THE USE OF NOISE FILTERS IN SWITCHING NEURAL STRUCTURES

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Abstract

There is demonstrated, according to Walsh's representations, the spectrum of an iteration-free quadratic form over GL_n (2) having the characteristics of white noise. Accordingly, the description of various spatial noise filters by arbitrary forms is proposed. A spectral method of synthesis of an arbitrary filter of noise approximating a given logical function is presented. The higher efficiency of the method in relation to the selection of the corresponding white noise filter is demonstrated. The variants of inclusion of filters in the neuro-structure are marked.

Key words: *noise filters, Walsh spectra, the neural structure*

1. INTRODUCTION

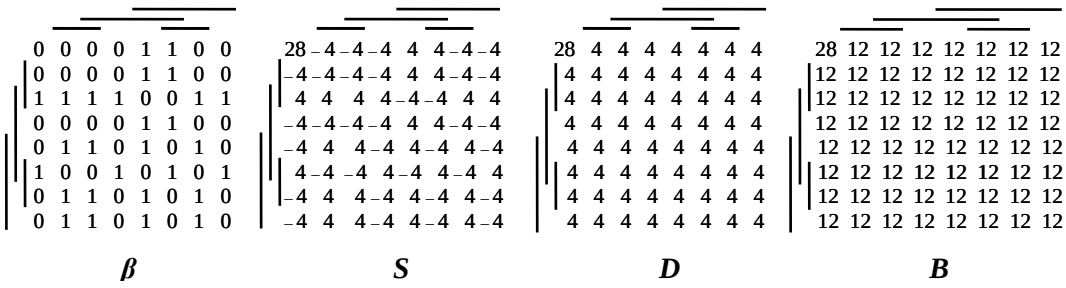
Karpovsky & Moskalev (1973) described iteration-free quadratic form (IFQFs) over GL_n (2) and noted the effectiveness of their use in the protection of information in transmission over communication channels. It was pointed out that IFQFs were Boolean functions with the best autocorrelation characteristics from that point of view. At the same time, the quality of autocorrelation characteristics used for signal transmission, is

$$B_N(\tau) = \sum_{x=0}^{N-1} f(x) f(x \oplus \tau) \pmod N,$$

where N is the number of points of function specification, determined by the value $\Delta_N = B_N(0) - \max_{\tau \neq 0} B_N(\tau)$.

Correspondingly, the functions for which $B_N(\tau) = const_{\tau \neq 0}$ have the best quality. A function in which the autocorrelation characteristic is the closest to the constant value at $\tau \neq 0$, is closer to the pseudorandom sequence of a given length N.

Fig. 1. Tables of Karnaugh logical functions of $\boldsymbol{\beta}$, its spectrum ***S***, the spectral density ***D*** and the autocorrelation characteristics ***B***.



The logical function $\beta(x) = x_1x_2 \oplus x_3x_4 \oplus x_5x_6$ can serve as an example of IFQFs. Function $\beta(x)$, its Walsh spectrum $S(\omega) = \sum_x \beta(x) \cdot wal(\omega, x)$, spectrum density $D(\omega) = |S(\omega)|$ and autocorrelation characteristics $B(\tau) = \sum_x \beta(x) \cdot \beta(x \oplus \tau)$ are shown in Fig.1.

The lines in tables in Fig.1 represent the respective variables $x_i, \omega_i, \tau_i, i = 1 \div 6$ of arguments x, ω, τ. The horizontal lines are related to variables with indices $i = 1 \div 3$, the vertical lines are related to variables with indices $i = 4 \div 6$. The spectral density $D(\omega)$ is constant for all argument values $\omega \neq 0$ which is typical for white noise. The autocorrelation characteristic for which $B(\tau) = const_{\tau \neq 0}$ =12 also correspond to it.

The same paper also demonstrates that the spectral properties of the quadratic form under consideration do not change with non-degenerate linear transformations $\sigma \in GL_n(2)$.

The linearized IFQFs $\beta^\sigma(x) = \beta(\sigma \otimes x) \pmod 2$ from variables *n* is also a function of a pseudorandom sequence or function of the white noise in the binary space L_n. Therefore, $\beta^\sigma(x) = \lambda_1\lambda_2 \oplus \lambda_3\lambda_4 \oplus \ldots \oplus \lambda_{n-1}\lambda_n$, $n-$ is the even number, where $\lambda_i = \lambda_{i1}x_1 \oplus \lambda_{i2}x_2 \oplus \ldots \oplus \lambda_{in}x_n$, $\lambda_{ij} \in \{0,1\}$, $j = 1 \div n$, and where λ_i is the i^{th} row of the matrix σ. Due to this definition the function $\beta^\sigma(x)$ will be further referred to as the white noise filter function β^σ.

A set of *N* binarized images is specified as a set of binary signals from ***m*** pixels, a set of *N* binary ***m***-bit vectors. In turn, a certain analysed class of images can be characterized by Boolean function in the space of all possible images - binary space L_m. It is quite obvious that the corresponding function is a complex function, the characteristics of which to a certain extent correspond to the characteristics of some kind of noise. Therefore, it is possible to assume that the use of white noise filters will be useful for solving the problems of pattern recognition.

Commutation neuro-structures (CNS) were previously considered in (Sychev, 2012, 2014). It was noted that the elements with a variety of functions can be used to control channel switches in a neural network. The efficiency of the neural network depends on the functional properties of the control elements.

In this regard, the goal of the work is to study the possibility of efficient employment of spatial filters of white noise and similar noise filters as the components of the switching neural-structure.

