Methods for Black-Box Diagnostics using Volterra kernels

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Abstract. *The method of a black-box diagnostics, founded on nonparametric identification of objects using integro-power Volterra series is offered. It provides a set of diagnostic features formed on base of multidimensional Volterra kernels: discrete values of Volterra kernels, heuristic features, moments and wavelet transform coefficients. It is researched a self-descriptiveness of provided features using classifier on base of back propagation neural nets. The diagnostic spaces are formed by method of all features combination selection.*

Keywords

Black-box diagnostics, nonparametric identification,
Volterra series, Volterra kernels, self-descriptiveness.

Introduction

At present in technical diagnostics the direction, founded on reconstruction of the models of diagnosed object [2, 6, 13], is widely developed. It is usually expected that faults change only parameters of object's model. During diagnostics, parameters of model are valued by parametric identification methods. However often, for example, at production of electronic equipment, most defects change not only parameters of object's model, but also its structure. This fact condition on using of the nonparametric identifications methods for building of object's models on base of experimental data "input/output".

Diagnostics procedure is executed in two steps. On the first step it gets initial information about object condition in form of response signal on test influences. On the second step this information is processed for separation of diagnostic features and building of decision functions for classification. The methods to statistical classification [3, 10] or neural networks [11] are used for building of decision functions.

The existing methods of the model diagnostics, founded on using of dynamic features, are limited only by linear models. Methods, which take the effects of nonlinearity into account, use information about features of static characteristics only. The real objects, as a rule, simultaneously possess nonlinear and dynamic features. Formally, any nonlinear dynamic object can be described by Volterra series [2, 8].

In given work it is offered a method of the model diagnostics, founded on nonparametric identification of object using models in form of Volterra series. Using methods of the statistical classification It is researched a self-descriptiveness of diagnostic features, formed on base of such models.

Nonlinear nonparametric dynamic models

As an informative description of object it is offered to use nonlinear nonparametric dynamic models in form of Volterra series. The Volterra series from many functional arguments $x_1(t),...,x_n(t)$ are used for description of the nonlinear multidimensional systems:

$$y_j(t)=\sum_{n=1}^{\infty}\sum_{i_1=1}^{v}...\sum_{i_n=1}^{v}\int_0^t...\int_0^t w^j{}_{i_1 i_2 ... i_n}(\tau_1,\tau_2,...,\tau_n)\prod_{k=1}^{n}u_{i_k}(t-\tau_k)d\tau_k \quad (1)$$

where j=1,2,…,μ, $\boldsymbol{v}$ – an amount of inputs, μ – an amount outputs, $w^j_{i_1 i_2 ... i_n}(\tau_1,\tau_2,...,\tau_n)$ – multidimensional weight functions or Volterra kernels of n order on i_1, i_2,...,i_n inputs and j output, symmetrical relative to τ_1, τ_2,…,τ_n; $u(t)$ – an input influence, $y(t)$ – a response of the object under zero initial conditions.

The collection of multidimensional Volterra kernels completely is determined as nonlinear as dynamic characteristics, and consequently, condition of object. Using of models on base of Volterra series allows to take into account nonlinear and inertial characteristics of object in greater depth and more exactly. It makes the model diagnostics procedure more universal and raises reliability of the diagnosis.

The diagnostic procedure in this case is reduced to determination of Volterra kernels on base of "input/output" experiment data in time [2, 5, 12] or in frequency [2, 7] domain. On base of taken Volterra kernels a set of diagnostic features is formed. In space of these features an optimal classifier is built.

It is necessary to note that in model diagnostics adequacy of object’s models have to understand not as an accuracy of the object’s response description, but as a self-descriptiveness of this model for reliable recognition of object’s condition. So, using Volterra kernels for building models for nonlinear dynamic objects it necessary to provide a high accuracy of estimation of sections of multidimensional Volterra kernels of small orders. In practice this is often quite enough for building of efficient classifier.

High accuracy of Volterra kernels estimation is reached by using of antinoise determinate identification methods, offered in work [7].

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 $F(H,S)$, linking object’s condition S with Volterra kernels $H=\{h_n(\tau_1,\ldots,\tau_n)\}^N_{n=1}$.

2. Function F(H,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(H,S) [3, 10].

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 (if a high-reliable equipment, for instance, integral microcircuits is diagnosed).

Forming of features space and data compression

Accuracy of object’s condition recognition is depended from the selected diagnostic features very much.

