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NEURAL NETS METHOD OF COMPUTER SYSTEMS DIAGNOSIS

Method of computer systems diagnosis using of the union of neural nets experts is presented in article. The union of experts is construction on the basis of neural networks architectures: networks ART2, Kohonen Self-Organizing Map, Three-Layer Perseptron.

artificial neural network, neural nets expert, diagnosis, computer system, self-organizing map, adaptive resonance theory, production rules

Introduction

Computer systems (KS) are complex microprocessor systems which are constantly modernized and improved. According to dynamics of development and expansion of KS application spheres, requirements to reliability of their functioning increase. It does actual a problem of development and introduction of more effective means of the KS control and diagnosis, especially at a stage of their operation [1].

Modern KS have a number of features which lead to backlog of dynamics of diagnosis means development and reduction of diagnosis process efficiency:

– absence or extremely high cost of specialized diagnostic programs and KS diagnosis hardware. Firms-manufacturers do not give them free of charge complete with hardware;

– dynamics of KS opportunities escalating leads to growth of a spectrum of hardware components and their continuous modernization. It does unprofitable purchase of highly tailored diagnostic equipment;

– operation phase KS is insufficiently provided by the documentation. At the same time at this stage it is necessary to provide diagnosis of extremely wide spectrum KS. Therefore success of an operation phase actually completely depends on a skill level of experts which maintain and serve computers.

The most widespread KS diagnosis methods are methods which are based on comparison real the test-vectors with reference, on use of two-place logic models, and as the statistical and determined methods [2, 3]. Construction of KS diagnosis means on the basis of the specified methods probably only under condition of presence of full mathematical, functional or other models. They are absent for modern KS at an operation stage.

The perspective direction of improvement of technical diagnosis means is using of an artificial intellect components by them, in particular, production rules, fuzzy logic, artificial neural networks (ANN) [4-8].

Basic advantages ANN are following opportunities:

– reception with their help of the information in cases when the researcher cannot specify functional dependences between parameters which characterize diagnosing object (DO);

– processing values of entrance vectors which was not in training sequence;

– acceleration of calculations at the expense them parallelization [9].

A number of industrial monitoring and diagnosis systems, which use ANN, are developed for such areas, as: medical diagnostics, power systems, a robotics, systems of the information defense, etc. [10-12].

In technical diagnosis ANN (there are Multi-layer perseptrons more often) are usual used for identification of faults and realized in the form of separate components of diagnosis means [13, 14]. The ANN input information are knowledge of structure and behaviors of diagnosis objects. Thus the leading part is played with behavioral aspects of structural or functional components of DO.

Modern KS diagnosis means which use intellectual components, do not provide a sufficient level of universality even at the decision of separate highly specialized diagnostic problems, therefore questions of their development and improvement are actual and require the further researches.

Formulation of a problem. For today KS operation phase actually is not provided by diagnosis hardware, therefore the dominating role playing software. Their primary goals are the estimation of a current condition of separate hardware components and informing a user about it [15]. Modern diagnostic utilities and programs of monitoring only fix separate KS parameters and characteristics and inform the user on their deviations. The user should lead independently an estimation of general condition KS, criticalities of the revealed deviations and their consequences.

In order to be fixed, deviations of characteristics should to exceed admissible limits which it is frequent are different for the same hardware making different manufacturers [16]. Presence of deviations of characteristics values which do not leave for admissible limits actually is not fixed and not traced.

Today actually it was not investigated questions: are complex regular insignificant deviations of parameters and characteristics values of KS hardware components possible to signal about occurrence of faults in current time or problems in the future? Modern diagnosis systems have no means of a complex estimation of current condition KS and its forecasting.

The research problem is development of intellectual diagnosis methods which would enable to lead complex estimation KS at a stage of it operation with the further specification of a hardware condition (or at need software) and to carry out forecasting condition KS.

Absence of full models KS complicates a task in view. For decision of this problem is necessary to develop neural networks which compensate absent parameters and characteristics values.

The decision of a task in view will enable to raise reliability of KS diagnosis and reliability of their functioning at an operation phase.

Decision of the problem

Information model and method of KS condition identification. By development of diagnosis means the high level of complexity modern KS limits use of modeling methods which are based only on consecutive decomposition KS by components and construction of their models. There are a number of qualitatively new properties arise at association of hardware and software components in computer system. They cannot be revealed by the analysis of separate components properties of such systems.

