Methodological Principles of Pyramidal and Parallel-Hierarchical Image Processing on the Base of Neural-Like Network Systems

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***Abstract*—The scientific research deals with organization principles of parallel-hierarchical transform for multistage perception and processing, compression and recognition of information in informational structure and computational systems which make use of computational scheme similar to neural. Unified methodological approach was developed for analysis of parallel processes. This approach considers influence of structural hierarchy in dynamics, in other words it tracks processes of spatial areas transformation of correlated and generation of uncorrelated in time elements of generated network, at the time of transition of the network from one stable stage to another.**

***Index Terms*—parallel processing, parallel-hierarchical network, image processing, pattern recognition**

I. INTRODUCTION

Constantly growing volume of data and computations, needed for processing of large arrays of information, for instance, images, requires higher level of performance of the systems involved in this process. Since the density of elements “package” in integrated circuits is determined by physical constraints, operation speed is limited by final speed of electromagnetic modes propagation from one element to another. It is possible to overcome this physical barrier only by means of pipelining of computational processes occurring in the system, that, in its turn, results in complication of system architecture.

Intelligent processing of information requires consideration of each element in a certain context of its connections, and it is possible only in computing system, having topographic structure with 3D location of processing elements (PE).

Such a structure of the system perfectly matches natural neurolike perception of sensor information [1, 2, 3]. The idea of hierarchical pyramidal processing of information was suggested for the first time in [4, 5, 6, 7].

Highly-efficient system of information processing could be realized adapting architecture to the corresponding data structure. But structure of data in the process of pyramidal processing changes from large fixed array on lower level to small flexible structure on upper level. The most interesting case is uniform non-distributed computational structures, which correspond to SIMD-system class, where some levels of identical PE operate in SIMD mode. Each level contains a great number of simple PE. Such system as PCLIP, PAPIA, GAM, SPHINX [8] belong to this group, as well as structures suggested by the authors and protected by certificates and patent for a device intended for realization of pyramidal processing of information [5].

In more sophisticated case of uniform distributed pyramidal computational structures some powerful identical processing units are integrated into hierarchical pyramidal structure.

Each processing unit corresponds to a part of processed data.

Such pyramidal system can operate both in SIMD and in MIMD-modes. Computational structures [1, 5] suggested by the author and protected by the certificates for a means and device, as well as systems Uhrs, Array/Net and EGPA [8] belong to this family.

II. THE MAIN PRINCIPLES OF PYRAMIDAL AND PARALLEL-HIERARCHICAL PROCESSING OF DIGITAL INFORMATION

Principle of construction of pyramidal hierarchical structure of data can be defined as a sequence of data arrays of the same information field at different levels of division: P = (A0, A1, A2,…, AL), where A_i – information field, i – number of permission level, $i = \overline{0, L}$. Such pyramid of information fields forms computational structure that allows of realize methods of intelligent sensor perception. Similar structure allows to control permission level of processed data and dimensions of analysis area. Dimensions of analyzed data “window” can be constant but moving from one level of location to another we can perform the processing of one and the same element of information field with varying degree of extension.

In this case the decision regarding the necessity of further processing can be mode at upper level of processing after the analysis of information field with small tolerance, each element of which contains integral criteria regarding corresponding fragments of output field at the lowest level, that leads to increase of processing rate.

The essence of pyramidal approach is simultaneous usage in the analysis of sequence of data arrays at various levels of

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hierarchy. It allows to realize the strategy "from general to the particular", that enables to realize the concept of neurolike processing. Each element of information field pyramid is characterized by three coordinates (*i, j, k*) where *i* – row, *j* – column, *k* – level.

Principle of construction of parallel-hierarchical data structure, realized in [1, 4, 10] can be defined as sequence of operations performed over the sets of data arrays forming the sets of information fields of various hierarchical levels, their interaction is carried out by pyramidal hierarchical structure and is realized on the base of networking architecture.

