 Classes mapping in future space x_1 and x_2: *a*) features set $\mathbf{V}_1$; *b*) features set $\mathbf{V}_2$

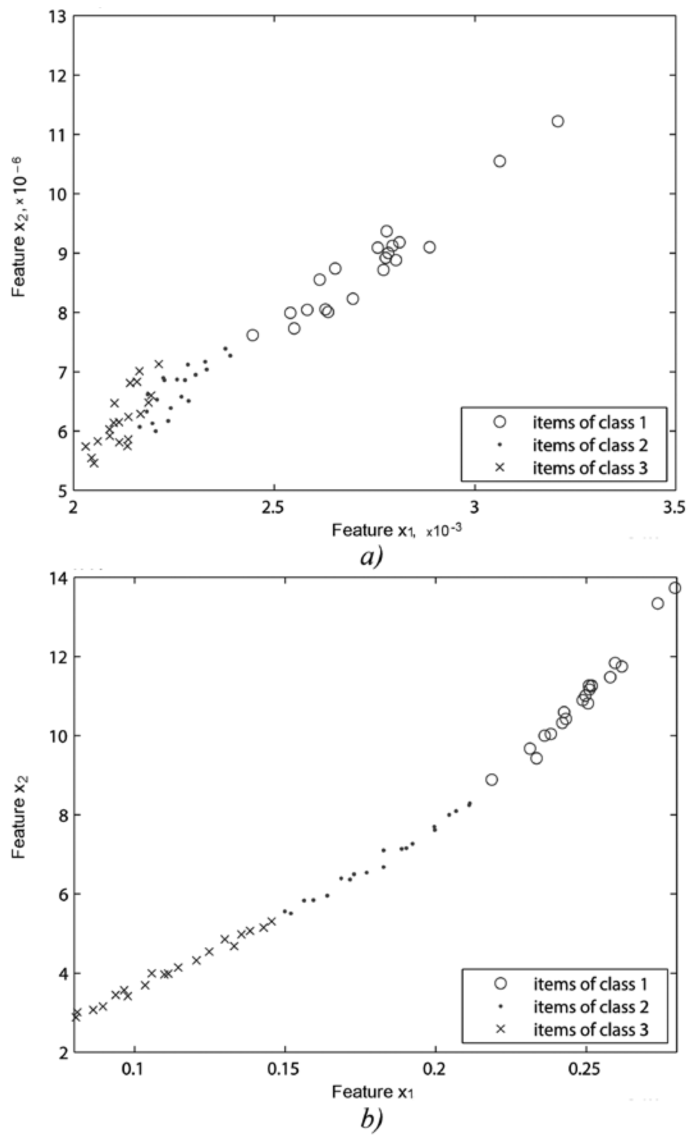

Fig. 7 Classes mapping in future space x_1 and x_2: *a*) features set $\mathbf{M}_1$; *b*) features set $\mathbf{M}_2$

V. STABILITY OF FEATURES SPACE VALUES TO ESTIMATION OF NOISY VOLTERRA KERNELS

It was analyzed a stability of value of features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$. The error in the estimates of Volterra kernels – is additive noise with zero expected value and variance depending of Volterra kernels extremum.

It was created 4 training sample based on noisy Volterra kernels of first order and diagonal sections of Volterra kernels of the second order with noise rate (Fig. 8) accordingly 1%, 3%, 5%, 10% of Volterra kernels extremum.

The best results of stability analysis are shown in Table II and Fig. 9.

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 a stability as on small as on big noise rates.

