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ANALYSIS OF PERFORMANCE OF COMPUTING DEVICES WITH ART *K*-VALUED NEURAL NETWORK

In this article, the using of the K-valued neural network of adaptive resonance theory for classification K-valued output signals of logic elements and devices of computer engineering is considered. This allows automating processes of identifying situations that may cause fails in digital devices.

Keywords: performance of computing devices, ART K-valued neural network, classification of K-valued signals, digital devices' fails.

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АНАЛИЗ ПРОИЗВОДИТЕЛЬНОСТИ ВЫЧИСЛИТЕЛЬНЫХ УСТРОЙСТВ С ИСПОЛЬЗОВАНИЕМ *К*-ЗНАЧНОЙ НЕЙРОННОЙ СЕТИ АРТ

В статье рассматривается использование К-значной нейронной сети адаптивной резонансной теории для классификации К-значных выходных сигналов логических элементов и устройств вычислительной техники. Это позволяет автоматизировать процессы идентификации ситуаций, которые могут привести к сбоям в цифровых устройствах.

Ключевые слова: работоспособность вычислительных устройств, К-значная нейронная сеть АРТ, классификация К-значных сигналов, сбои в цифровых устройствах.

The problem statement and analysis of related works. Presently, it's impossible to analyze capacity of the designed devices without application of the different design system. These are well-known systems of Boole functional design ORCAD [1] and PCAD [2], systems of analog design MICROCAP [3]. However, most of the binary design systems do not allow to get the complete picture of complicate modern fast-operating microcircuits with the high integration degree switching character, and the analog systems do not allow analyzing difficult devices. In this connection, it is suggested in [4] to use a computer-aided design based on *K*-value differential calculation, which allows more complete, in comparison with binary design, to present the processes of Boole signals' switching and simulate difficult enough computing devices. However, the practical usage of this design system requires the information, which of the obtained switching processes are of fail risks and which ones are the correct switching from one stable state to other one.

Regarding this, the example of development of programmatic realization of a neuron network which was used for determinating types of switching signals in logical elements on the basis of thirteen-digit alphabet of Fantozi [6] was considered in the article [5]. A two-layer neuron network on the basis of *K*-value neurons, trained on the basis of Hebb's rule for *K*-value neurons, was used. In practice, however, data which is used for training or self-training a network are often incomplete. For example, if we consider an image, which refers to a new class, and it is to be recognized, the ordinary two-layer neuron network fails to do this task [7, 8, 9]. The Hebb's neuron network can't identify new images, and also doesn't have an ability to resume the training process, because of the new image training results in distortion of the already memorized information. That's why, for correct training, all the memorized information must be used. Thus, two-layer or multi-layered networks using the Hebb's algorithm for training or method of error back-propagation don't have the stability property, i. e. the property of saving the known information by memorizing the new information.

The networks of adaptive resonance theory (ART) were developed for solution of this problem. Namely, this is about memorizing of new classes of images by a neuron network without distortion or loss of the already stored information [10]. In this case, it is suggested to use ART neuron networks for correct switching and switching, which contains the information about the fail risks during transition of logical signals from one stable state to other one.

At the input image of signal, the network of ART-1 tries to associate it with some class from a number already available. In particular, it can be one of types of switching of output logical element from one stable state to other one. If the class of switching is found successfully, classification of signal is accomplished. Thus a signal can be referred either to the class of the correct switching or to the class of signals, which are of the fail risks. If the corresponding class was not found, a new class is created. After that the created signal is used as a prototype (typical representative) for a new class. Here, the known classes do not change.

The article goal is development of *K*-value neuron network on the basis of adaptive resonance theory for classification of signals, which occur while digital computing devices are designed in the design system based on *K*-value differential calculation.

The main chapter. Let's consider an ART *K*-value neuron network which classifies thirteen types of signals in the *K*-value type by using the seven-digit alphabet. The input data are obtained from design system based on *K*-value differential calculation. The thirteen typical signals which are obtained from this system are shown in the Fig. 1.