Construction of information models on the basis of the experiments data or supervision over real computer systems is one of the variants decision this problem. Thus structure KS practically is not displayed in information models. Means of monitoring and knowledge of experts-diagnosticians start to play a vital part. They are the basic source of the information about KS parameters and characteristics [17].

For diagnosis is necessary to lead identification of KS condition. As parameters-attributes which characterize condition KS, we shall consider: the information which characterizes hardware components - a source voltage, the processor frequency and temperature, the size of main memory, frequency of the system bas, SMART characteristics of hard disks, of coolers rotation frequencies, etc. If it need we shall consider also parameters of operational system and the applied software. A set of values of the specified parameters we shall name *the information description* of KS condition and we shall present in the form of a vector $x(\omega)=\left|x_i(\omega)\right|_{i=1}^{n}$, where $\omega\in\Omega$ – some certain KS condition from set of all conditions.

The material for formation of the information description vectors is the information collected from different sources:

– during monitoring KS at an operation phase;

– during testing KS by firms - manufacturers;

– the data collected by the user at testing KS in different operating modes at different loadings;

– the data received on the basis of modification in information vectors who characterize ideal condition KS;

– expert data on the basis of whom descriptions of failure conditions KS are formed.

This information characterizes a condition of separate components and computer system as a whole and is kept in knowledge bases of intellectual diagnosis means. Completeness of the information description depends on quantity of elements of a vector $x(\omega)$.

The problem of conditions KS identification consists in definition of classifying functions $R(\omega)$ or characteristic functions $R_k(\omega)$ of classes to which these conditions belong. As the information for definition of these functions we shall present the collected information in the form of sample values which characterize conditions KS:

$$\{x(\omega_h),\ R(\omega_h)\}_{h=1}^{m}\ , \qquad (1)$$

where $x(\omega_h)$ – a vector of parameters-attributes of condition KS; $\mathrm{R}(\omega_\mathrm{h})$ – characteristic function which identifies condition KS.

If need we can used detailing characteristics of conditions: $z(\omega)=|z_j(\omega)|_{j=1}^{q}$. They enable to concretize condition KS, for example, to specify types of faults of its components.

Let's consider in this case, that for identification of condition KS on the basis of the information description of a condition and detailing characteristics of this condition $\{|x_i(\omega)|_{i=1}^{n}, |z_j(\omega)|_{j=1}^{q}\}$ is necessary to define a class to which the condition Ω_k belongs. Result of diagnosis will be characteristic function of a class to which condition KS belongs. Unknown values we shall define $R(\omega)$ similarly (1) with inclusion of the information on value of set $z(\omega)$ elements:

$$\{x(\omega_h),\ R(\omega_h),\ z(\omega_h)\}_{h=1}^{m}. \qquad (2)$$

For reference of condition KS to corresponding class we shall somehow choose K kernels of classes $\{c_k\}$, $k=1,...,K$. We shall define kernels of classes $\{c\}=c(\omega_1),...,c(\omega_k)$ in space Ω_k, as conditions (information descriptions) which are typical for the class: $c(\omega)=|c_i(\omega)|_{i=1}^{n}$.

Affinity of a condition to a kernel we shall estimate numerically, namely we shall enter a measure of affinity $d(x(\omega_i),c(\omega_i))$ which that smaller, than is more object (the current information description) is similar to a kernel of a class (the typical information description). As a measure of affinity is used the Euclidean distance:

$$d(x,c)=\sum_{i=1}^{n}(x_i-c_i)^2\,. \qquad (3)$$

At constant partitioning we shall construct function $R(\omega)$ so that to minimize a total measure of affinity for all set $x(\omega_h)$:

$$\min\{D=\sum_{h}\ \sum_{i}(x_i(\omega_h)-c_i(R(\omega_h)))^2\}\,, \qquad (4)$$

$h=1,...,m,\ i=1,...,n$.

The problem of search of a minimum D is equivalent to search of a maximum of expression:

$$\min D=\max\sum_{h}\sum_{i}x_i(\omega_h)c_i(R(\omega_h))\,. \qquad (5)$$

Having received function $R(\omega)$, we have an opportunity to each following information description $x(\omega)=|x_i(\omega)|_{i=1}^{n}$ to set up a correspondence condition KS from all set of conditions and if necessary to lead specification of a condition.

Dynamics of condition changing during some period of time $T=\{t_i\},\ i=1,...,l$ is a basis for forecasting condition KS in the future.