Networking transformations are non-linear transformations, their can be imagined in the form of networking model. As a result of direct networking parallel-hierarchical transformation of image matrix $\mu(i,j)$; having dimensions $S \times n_S$ on-dimensional matrix $\varphi\ (t,p)$ will be formed, its elements are determined as:

if $\mu\ (i\,,j)\ =\ \sum_{i=1}^{n_S} a_i^j$ and the number of levels

$k=\sum_{p=0}^{c}\ (3p+2)$ where c=0,1,2,

then $\overset{k}{\underset{t=2}{\Phi}}\left[\sum_{j=1}^{s}\ \sum_{i=1}^{n_S}\mu(i\,,j)\ \right] = \sum_{t=2}^{k}\ a_{11}^t$ where

$\sum_{t=2}^{k}\ a_{11}^t\ =\ \varphi(t\,,p)\cdot$

In this case, for each output element of networking transformation execution of the relation is valid

$$\varphi(t\,,p)\ =\ \Phi(j\,,i\,,t\,,p)\ \sum_{j=1}^{s}\sum_{i=1}^{n_S}\ \mu(j\,,i), \tag{1}$$

where $\Phi\left(j\,,i\,,t\,,p\right)$ - cell of non-linear direct networking transformation, set over the elements of output image.

Relation (1) in vector form is the following

$$\varphi=\Phi\cdot f\ , \tag{2}$$

where $f\ (\ j\,,i)\ =\ \sum_{j=1}^{s}\sum_{i=1}^{n_S}\ \mu(j\,,i)\ \cdot$

Output image can be obtained by means of reversed networking parallel-hierarchical transformation, described by the relation:

$$\hat{f}(j\,,i)=\Phi^{-}(j\,,i\,,t\,,p)\ \sum_{t=2}^{k}\sum_{p=0}^{c}\ \varphi(j\,,i), \tag{3}$$

where $\Phi^{-}\left(j\,,i\,,t\,,p\right)$ - cell of non-linear reversed networking transformation. The procedure of $\Phi^{-}\left(j\,,i\,,t\,,p\right)$ construction in the form of pseudo convolution matrix, that provides exact evaluation of $\hat{f}=f$ is considered in previous research [11].

Reversed networking transformation in vector form is the following:

$$f\ =\ \Phi^{-}\ \varphi\ \cdot \tag{4}$$

III. THE ANALYSIS OF APPROACHES OF SENSOR INFORMATION AND IMAGE PROCESSING

Nowadays two approaches regarding the origin of signals description are considered: detector-based approach and space-frequency [12]. Detector-based approach assumes the existence of operators, allocating elements of the image occurring most frequently, that is, allows to realize the transition from pipeline description to larger elements of the image, that enables to reduce considerably redundancy.

Space-frequency approach assumes, that in visual crust the transition to description of quasi-holographic type occurs, that is, value of the signal is coded not in separately taken point, but is distributed along its circumference.

In accordance with space-frequency approach, crust receptive fields describe images decomposing them by preset system of basic functions, for instance, by Fourier trigonometric series. For denomination very economic space-frequency description is required.

For recognition of studied image only degenerated description is sufficient, which contains only several (not more than five) harmonics.

In simplified manner the process of perception of sensor signals of human feeling organs can be presented as interconnected iterative process of parallel space-frequency comparison of signals set and separation from the given set the subsets of general any various (different) characters-signals (CS) [13]. Each new totality of different characters-signals generates by means of evolution, new subset of general characters-signals.

The given process of sensor information perception in space-frequency system (SFS) occurs constantly in time and simultaneously (parallel) in all systems of human perception organs.

The totality of general characters-signals is directed into the crust of human brain by in dependent routes, creating the set of various general characters-signals, on the basis of which new sets of general and various characters-signals are formed.

Each new set of general and various characters-signals characterizes new hierarchical level of sensor information processing.

Samples of the environment are constructed at later stages of sensor analysis by means of integration of maximally processed (filtered) data, sent across filters of separate sensor systems.