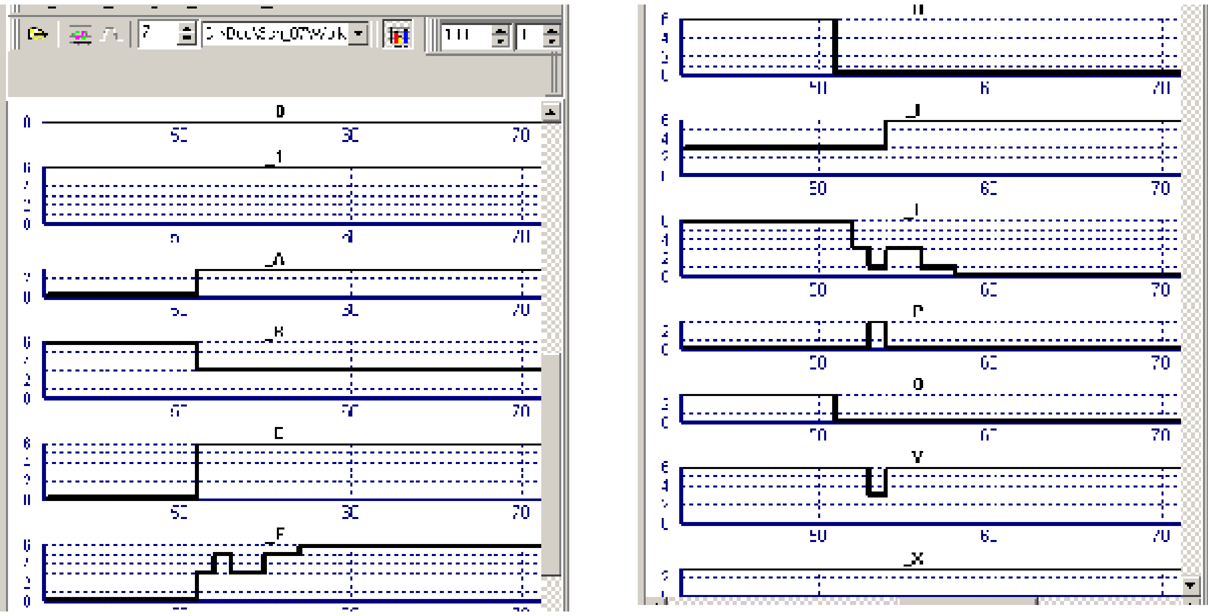

Fig. 1. Thirteen types of signals in the *K*-value type by using the seven-digit alphabet, obtained in the system on the basis of *K*-value differential calculation

According to using the seven-digit alphabet, the following thirteen types of signals are used [5]: the first from the top signal "_0" corresponds to the static binary signal of zero level, next signal "_1" is the value $K-1$, relating to the value of level of static binary "unit", next signal "_A" corresponds to the transition from zero to the indeterminate state $(K-1)/2$, signal "_B" corresponds to the transition from $K-1$ to the indeterminate state $(K-1)/2$, "_E" corresponds to the transition from zero to $K-1$, "_F" corresponds to dynamic fail risk during the transition from zero to $K-1$, "_H" corresponds to the normal transient process from $K-1$ to zero, "_I" corresponds to the transition from the indeterminate state $(K-1)/2$ to $K-1$, "_L" corresponds to dynamic fail risk during the transition from $K-1$ to zero, "_P" corresponds to static fail risk in the zero, "_O" corresponds to the transition from the indeterminate state $(K-1)/2$ to zero, "_V" corresponds to static fail risk in $K-1$, signal "_X" corresponds to the value of indeterminate state $(K-1)/2$ at binary presentation of signals. These signals must be stored in memory of *K*-value neuron network ART-1K whose architecture is shown in Fig. 2.

Architecture of the network consists of three groups of neurons: field F_1 of input processing neurons, which, in its turn, consists of two layers *S*- and *Z*-elements; layer of recognition *Y*-neurons and control neurons R, G_1, G_2 (Fig. 2).

Field F_1 of input processing neurons consists of two layers – the input layer of *S*-elements and the interface layer of *Z*-elements. The input layer perceives the image and passes the obtained information to the neurons of the interface *Z*-layer and the controlling neurons R, G_1, G_2. Every element Z_i (i = 1, …, n) in the interface layer relates to every element Y_j (j = 1, …, m) of the recognizing layer Y by two types of the weighted connections. Signals from the peripheral layer are passed to the layer Y by bottom-to-top connections with weights W_{ij}^1, and from the recognizing layer to the interface – by connections with weights W_{ji}^2, (j = 1, …, m, i = 1, …, n). Because of great number of connections only one pair of connections with weights W_{ij}^1, W_{ji}^2 between the interface and recognizing layers of elements is shown in Fig. 2.