Mathematically the problem of the diagnostic features selection is formulated as follows. Let the source p-dimensional features space **X** is given. It is necessary to find the transformed space **Y**, elements of which are q-dimensional vectors and $q<p$. Formally, this problem is concluded in construction of transformation $\mathbf{A}: \mathbf{X} \to \mathbf{Y}$, which associates required feature space with source one. Decision of this problem can be reached by two ways.

The first of them is founded on comparison of different features collections for estimation of their effectiveness at recognition process. In this work, effectiveness of selected features collection is estimated by results of classification of test set of objects using decision functions, taken by one of training algorithm. Features collections, which probability of correct recognition is small, are rejected. A features collection, for which adding of any new feature doesn’t enlarge or enlarge a little a self-descriptiveness of all collection is selected as diagnostic features space. If features are statistical independent, than a diagnostic features space can be formed by estimation of self-descriptiveness of each feature and by exclusion of some features, which self-descriptiveness is not enough. At such procedure of diagnostic features space forming the self-descriptiveness values of features aren't changed. It only decreases their number.

The other way for decision a problem of the diagnostic information compression at classification of object's conditions is concluded in building of transformation of measurements vector from source space to space of smaller dimension [3, 10]. The classification procedure of object's conditions in new features space will be simpler, because a volume of processed diagnostic information decreases. The reduction of the features space dimension allows to use more complex nonlinear decision functions which increase a quality of recognition. However, unlike described above method of diagnostic features selection, this method doesn't provide the reduction of measurements amount. In this case new features don't have a physical sense, but have only abstract informational one.

Discrete values of Volterra kernels and object's responses. Description of object can be taken as a finite set of discrete values $\mathbf{x}=(x_1,x_2,...,x_p)$ of sections of multidimensional Volterra kernels or frequency characteristics of object: $x_k=y(t_k)$, where $t_k=k\Delta t$, $k=1,2,\ldots,p$.

The heuristic features. In many cases it is possible to form some heuristic features, which can enter as components in features vector. As such heuristic features in work it is proposed:

1. Extremum of the absolute value of section of n dimensional Volterra kernels;

$$\max_{t\in[0,\infty)}\left|w_n(t-T_1,t-T_2,\ldots,t-T_{n-1},t)\right| \tag{2}$$

2. Point of extremum t_{max};

3. Function derivation at the point t_{tp};

$$\frac{dw_n(t-T_1,t-T_2,\ldots,t-T_{n-1},t)}{dt} \text{ at } t=0 \tag{3}$$

4. Integral of the function's absolute value;

$$\int_0^\infty |\,w_n(t-T_1,t-T_2,\ldots,t-T_{n-1},t)\,|\,dt \tag{4}$$

5. The time of a transient process t_{tp}.

Here $T_1,T_2,...,T_{n-1}$ define diagonal section of n-dimensional Volterra kernels ($T_1\geq T_2,\geq...\geq T_{n-1}$). Using of such heuristic features often allows to reduce the dimension of a source features vector a lot.

The moments of Volterra kernels. More universal approach to forming the diagnostic features vector consists in use of so-called moments of object's Volterra kernels. This moments are calculated by the formula:

$$\mu_{ij..k}^n=\int_0^\infty\!\!\ldots\!\int_0^\infty \tau_1^i\tau_2^j\ldots\tau_n^k w_n(\tau_1,\tau_2,\ldots,\tau_n)d\tau_1 d\tau_2\ldots d\tau_n \tag{5}$$

here $i,j,...,k = 0,1,\ldots,\infty$, $i+j+...+k= r$ – an order of the moment.

In this work the moments of the Volterra kernels sections are considered:

$$\mu_r^n=\int_0^\infty t^r w_n(t-T_1,t-T_2,...,t-T_{n-1},t)dt \tag{6}$$

Wavelet transform of Volterra kernels. The Method of compression of diagnostic information on base of wavelet transform [1] presents a big interest too. Wavelet processing of signal provides the efficient compression with small losses of information, so raising self-descriptiveness of each discrete value to function.

Direct continuous wavelet transform of the function $w_n(t-T_1,t-T_2,...,t-T_{n-1},t)$ is determinated by calculation of wavelet coefficients by the formula:

$$C(a,b)=\int_0^\infty w_n(t-T_1,t-T_2,...,t-T_{n-1},t)a^{-1/2}\psi(\frac{t-b}{a})dt \tag{7}$$