For sensor systems the characteristic feature is hierarchical organization of analysis and synthesis of information, being processed [14]. In certain systems the ascending character of such filtration is provided, where as in others – the descending character.

The process of synthesis, i.e., formation of images of material world occurs in reversed sequence, that is, on each hierarchical level a set of new and various "representation" of characters-signals is formed from stored in operative or constant memory of human brain the totality of various "representations" of characters-signals.

Junction of sensor data with hierarchal generalized information, taken from human memory allows to interpret the sets of general characters-signals at each hierarchical level.

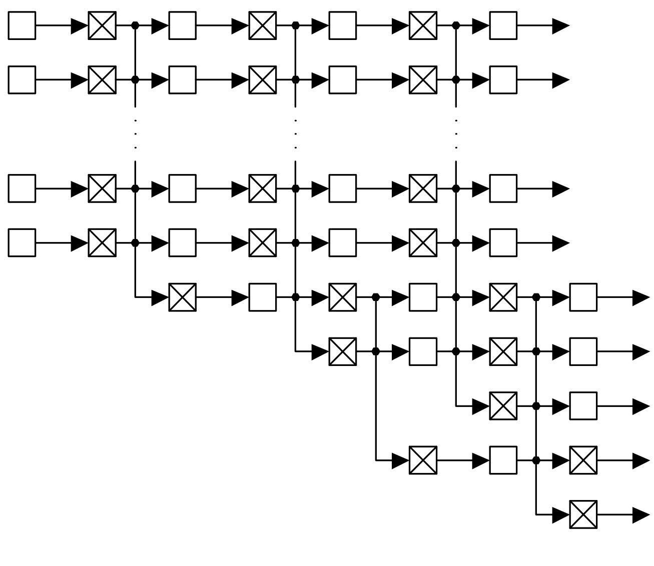
Thus, at structural level the process of neurolike processing can be presented as parallel-hierarchical and interconnected process of information analysis in a number of sensor zones with hierarchical levels of still higher order, the highest of which form sets of maximally generalized and various characters-signals.

The suggested approach coincides with fundamental concept of American physiologist V.Mauntcastle [15]. In accordance with Mauntcastle's theory, cerebral cortex consists of complex multi-cellular assembles, basic unit of which is formed by approximately hundred of vertically connected neurons of all lager of cortex, united in still larger unit – module. Modules are grouped in larger clusters, forming primary visual, acoustic or moving cortex depending on the source from which the given clusters obtains the information. Processing of information is carried out in parallel channels, each of these clusters, that performs one principle function, contains smaller subgroups of vertical units, each unit being connected with special subgroups of other clusters, performing mainly other functions.

Interconnected subgroups are sections of the network, connected by a determined law, the given network can be widely distributed along the cortex. Realization of the most complex function – ability to reach certain abstract conclusion is the result of activity of the whole distributed network.

IV. NEURAL-LIKE NETWORK MODEL FOR PARALLEL-HIERARCHICAL PROCESSING OF DIGITAL INFORMATION

Thus, the given section investigates networking structure (Fig 1), that allows to simulate principle of operation of distributed neural network [11] and due to spatial distribution in time, creates determined network (Fig 1). In neurobiological interpretation, presented in Fig 1 crossed box designates converge structure, and simple box – diverge structure.



□ - the set of various states of space-frequency system (SFS)
⊠ - general states of SFS.

Figure 1. Structure of parallel-hierarchical network of neurolike type.

Such a network consists of the totality of sub-networks (Fig 2) of characters formation regarding the states of SFS, the structure of which is uniform and consists of a number of interdependent hierarchical levels.

Algorithm of network operation is universal and means parallel-hierarchical formation of the sets of general and various CS, regarding SFS. Generalization of all forms of sensor information is carried out at the final stage of conversion of extra hierarchical processing of each type of sensor information. Thus, the process of generalization between various types of sensor information starts only when construction by the determined totality of characters is over.