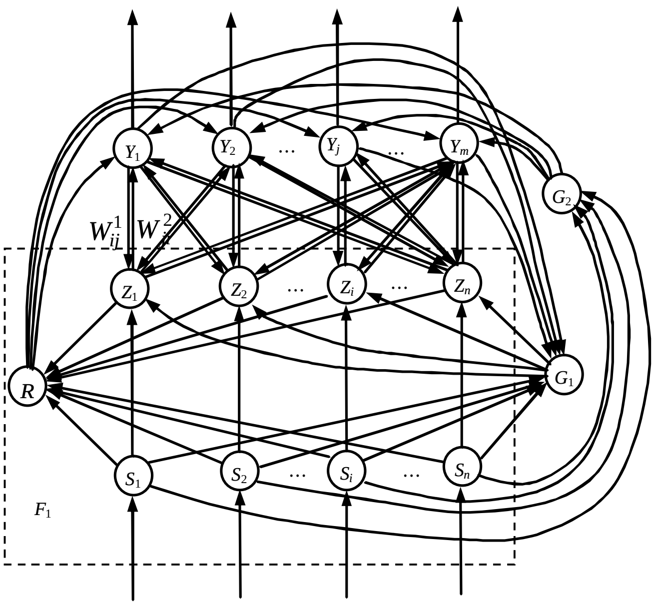

Fig. 2. Architecture of neuron network ART-1K

Layer Y is the layer of competitive or competing neurons. At any moment every element Y_j (j = 1, ..., m) of the recognizing layer is in one of three states:

- active (output signal $U_{\mathrm{out}Y_j}$ of neuron Y_j is equal to d: $U_{\mathrm{out}Y_j} = d$; $d = 6$ for ART-1K, at value of source alphabet $K = 7$;
- inactive ($U_{\mathrm{out}Y_j} = 0$, but a neuron can participate in the competition);
- inhibited ($U_{\mathrm{out}Y_j} = -1$ and a neuron is not allowed to competitions).

After producing of input image, one recognizing neuron is active only, all other ***Y***-elements have zero or subzero output signals. In the training mode, the selected recognizing neuron is allowable to be trained by the input image only in the case, when its weighting connection vector from the layer ***Y*** to ***Z*** is similar to the input vector. This solution is made with help of ***R***-neuron and a special parameter, which is named as parameter of similarity, and signals, which are transferred from the input and interface layers of elements. The selected recognizing ***Y***-element is either trained or inhibited (reset) with further excluding it from the set of the competing ones. The inhibition is performed in the case, when there are repeats of the same input image, and if new candidates to training are selected from ***Y***-layer.

Most connections, which are shown in Fig. 2, are excitant: from the input layer of ***S***-elements to the neurons R, G_1, G_2 and ***Z***-layer, from neurons G_1, G_2 to neurons of layers ***Z*** and ***Y***, correspondingly. Inhibiting signals pass the great numbers of connections from interface elements to ***R***-neuron and from ***Y***-neurons to element G_1, from ***R***-neuron to the winner neuron in the recognizing layer only. All connections of the network ART-1K pass ***K***-value signals from an alphabet $M = \{0, 1, 2, \ldots, K - 1\}$.

Every element in the interface or ***Y***-layer of the network ART-1K has three sources of input signals. Any interface element Z_i ($i = 1, \ldots, n$) can get signals from an element S_i of the input layer, from ***Y***-layer elements, and neuron G_1. Analogously, element Y_j ($j = 1, \ldots, m$) can get signals from interface elements, neurons R and G_2. For switching neurons of interface or recognizing layers to active state, the existence of two sources of input excitant signals is needed. As each of the examined neurons has three possible sources of signals, the condition of excitation of these neurons was named by "rule two-from-three".

In the initial state, the neurons R, G_1, G_2 and input layer S have zero output signals. When ***K***-value components of the image are input into the ***S***-elements, a part of them, which gets nonzero input signals ($U_{\mathrm{out}} > 0$), is switched to excited state. Excitant signals from the outputs of these neurons switch neurons G_1, G_2 to the state "6", and also come to the input of the corresponding neurons of the interface layer. Neurons of the interface layer, which got the signals from the input layer neurons and element G_1, by the rule two-from-three, pass to active state and send their excitant signals via connections with weights w_{ij}^1 ($i = 1, \ldots, n$, $j = 1, \ldots, m$) on the inputs of neurons Y_j in the recognizing layer. The neurons of the recognizing layer pass to active state by rule two-from-three while they get excitant signals from the elements of the interface layer, and from the element G_2 as well. Output signals of active ***Y***-neurons are determined by the expression

$$U_{\mathrm{out}\,Y_j} = U_{\mathrm{inp}Y_j} = \sum_{i=1}^{n} W_{ij}^1\, U_{\mathrm{out}Z\,i}, \quad j = 1, \ldots, m,$$

and meet the condition $0 < U_{\mathrm{out}\,Y_j} \le 6$.

Then a lateral process of selection of the unique element J with a greatest output signal takes its place in ***Y***-layer neurons. All the ***Y***-layer neurons, except the winner Y_J, are switched to the nonactive state "0" ($U_{outY} = 0$), and winning neuron – to the state with the unit (K = 6) output signal. The winning ***Y***-neuron signal inhibits the controlling neuron G_1, and also comes to the interface layer neurons' inputs via connections with weights W_{Ji}^2. Because the elements of the interface layer are under the rule two-from-three, when the excitant signal from the neuron G_1 is absent, the interface elements which get the signals from both the input layer element and the winning Y_j-neuron recognizing layer, are in the active state only. The inhibiting signals of the interface layer active elements come to inputs of ***R***-element, which gets excitant signals from the neurons of the input layer also. Depending on the ratio between values of excitant and inhibiting signals, the output signal of the controlling element R is determined.