Union of the neural networks expert. The artificial neural networks are used for realization of KS diagnosis process on the basis of information model and for realization of method of identification KS condition. We shall involve the SOM and the network of ART2 architecture for an initial estimation of condition KS [18, 19].

Using of SOM is caused by its property of maintenance of local character of training within the limits of everyone cluster and accordingly absence of effect of uniform distribution of a mistake of training between clusters (unlike multi-layer networks with return distribution of a mistake). The essential role at a choice of this architecture is played also with an opportunity of visualization of a conditions KS trajectory on a map.

Using of network ART2 enables to lead clustering of known conditions, to organize detection of not described before conditions and the further self-training of KS diagnosis means.

Both networks are trained without the teacher that does not limit their opportunity on revealing of conditions KS unknown before.

The estimation of clustering accuracy is carried out with using of such means, as Hinton diagram which represents the diagram of training mistakes by clustering. A mistake of data in everyone cluster (a degree of ill-posedness) is proportional to the size of a corresponding square. At this stage we can carry out identification of condition KS only in areas with a "small" degree of ill-posedness. If the condition comes across in area with the "big" degree of ill-posedness it will be necessary to lead the further refined of a condition.

For this purpose, the further decision on generation of set three-layer perseptrons and production procedures makes depending on quantity received clusters, quality of training (quantity of "big" squares on Hinton diagram) and estimations of volumes of the available in the knowledge base information about separate components KS. The choice of means depends on that what type of information in the knowledge base are more. If there is a sufficient volume of the expert information on a condition of a separate component we will form system production rules which enable to lead a logic conclusion and to specify a condition of a component. If for an estimation of a condition there is enough of monitoring data then generated and trained three-layer perseptron for this component.

On the basis of chosen ANN architecture and their roles at recognition of condition KS we shall generate the hierarchical integrated construction and we shall name its union of the neural networks experts for identification of KS condition.

At realization neuralnets information models KS is necessary to pay attention of minimization of training mistakes and mistakes of ANN generalization and to lead an estimation of ill-posedness of a problem.

The task is correct, if it has a unique decision at all admissible input data and this decision stability against changes (small) input data. The task of identification of KS condition is partially (conditionally) correct. Uniform and stable solution for it we can receive only for some subsets of input values set on the basis of the expert information and data of monitoring (the list of all possible malfunctions KS does not exist). The differential estimation of conditional correctness areas for the combined task is given with Hinton diagram.

Method for formation of union of the neural networks experts. The method consists in the following. We collect from specified above sources the information which describes KS and its components. On the basis of this information we build information model KS, namely we form sets $\{x(\omega_h)\}$, $\{z(\omega_h)\}$, $\{R(\omega_h)\}$. We spend normalization elements of sets.

We generate corresponding SOM and training it. We shall present the output layer of SOM in the form of a bidimentional grid which units are conditions KS. Quantity of units is $v \geq K$. We shall carry out designing input vectors on a bidimentional grid. Network weight w_{ij} we shall consider as components of classes $\{c_k\}$ kernels. At a train level SOM builds display of set of current information descriptions KS in a map of conditions of system $\{|\,x(\omega_h)\,|_{h=1}^{m}\} \to R_k(\omega)$. Among educational vectors necessarily there should be a vector which displays "ideal" condition KS. Each output neuron with quantity of inputs equal to quantity of an input vector elements, gives one of values D on an output. The output neuron which has the maximal value will define a class to which the entrance information description of a condition belongs: $\max D(x(\omega)) = R_k(\omega)$.

We generate and training network ART2. Network ART2 realizes clustering algorithm, which similar to algorithm "the consecutive leader". According to this algorithm the first input vector $x(\omega_h)$ is considered the sample of the first cluster. The following input vector is compared to the sample of the first cluster. The input vector will belong to the first cluster if the distance between it and the sample of the first cluster will be fewer thresholds specified by the developer. Otherwise, for the second entrance signal it will be created separate cluster. This process repeats for all following input vectors. Thus, the number of clusters grows in due course and depends both on value of a threshold, and from the metrics of distance which is used for comparison of input vectors and samples of classes. At successful recognition of an input vector updating of the sample by performance of operation AND is carried out. As a result the new sample is the sample on the previous step plus an input vector. It enables a network to adapt to minor alterations in input vectors. Restrictions on quantity neurons in a output layer are defined only by opportunities of used equipment and desire of developers. The special parameter of the control (vigilance) allows to adjust accuracy of input vectors concurrence of the information description of condition KS.