"Intelligent" level of distributed network is determined by the degree of generalization of sensor information in its branches. The greater level of generalization of sensor information where its passage along the branches of the network, the higher is its "intelligent" level. The idea of application for processing of sensor information the formation of totalities of general and various states of network also coincides with investigations carried out by American psychologist D.Bruner [12], who experimentally proved, that the human being has a tendency "to see in known separate cases the examples of general rule". Proceeding from the results of his research D.Bruner made important conclusion: ability of formation from separate cases the examples of general rule is a part of specific heredity of a human being as a species. This assumption is proved by the idea of "homeostasis", that highlights both "permanency" and "relativity of permanency", suggested in fundamental work written by V.Kennon [12]. According to Kennon permanent conditions, maintained in a body, can be named as equilibrium or in suggested terminology, general state of STS.

Suggested and investigated in the given work networking method combines two above-mentioned competing approaches regarding the nature of redescribing signals-detector approach and space-frequency approach and describes image, decomposing it applying adaptive system of basic functions, formation of which depends on the structure of image itself.

The essence of parallel-hierarchical approach is simultaneous application of the sequence of sets of data arrays, which form sets of information fields at various hierarchical levels, recursive formation of new sequences of information streams at various hierarchical levels, that allows to realize the strategy of multilevel interaction from "general to partial". Each element of parallel-hierarchical pyramid is characterized by four coordinates (i, j, k_1, k_2), where k_1 – level of the pyramid of the first level, k_2 – level of parallel-hierarchical pyramid of other levels. Pyramidal computational structure based on PH transformation will create the network in the form of parallel-hierarchical pyramid.

Here, for each pyramid, its own PE is used and the number of PEs is determined by the total number of branches of PH network.

In general form the methodology of PH network formation can be presented in formalized form, proceeding from the following assumptions. Let the set of flows of input data be. The problem appears: how parallel computation process in real time can be organized to obtain strictly distributed in time and hierarchy computational network? This problem can be solved considering the principle of construction of the following computational network: Let us consider methodological peculiarities of multilevel organization of PH network [1, 4, 9-11], presented in Fig 3; for this purpose it is necessary to obtain functional description of basic network. We will process or transform the set of input data flows at various (k) hierarchical levels. Each level is the totality of PEs, functioning at strictly fixed moments of time (t_j).

Let n_1 functions $f_1(t), f_2(t),..., f_{n_1}(t)$, be. The given functions will be described at various hierarchical levels of their representation from 1st to j-th $(j = 2l, l = 1,2...$ and $j = 2l + 3,\ \ l = 0,\ 1,\ 2,...)$

$$\begin{aligned}
&\sum_{j=1}^{n_1}\sum_{i=1}^{n_{j1}} f_{j1}(t-i\tau) = \sum_{j=1}^{n_2}\sum_{i=1}^{n_{j2}} f_{j2}(t-2ij\tau) = \\
&= \sum_{i=1}^{n_{13}} f_{13}(t-(2i+3)\tau) + \sum_{i=2}^{n_{23}} f_{23}(t-(2i+3)\tau) + \\
&+ \sum_{i=3}^{n_{33}} f_{33}(t-(2i+3)\tau) + \dots \\
&+ \sum_{i=n}^{n_{n3}} f_{n3}(t-(2i+3)\tau) = \\
&= \sum_{i=1}^{n_{14}} f_{14}(t-(2i+6)\tau) + \sum_{i=2}^{n_{24}} f_{24}(t-(2i+6)\tau) + \dots \\
&+ \sum_{i=n-1}^{n_{(n-1)4}} f_{(n-1)4}(t-(2i+6)\tau) + \\
&+ \sum_{i=n}^{n_{m4}} f_{n4}(t-(2i+6)\tau) = \dots \sum_{i=1}^{n_{12l}} f_{12l}(t-(2i+6l)\tau) + \\
&+ \sum_{i=2}^{n_{22l}} f_{22l}(t-(2i+6l)\tau) + \dots \\
&\dots + \sum_{i=n-1}^{n_{(n-1)2l}} f_{(n-1)2l}(t-(2i+6l)\tau) + \\
&+ \sum_{i=n}^{n_{n2l}} f_{n2l}(t-(2i+6l)\tau) = \\
&= \sum_{i=1}^{n_{1(2l+3)}} f_{1(2l+3)}(t-(2i+6l+3)\tau) + \\
&+ \sum_{i=2}^{n_{21(2l+3)}} f_{2(2l+3)}(t-(2i+6l+3)\tau) + \dots \\
&\dots + \sum_{i=n-1}^{n_{(n-1)(2l+3)}} f_{(n-1)(2l+3)}(t-(2i+6l+3)\tau) + \\
&+ \sum_{i=n}^{n_{n(2l+3)}} f_{n(2l+3)}(t-(2i+6l+3)\tau),
\end{aligned} \tag{5}$$