When ***R***-element output signal is equal to zero the resonance occurs in the neural network and the training of the connection weights of the winning ***Y***-neuron runs. When the output state is equal to unit, the winning ***Y***-neuron is inhibited ($U_{outY} = -1$), and, in fact, it loses possibility to take a participation in the competition when the input image is input. Then in ***Y***-layer the new winning neuron is chosen. If the input image isn't enough similar to the one of the memorized ones, all of the used ***Y***-neurons appear inhibited and as the winner will be selected from the unused neurons, which memorizes the new image in its weights.

On the basis of the rapid training, the method [11] for training the neuron network ART-1K is accepted. For instance, this method can be used for analyzing performance of the adder [11].

Signals at the input, output and at the internal elements of the adder can have a form of switching processes seen in Fig. 1, where 13 types of signals from the Fantozi alphabet are shown, each of which can be on every input of the multidigit adder as informative signal, and they correspond to ***K***-value signals of the design system on basis of ***K***-value differential calculation. This ***K***-value signals ($K = 7$) are explored within the 17-cycles-window (Fig. 3), which corresponds to duration of delays of the adder elements. At the input of ***K***-value neuron network ART-1K they are transformed into a vector of dimension 17×7 = 119 elements. A type of ***K***-value signals at the input of the block of signal automated identification is shown in Fig. 4.

In real devices, the type of switching signals can be close to the shown ones, but not coincide fully along with such varying. Therefore, training the neuron network ART-1K was executed on signals, where each of them was in the field, having three ranges in accordance with the seven-digit alphabet: [0 – 1], [2 – 4], [5, 6], as it is shown in Fig. 4.

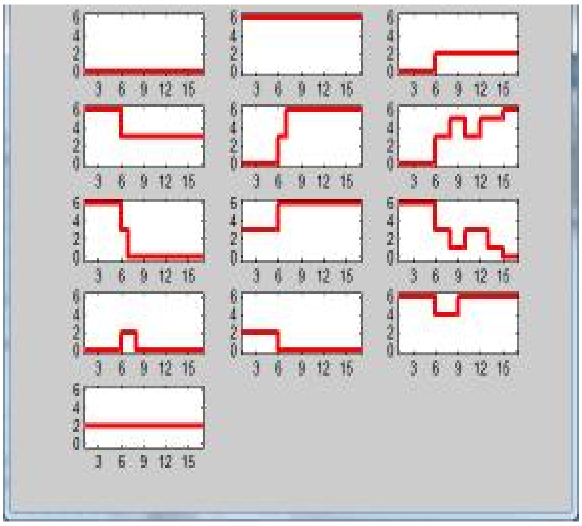

Fig. 3. *K*-value signals at the input of the neuron network ART-1K

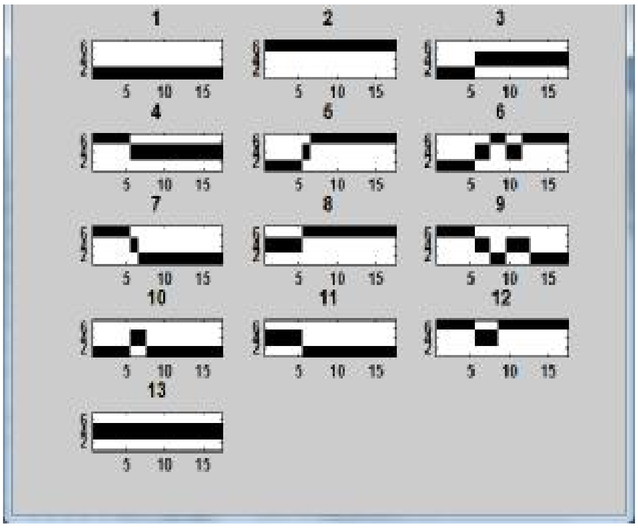

Fig. 4. Fields of *K*-value signals at the input of the neuron network ART-1K in the training mode

After training, the neuron network was tested signals from the Fantozi alphabet. Each of those signals belongs to the mentioned ranges of deviation. Based on the experiments, it was concluded that the developed neuron network correctly classifies 95 % of the produced signals.

Conclusions. Thus, based on the adaptive resonance theory and discrete neuron network ART-1, the *K*-value neuron network has been developed for classification signals, which can appear during digital devices simulation by the simulation system based on *K*-value differential calculation. The method of applying the neuron network ART-1K for analyzing performance of computing devices has been developed. The testing of the developed neuron network confirmed its functionality and possibility to apply the network in the simulation system based on *K*-value differential calculation.

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