Event-threading calculation algorithm complexity estimation

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In this paper it is considered a new variant of artificial neural network (ANN) and calculation algorithm so-called event-threading ANN. The classical model of ANN is enhanced by introducing the notion of event-threading that allows decreasing computational complexity from O(n) down to O(ln n).

***Index Terms*—event-threading, ART neural networks, algorithms, computational complexity, associative memories.**

I. INTRODUCTION

Nowadays there exist several models of ANN and their realizations. Classical ANN models were defined by Hoff [1] and Hopfield [2] and modifications of ANN were described by Nell Dale [3]. It is known that ANN solve many classes of problems such as patterns classification, clustering, categorization, functions approximation, predicting, forecasting, optimization, associative memory and so on.

II. PRELIMINARY

Algorithm *et*ANN handles input data using new principles and methods based on parallel algorithms, event-driven model [4] and new approaches of ANN training and synthesis of trained network. Using *et*ANN allows decreasing the number of operations from *O(n)* (classical models) down to *O(ln n)* (*et*ANN mode). Posterior synthesis of trained *et*ANN decreases the number of connections between neurons by deleting insignificant relations, leading to a simpler system.

In the case of event-threading algorithm on each step there occur operations only in *significant* neurons and connections. Classical algorithms recalculate all ANN weights on each step, where the number of operations is up to *O(n)* [5]. Complexity of *et*ANN algorithm is *O(ln n)*, and after the training is finished, all insignificant weights are removed and complexity becomes much less than at the start-up.

III. MATHEMATICAL MODEL OF ALTERNATIVE ANN

Artificial neural network is a directional graph with weighted connections and artificial neurons in its nodes. By architecture ANN connections can be grouped in two classes - direct propagation networks with graph without loops and recurrent or back-propagation networks.

Contingencies of the classical ANN:

1. Calculation of neuron output is intended to be instant and without delays. It is not possible to simulate the dynamic systems with *internal state* with the help of these neurons [8].
2. Absence of neural impulses. There is no modulation of *the signal level by density of impulses* like in neural system [3].
3. Absence of precise algorithms in activation function selection [9].
4. Absence of mechanisms of network functioning integral control [9].
5. Excessive formalization of *threshold* and *weights* concepts. In living neurons *numerical threshold* does not exist. It dynamically changes depending on the activity of neurons. *Living* synapses possess plasticity and stability: *weights* are configured depending on the signals passing through synapses [10].
6. Variability of *natural synapses types* which differ by localization and functions. Inhibitory and excitatory synapses in this model are implemented in the form of opposite sign weights [7].
7. Difference between graded potentials and nervous impulses in *ANN* model cannot be traced [10].

For more faithful modeling of natural neural networks (BNN) there were used literary sources from the domain of biology. Chemical and electrical reactions in human brain in abstract terms can be treated as processes, merging in dynamical system (DS), as brain is a giant *dynamical system* [3].

Analogous signal is transmitted only via axons where neuron's perikaryon is charged by sufficient impulse for emission of neurotransmitters in consideration of adiaphoria (temporary lock of the neuron after signal transmission). Size, perikaryon form, length and dendrites form, axon length, form and dendrites tree length, type and volume of neurotransmitters define inner parameters of DS. Density of neurons per volume unit also depends on myelin sheath thickness. *Speed of signal transmission depends on the length and diameter of axon: wider axon → faster speed* [7].

Neurons emit activating and inhibitory signals, which decrease the activity of dendrite-connected neurons. Neuron accumulates activating and abscopal signals from dendrite-connected neurons and forms post-synaptic signal. Input signals transformations into output signal occur when summary charge of neuron exceeds certain specific threshold [3].

Neurons interconnections have inner structure different from classical *ANN* models. Classical ANN models generally are presented in the form *n*-partite graph K ($n_1,\ldots,n_m$), where n_i - size of layer (part); each neuron from layer *i* is connected with each neuron from layer *i*+1, where *i* from [1,*m*] in case of direct propagation networks, or is connected with each neuron from layer j in general case (back-propagation).

Neuron's excitation power is coded by speed of signals emission. Higher level of activation or higher post synaptic potential defines faster speed of signals emission. Signals transmission uses impulse-coded modulation, and cells from different brain zones use the same coding method.

Alternative ANN realization is adequate to BNN functionality:

1. Delays in BNN occur when neuron waits neural signals from connected neurons and output signal is emitted when neuron accumulates necessary impulse. Each neuron has its own independent inner state and current charge.
2. Alternative model provides analogue-class – *artificial neural impulse* (signal). *Event-threading* technology allows possibility of synchronous and asynchronous computations execution so far as input signals are incoming.
3. Artificial neuron possesses its *own* activation function.
4. Artificial neuron represents an integral unit which depends on its own inner parameters: training speed, threshold function, etc.
5. Neural signal is transmitted deep into neural network after checking on threshold value for a specific neuron by all input signals summation from connected layers.
6. Alternative mathematical model allows possibilities to organize all the types of synaptic connections; methods of *event* type can be overridden more than once (*multicasting*) in domain of the given model or system.
7. Signals (artificial neural impulses) represent an analogical class with a set of values and methods of self-organization and auto-configuration.

IV. ALGORITHM COMPLEXITY COMPARISON

Complexity calculation of classical ANN algorithm realization in case of 3-layered network structure depends on the following parameters: n_i size of input layer (number of analyzed parameters), n_h - hidden layer size (sum of all possible values of analyzed parameters in n_i) and n_o - size of output layer (predicted parameters). The following relations are correct

$$n_o < n_i << n_h \tag{1}$$

Number of operations in this case $W_{cls} = n_i \times n_h \times n_o$. Being based on the inequality (1) complexity is equal to

$$O(n_i \times n_h + n_o \times n_h) = c \times O(n_h) \tag{2}$$

where $c = n_i + n_o$ having very small value, can be ignored. Then complexity is $O(n)$ for all epochs on training, testing and data-handling stage.

Number of output signals S_{out} in *et*ANN from layer a_i to a_i is between $ln\ a_i$ and $ln\ a_j$ when on training stage it is used $th(s)$ or $(1+e^{-s})^{-1}$ as threshold function. Value $ln\ a_i$ in *et*ANN represents frequency of threshold exceeding.

In alternative case number of operations is equal to $W_{et} = n_i \times ln\ n_h + ln\ n_h \times ln(\ ln\ n_o)$ and depends on current training value of the analyzed parameters. Number $ln\ n_h$ represents operations quantity which are executed when threshold value exceeds and *et*ANN complexity is estimated by $\boldsymbol{O(\ ln\ n\ )}$.

V. CONCLUSION

Essential modification of classical ANN structure consists in elimination of all *unessential* connections (threads) after handling by *et*ANN calculation algorithm and introduced dynamics considerably reduces delays in calculations because all operations take place in real-time.

New theoretical mechanism for data handling on testing and application stage of ANN development, being based on asynchronous threads in networks and developed tools, solves formulated problems more effectively and much faster.

Performance increase is reached by parallel work of all neurons and software architecture based on alternative model. *Et*ANN is oriented to eliminate three classical problems related to parallelism support in software applications. Classical problems in parallel (multithreading) programming are double blocks, lack of blocks elimination, incorrect blocks order and execution of block operations in critical important sections of the application. Errors of this kind lead to serious and unpredictable performance degradation. In the developed software this problems are solved with the aid of integrated operating system (32bit) technologies [4].

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