where τ - delay of the next function formation regarding the previous function. n_{jk} – number of functions of j-th decomposition of k-th functional level.

Functions of the first level can also be presented as:

$$\sum_{j=1}^{n_1}\sum_{i=1}^{n_{j1}} f_{j1}(t-i\tau) = \sum_{j=2}^{k} f_{1j}(t-(3j-4)\tau)\cdot \tag{6}$$

The right part of the expression (6) forms tail functions $f_{1j}(\cdot)$, obtained as a result of functional transformation (5).

Analyzing networking transformation (5) we can make a conclusion that in the process of creation of each level temporal shift (τ) is formed, availability of which leads to obtaining of trail functions.

At the first level input flows of data are processed in independent parallel branches at the second level (k = 2); transition at the next third level processing at structurally-functional level can be presented in the form:

$$f^{kp_1}_{n_1n_2}(t) = F\left(\bigcup_{j=1}^{p_1} f^{(k-1)j}_{(p_1-j+2)1}(t_{j+2})\right), \tag{7}$$

where p_i – number of branch, n_1, n_2 – number of the element in the branch and number of the network (n_2 = 1), n_1 = p_i = 1, 2, ...; F – functional operator, that determines criterion of selection of general part while data flow processing $f(t)$. At all hierarchical levels (k = 2, 3, 4) the given process can be presented in the following form:

$$f^{kp_1}_{n_1n_2}(t) = F\left(\bigcup_{j=1}^{p} f^{(k-1)\left(\left]\frac{p}{j}\right[\right)}_{(p_1-j+2)1}\left(t_{j+2(k-1)}\right)\right), \tag{8}$$

Process of data flow transition from the previous level of PH network on the next level can be presented by the formula

$$M(k) = \bigcup_{j=1}^{k} M\left]\frac{k}{j}\right[, \tag{9}$$

where $\left]\frac{k}{j}\right[$ - indicates dimensions of the set M or k-th level., $k = \overline{1,\ n^2}$, n – number of output sets, $|k| \le n^2$.

In [11] it is shown that structural model of PH network organization can be described by means of six functional sets, that allows to formalize structural organization of special links in PH network. Let us introduce such notions and definitions for analysis of structural-functional arrangement of PH network.

Definition 1. Convolution of elements with coordinates $a_{1i}(t_j)$ and $a_{2i}(t_j)$ regarding p_{1j} -th; and $p_{1(j+1)}$ -th branches of j-th level are elements with coordinates $a_{(i+1)1}(t_{j+1})$ and $a_{(i+1)2}(t_{j+2})$ of p_{1j} -th branch of (j+1)th level.

Truncated convolution of elements with coordinates $a_{1i}(t_j)$ and $a_{2i}(t_j)$ regarding p_{1j} -th and $p_{1(j+1)}$ -th branches of j-th level is the element with coordinate $a_{(i+1)1}(t_{j+1})$ of p_{1j} -th branch of (j+1)th level.