We spend clustering conditions KS with using of test sample. If it need we coordinate the results of clustering conditions of both neural networks. If results essentially differ, is necessary to adjust quantity of output neurals in SOM and control parameter of the network ART2.

We estimate quality of training and quality of generalization both ANN with using of Hinton diagram. Under condition of enough of educational data in the knowledge base for "big" squares of the diagram we shall generate set three-layer perseptrons and we shall lead their training. Otherwise we shall generate production rules and on their basis we shall create production procedures for realization of a logic conclusion about condition KS. As a result we shall receive the union of neural networks experts for identification of condition KS.

The blocks diagram of the union of neural networks experts is presented on fig. 1.

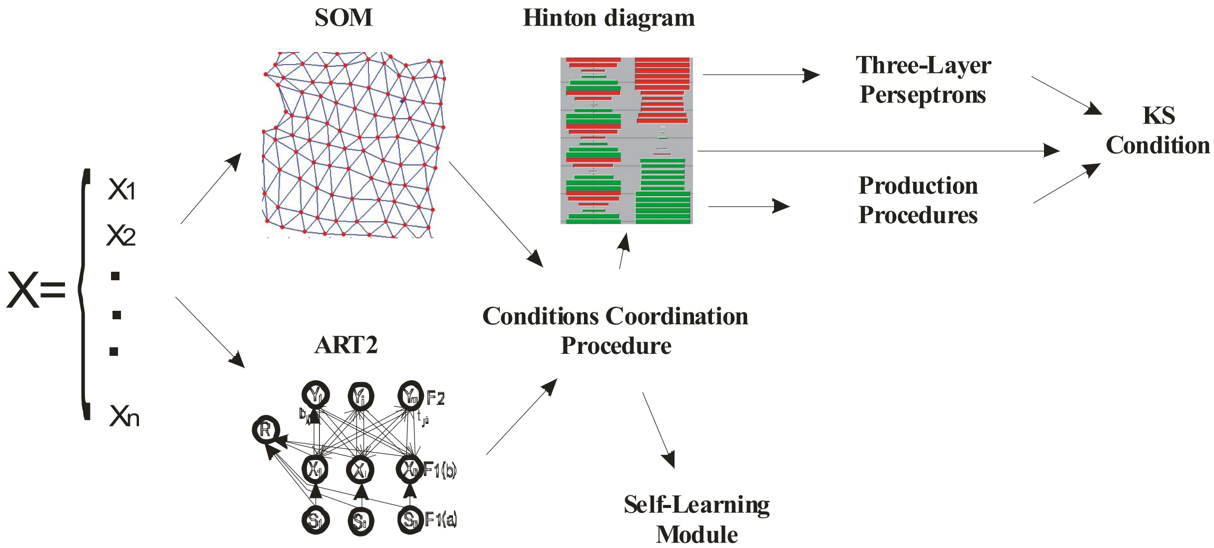

Fig. 1. Method for identification of condition KS using of the union of neural networks experts

KS diagnosis using of the union of neural networks experts. Diagnosing KS by using of the union of neural networks experts as follows:

– identification of condition KS is carried out in parallel with use of SOM and networks ART2:

– $\{|x_i(\omega)|_{i=1}^{n}\} \to R_k(\omega)$ or

$$\{|x_i(\omega)|_{i=1}^{n}, |z_j(\omega)|_{j=1}^{q}\} \to R_k(\omega);$$

– we coordinate results of identification of condition KS and we make a decision on need of specification of a condition. If network ART2 reveals a new condition we will bring the information about it in the self-training module;

– if an active output of networks is condition KS from area with a "small" degree of ill-posedness then it is considered identified. If an active output is the condition from area with the "big" degree of an ill-posedness then is necessary to lead its specification with use of the corresponding expert – perseptron or production procedures;

– at presence of set of conditions consecutive identification results is necessary to display them on SOM and to carry out forecasting condition KS.

Conclusions

The offered approach enables to raise reliability of KS diagnosis due to use of the union neural networks experts for identification and the subsequent specification of conditions KS and its components. Universality of a method of formation of the union of neural networks experts is defined only contained and quality of the information about KS in knowledge bases of intellectual means of diagnosis. Reliability of functioning KS increases due to a possibility of forecasting of its conditions with use of SOM and sets of the previous results of conditions identification.

The offered models and methods are a basis for creation of intellectual KS diagnosis means.

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