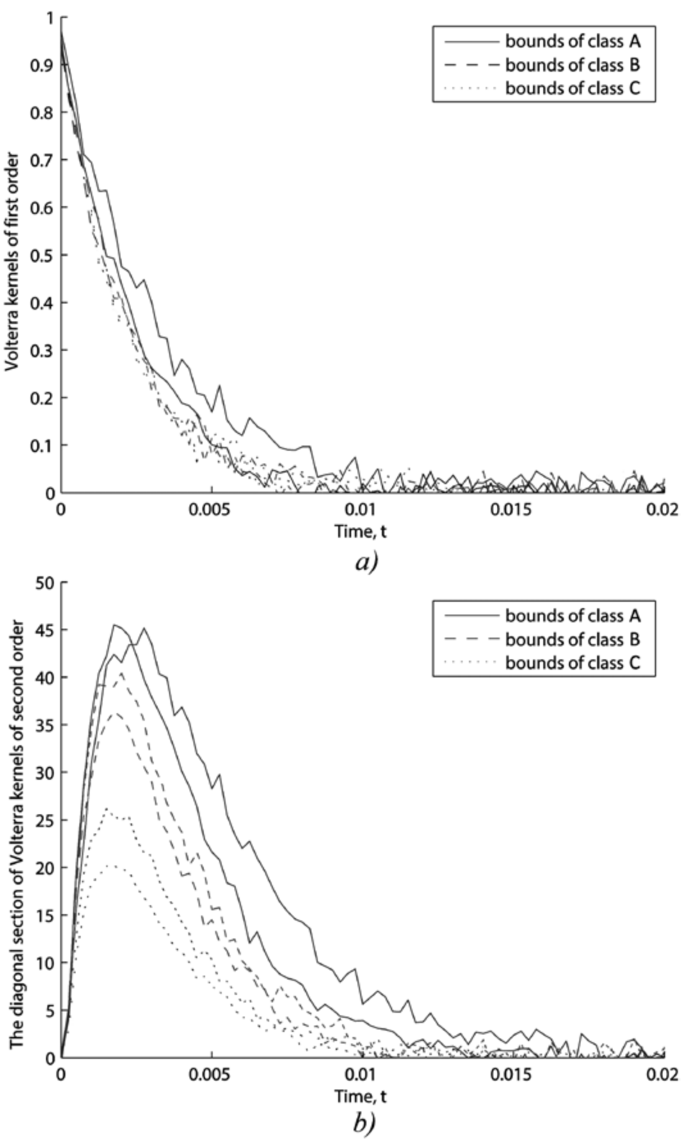

Fig. 8 *a*) Volterra kernels of first order $w_1(t)$, *b*) the diagonal section of Volterra kernels of second order $w_2(t,t)$ for $\delta=\delta_n$, $\delta=1.3\delta_n$, $\delta=1.6\delta_n$ at noise acting

Table II: 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

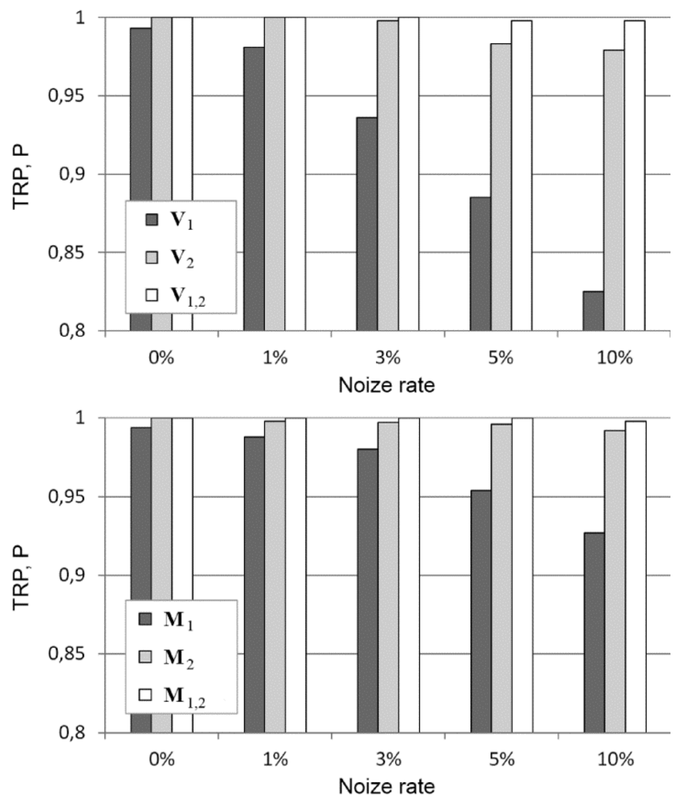

Fig. 9 Diagnostic quality for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{V}_{1,2}$, $\mathbf{M}_{1,2}$ under the influence of noise for Volterra kernels estimations

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.

For noise immunity solution in this case we consider a sets, combining a features based on discrete values of Volterra kernels of the first order ($\mathbf{V}_1$) and diagonal sections of Volterra kernels of the second order ($\mathbf{V}_2$) $\mathbf{V}_{1,2}=\mathbf{V}_1\text{U}\mathbf{V}_2$: $x_i= w_1(t_i)$, $x_{i+1} = w_2(t_i,t_i)$, $i=\overline{1,10}$.