Definition 2. Convolution of elements with coordinates $a_{(i+1)1}(t_{j+1})$ and $a_{(i+1)2}(t_{j+2})$ of p_{1j} -th branch of (j+1) -th level are elements with coordinates $a_{1i}(t_j)$ and $a_{2i}(t_j)$ regarding p_{1j} -th and $p_{1(j+1)}$ -th branches of j-th level. Truncated convolution of element with coordinate $a_{(i+1)1}(t_{j+1})$ of p_{1j} -th branch of (j+1)th level are elements with coordinates $a_{1i}(t_j)$ and $a_{2i}(t_j)$ regarding p_{1j} -th and $p_{1(j+1)}$ -th branches of j-th level. Similarly to definitions 1 and 2 we can introduce the notion of convolution, scanning and truncated scanning for numerous variables.

Definition 3. Current convolution of elements a_1 and a_2 is the convolution of the given elements at any moment of time t_j.

Definition 4. Prior convolution of network elements regarding current convolution is such network convolution that is located at the same number of convolutions from the tail element regarding current convolution.

For instance, while coding of current convolutions of PH transformation it is necessary to perform analysis of masking function of the prior convolution. If mask function of the given convolution equal 1, then current convolution is composed of one element of the branch, content of which is transferred on the element of the next convolution in accordance with definition 2 and operation of truncated convolution is performed.

For demonstration of direct and inverse PH transformation let us introduce the notion of complete mask network $C^{(m)}(i,j)$; that was formed from basic $C_1^{(m)}(i,j)$ and tail mask networks $C_2^{(m)}(i,j)$. Also as in the case of networking basic network for $C^{(m)}(i,j)$ and $C_1^{(m)}(i,j)$, $C_2^{(m)}(i,j)$ relations (8) and (9) are valid. The elements of mask network are binary, i.e., $C^{(m)}(i,j)\in\{0,1\}$ and such system is valid for them:

$$C^{(m)}(i,j)=\begin{cases}1, \text{ if } a_1=a_2=a_m=\ldots=a_{M(.)}\\ 0, \text{ else.}\end{cases} \quad (10)$$

where $a_{M(.)}$ – the last element of the set $M(\cdot)$ in expressions [11]. In general $C^{(m)}(i,j)$ determines the value of mask function of elements $a_1(f_j), a_2(f_j), \ldots$ convolutions.

The usage of such mask function of convolutions is of practical importance

$$C^{(m)}(i,j)=\begin{cases}1, \text{ if } a_1=a_2=r\\ 0, \qquad \text{else}\end{cases}, \quad (11)$$

where $r =$ 0, 1, 2...

This is connected with the fact that in complete basic network [11], more than 50% of convolutions, if n ≥ 4 – are convolutions, composed of two elements. This regularity is determining, for example, while elaboration of PH networks for compression of data flow.

Using over the double convolutions the operation of truncated convolution and its mask function as well as considered structural-functional model of basic network, we can present in concise form the input flow of information.

Coding based on PH transformation is realized by means of such generally accepted rules:

1. While coding of current convolution of PH network the analysis of mask function is performed. If the given function $C^{(m)}(i,j)=1$, then mask function of current convolutions not fixed. In inverse case, when $C^{(m)}(i,j)=0$, mask function of current convolution is fixed. If $C^{(m)}(i,j)=1$, then the element content of current convolution of the previous level (smaller) is transferred to the element of the next level (larger) with the address, content of which differs from zero. In other case, if mask function of the previous convolution $C^{(m)}(i,j)=0$, then the element content of the previous level (smaller) is transferred to the element of the following level (larger) with the same address.
2. Storing of the content of fail element of the network takes place.
3. Routing of the content of input elements occurs from one level (smaller) to another level (larger) fill its fail element.
4. If mask function of the previous convolution $C^{(m)}(i,j)=1$, then current convolution is formed of one element, which will form truncated convolution at the next level. In inverse case, when $C^{(m)}(i,j)=0$, current convolution is formed of two elements, forming convolution at the next level of the network.
5. If previous convolution is formed of one element, i.e., truncated convolution, then mask function of current convolution is not fixed.
6. If elements of current convolutions coincide with one of the variants of previous convolutions, mask functions of which are $C^{(m)}(i,j)=0$, them mask functions of such current convolutions are not fixed.