Similarly we consider a features set, combining a features based on Volterra kernels moments of Volterra kernels of the first order ($\mathbf{M}_1$) and diagonal sections of Volterra kernels of the second order ($\mathbf{M}_2$) $\mathbf{M}_{1,2}=\mathbf{M}_1\text{U}\mathbf{M}_2$.

The best results of stability analysis for the features sets $\mathbf{V}_{1,2}$ and $\mathbf{M}_{1,2}$ also are shown in Table II and Fig. 9. The both features sets $\mathbf{V}_{1,2}$ and $\mathbf{M}_{1,2}$ have better noise immunity than features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$. The features set $\mathbf{M}_{1,2}$ have the better noise immunity over $\mathbf{V}_{1,2}$ on a high noise rates.

According to the data in Table II the functions of TRP deviation depending on noise rates (Fig. 10) are build. 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 II it is given a combination of features $\{x_1, x_2, x_{10}, x_{17}\}^*$ for the features set $\mathbf{V}_{1,2}$. At zero-noise rate it provides maximum diagnostic quality. But when the noise rate increases the diagnostic quality of the features combination is reduced considerably (Fig. 11).

VI. ROC ANALYSIS OF A CLASSIFIER SYSTEM

Classifiers built in different systems of features sets further investigated using the ROC-analysis.

ROC-curve show dependence of number of correctly classified true positives (*TP*) from the number of incorrectly classified false negatives (*FN*). So ROC-curve demonstrates the tradeoff between sensitivity *Se* and specificity *Sp*.

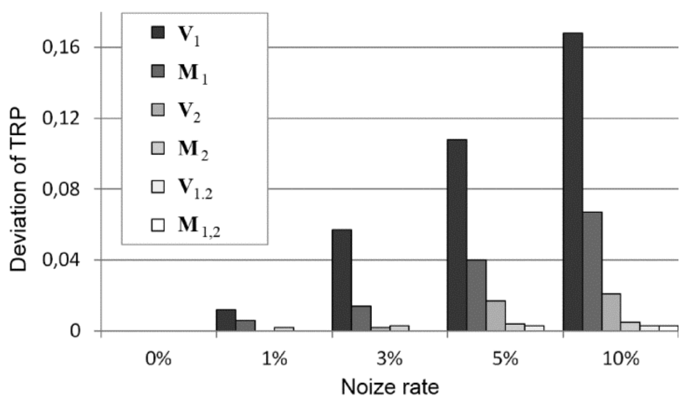

Fig. 10 TRP deviation for features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{V}_{1,2}$, $\mathbf{M}_{1,2}$ under the influence of noise for Volterra kernels estimations

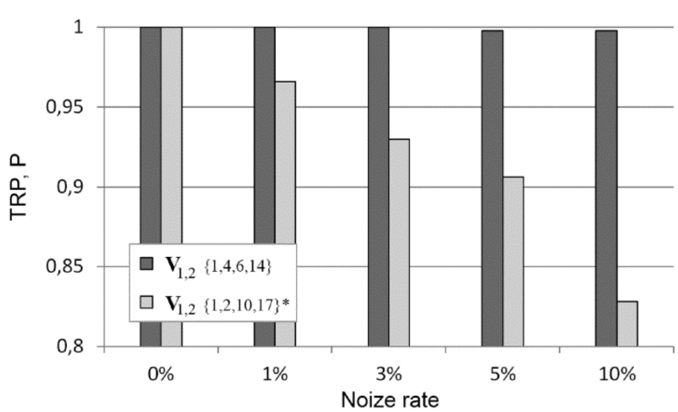

Fig. 11 Diagnostic quality for different combinations of features set $\mathbf{V}_{1,2}$ under the influence of noise

Sensitivity and specificity are determined by an expressions:

$$Se = \frac{TP}{TP + FN} \cdot 100\% , \tag{14}$$

$$Sp = \frac{TN}{TN + FP} \cdot 100\% , \tag{15}$$

where *TP* – number of true positives, *FN* – number of false negatives, *TN* – number of true negatives, *FP* – number of false positives.

The average ROC-curves for two discriminant functions $d_1(\mathbf{x})$ and $d_2(\mathbf{x})$ based on features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{V}_{1,2}$ and $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{M}_{1,2}$ are shown in Fig. 12. The curves are built for the case of acting a noise with rate 10% of Volterra kernels extremum.