General rules of decoding realization:

1. Decoding is performed over the content of each tail element of the network, starting with the east one.
2. Routing of the content of the tail element is performed from the previous level (smaller) to the next level (larger).
3. If mask function of the previous convolution of elements, forming while scanning the element of the next convolution equals one, that is, the content of these elements while coding, coincides by value, then the content of the element of previous level is transferred to the element of the next level, content of which differs from zero. In inverse case, mask function of the previous convolution of elements equals zero. That is, if the content of these elements while coding, does not coincide by the value, then the content of the element of the previous level is transferred to the element of the next level with the same address.

These general coding and decoding rules for PH transformation are applied in algorithms of parallel-hierarchical computational structures and problems of pattern recognition, image processing and compression of data information flows, considered in the advanced research [11, 16-19].

V. CONCLUSION

The set up of results obtained in the scientific researches solves important problem, based on methodological concept of parallel-hierarchical transformation, that enables signal processing on the basis of pyramidal method and carry out compact parallel transformation on different levels of information field areas hierarchy. Developed theoretical fundamentals and examples of PH transformation application enabled to new technologies of multidimension information fields analysis.

The approach in the form of system-based neurobiological fundamentals for development of concept base of parallel-hierarchical networks as the model of neurolike circuit for information processing allows to model applying convergence-divergence structures important features of computation organization in the cortex - topographic character of representation, simultaneous signal action (parallelism), rough hierarchy of cortex and spatially–correlated in time perception mechanism. All this permits to create methodological fundamentals of structural-functional organization of parallel–hierarchical networks and allows to realize modeling of temporal shift between branches of the networks. The temporal shift available results in creation the possibility to design parallel–hierarchical structures and computing devices [3, 16-19].