The diagonal line corresponds to the “useless” classifier, i.e. the indistinguishability of two classes.

The Fig. 12 shows that the most effective classifiers are those that use diagnostic features sets based of Volterra kernels diagonal sections of second order. Classifier based on Volterra kernels moments provides the best quality of the recognition.

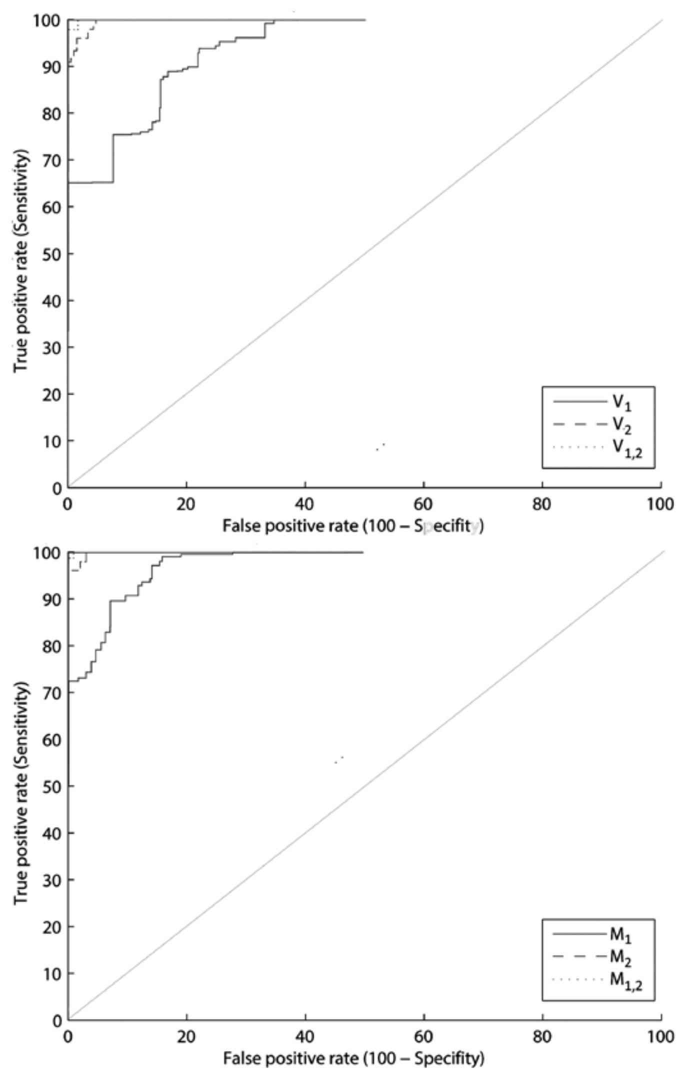

Fig. 12 ROC-curves for the classifier systems based on features sets $\mathbf{V}_1$, $\mathbf{V}_2$, $\mathbf{V}_{1,2}$ and $\mathbf{M}_1$, $\mathbf{M}_2$, $\mathbf{M}_{1,2}$

VII. CONCLUSION

In this work it is offered method of constructing an intelligent computing system for diagnostics of nonlinear dynamic objects. The method founds on using an integro–power Volterra series as object's models.

On the basis of these models the diagnostic features space constructs. There are discrete values of Volterra kernels of the first order and diagonal sections of Volterra kernels of the second orders as well as the 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 diagnostic value 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. This conclusion is also confirmed by the results ROC-analysis.

Each features set in the conditions of noise absence generally 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 considered informational technology for intelligent nonlinear dynamic objects diagnostics and nonparametric dynamic models based on integro–power Volterra series. The features set based on Volterra kernels moments is most preferred when constructing intelligent system for complex nonlinear dynamic objects diagnostics.

Suggested diagnostic technology allows to determine the deviation of process parameters in switched reluctance motor electromechanical transducer. It is possible to construct classifiers by motor parameters: air backlash, the rotor diameter, the stator diameter, the rotor and stator pole width, the length of the machine, the number of turns in a phase.

Also, using this technology it is possible to determine the degree of aging of electrical steel and copper.

Consequently, it is possible diagnosing during the acceptance and periodic tests. In this case, after the completion of classifier training on the stage of diagnosing the recognition process of the motor state is almost done in real time.

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