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APPENDIX A

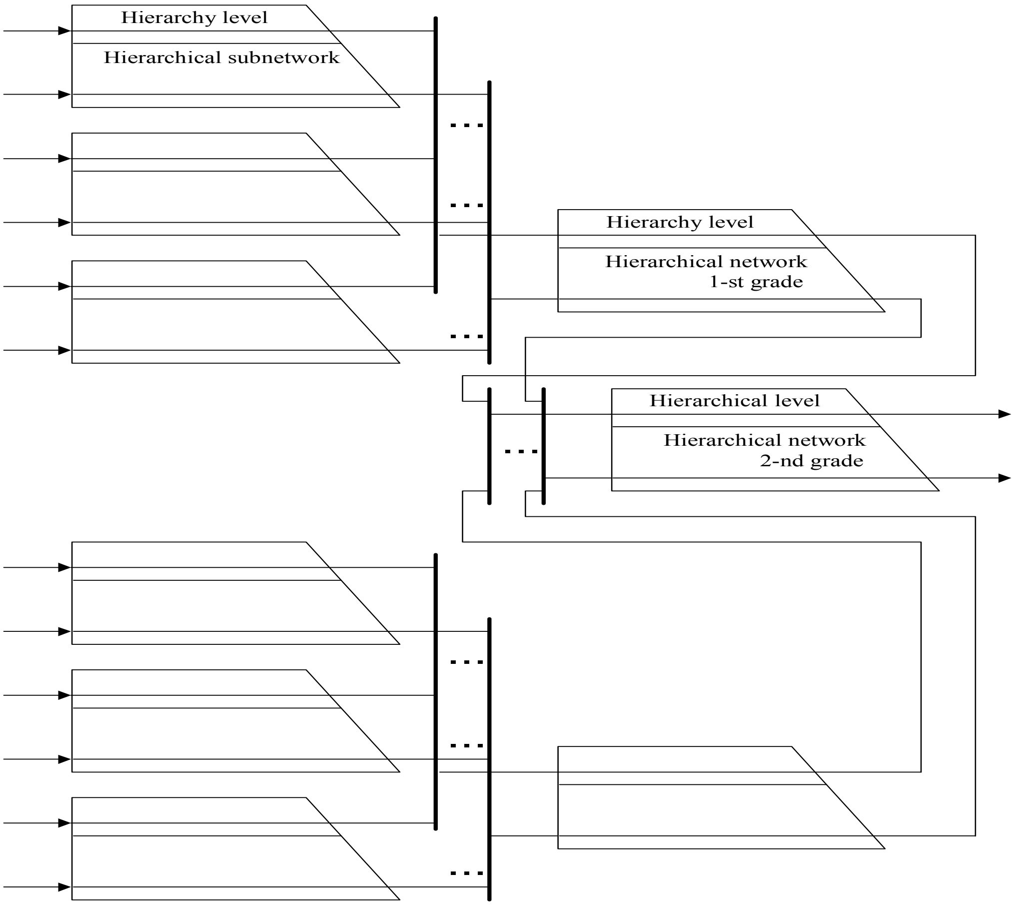

Figure 2. Structure of hierarch-hierarchical network.

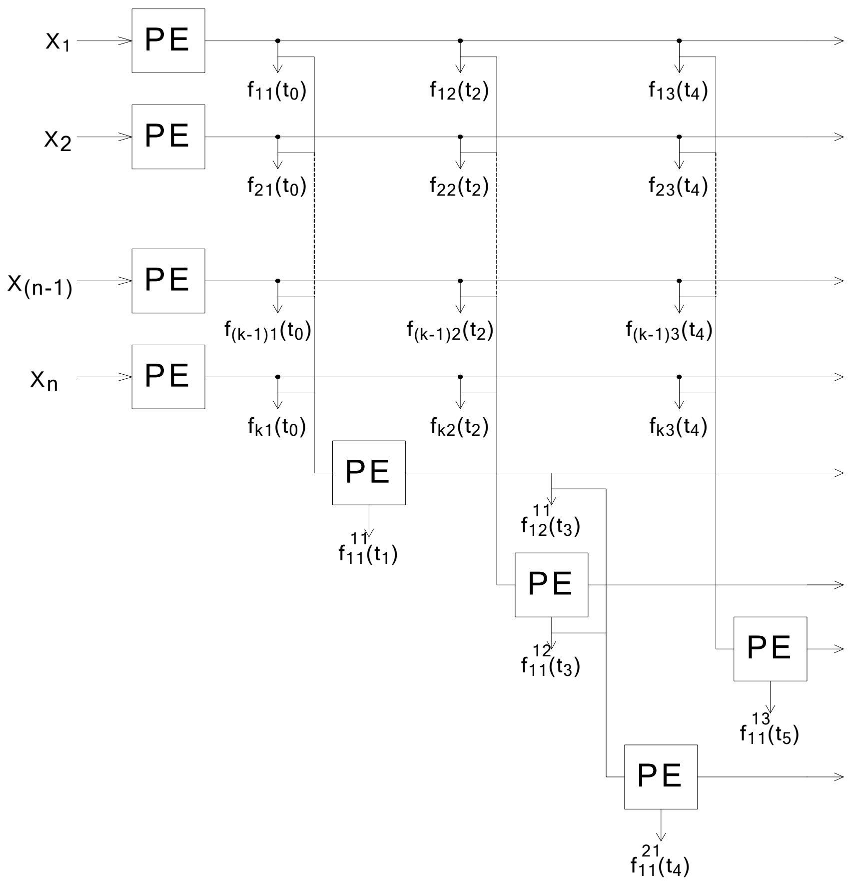

Figure 3. Structural diagram of interaction of information flows in parallel- hierarchical computational structure.