2. NOISE FILTERS

It should be noted that in case the neural-structure implements the complex logical functions with a large number of variables corresponding to the tasks of images recognition, the power of $\{\beta^\sigma\}$ class of white noise filters is insufficient. To increase the possibilities of using filters it is advisable to involve filters of diverse noises. Moreover, it is not advisable, for example, to focus on the classification of colour noises accepted in physics.

Here determination of the spatial noise filter is based on the operation of mixing signals – the operation of modulo 2 addition of signals from the outputs of some devices, for example, from the outputs of artificial neurons:

$$\rho(x) = \bigoplus_{i=1}^{m} \nu_i^{\alpha}(x), \quad (1)$$

where $\rho(x)$ is a logical function of noise filter ρ,

$\nu_i^{\alpha}(x) = \nu_i(\sigma_i \otimes x \oplus \eta_i) \pmod 2$, $i = 1 \div m$,

$\nu_i(x)$ is the logical function of an artificial neuron ν_i,

$\alpha = (\sigma_i, \eta_i)$ is affine mapping,

σ_i is a binary matrix of linear transformation on the inputs of the i^{th} neuron,

η_i is the vector of the inversion of place values the converted argument.

Besides, the condition of forming the iteration-free function of the noise filter is omitted.

It should be noted that a fairly simple special case of expression (1) occurs when the filter ρ is formed by a combination of local filters φ_i of arbitrary frequency

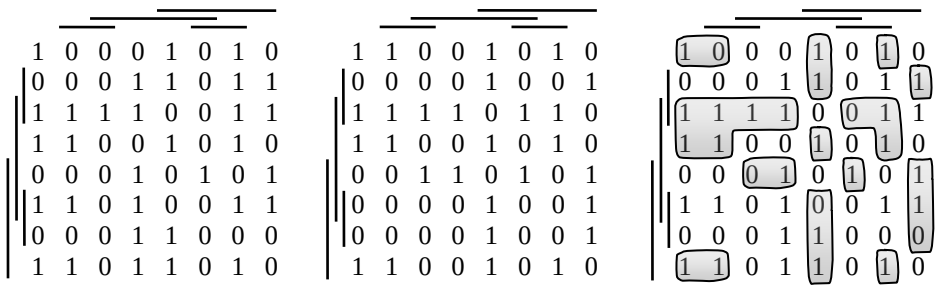
$$\rho(x) = \bigoplus_{i=1}^{m} \varphi_i(x), \quad (2)$$

where the local filter φ_i of frequency *k* is determined by an expression $\varphi_i(x) = \prod_{j=1}^{k} \lambda_j$, moreover, the frequency *k* can vary for different *i*.

For example, a white noise filter $\beta^{\sigma}(x) = \bigoplus_{i=1}^{m} \varphi_i(x)$, consists of local filters φ_i, $i = 1 \div m$, $m = n/2$, of frequency *k* = 2

When optimizing the CNS, the purpose of mixing is to construct a noise filter ρ providing the best approximation of the given function *f (x)* on a set of fragments X_i of its area of definition X, $X_i \subseteq X$, $i = 1 \div q$, where *q* is the number of switches of channels of the vertical column of CNS.

Fig. 2. Example of approximation of an arbitrarily specified logical function $f(x)$ by means of function $\beta^{\sigma}(x)$ of filter β^{σ}.



a) b) c)

Karnaugh table (a) in Fig. 2 shows the function *f (x)*, different $\theta_f = 0$, the table (b) demonstrates the white noise function $\beta^\sigma(x) = \lambda_1\lambda_2 \vee \lambda_3\lambda_4 \vee \lambda_5\lambda_6$,

$$\lambda_1 = x_2 \oplus x_3, \quad \lambda_2 = x_3 \oplus x_5 \oplus x_6, \quad \lambda_3 = \bar{x}_3, \quad \lambda_4 = x_1 \oplus x_4 \oplus x_5,$$
$$\lambda_5 = \overline{x_3 \oplus x_5}, \quad \lambda_6 = \overline{x_2 \oplus x_3 \oplus x_4 \oplus x_5 \oplus x_6}$$

$$\sigma = \begin{vmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 1 & 1 \end{vmatrix}, \text{ vector of inverting } \eta = (001011),$$

Affine mapping $\alpha : x^\alpha = \lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6) = \sigma \otimes x \oplus \eta$

and table (c) shows the original function *f (x)*, the values of which are shaded with grey where $\beta^\sigma(x) = 1$.

Let $X_1 = \{x : \beta^\sigma(x) = 1\}$ and $X_0 = \{x : \beta^\sigma(x) = 0\}$. It is clear that $L_n = X = X_1 \cup X_0$. The distribution of the quantities of the unit k_1 and zero k_0 of function *f (x)* values on the fragments X_1 , X_0 is given in the table below (table 1):

Table 1. Distribution of values of function $f(x)$ according to the values of white noise filter $\beta^\sigma(x)$.

X	$X_0 : \beta^\sigma(x) = 0$	$X_1 : \beta^\sigma(x) = 1$
$k_1 : f(x) = 1$	9	23
$k_0 : f(x) = 0$	27	5

According to the definition of different of the function (Sychev, 2017) the following should be noted. If the original *f (x)* has a different $\theta_f = 0$ on the whole space L_n, then the corresponding differents of the function on the fragments X_0 and X_1 take values $\theta^0_{f\beta} = \log_2(k_1 / k_0) = \log_2(9/27) = -1.5850$ and $\theta^1_{f\beta} = \log_2(k_1 / k_0) = \log_2(23/5) = 2.2016$. Here it is seen that the noise filters are quite efficient for forming the fragments of homogeneous values of the analysed functions and are quite applicable as control elements of switches of channels in the CNS.

When forming a noise filter *p* with the corresponding function *p (x)*, there should pay attention to the different of the implemented function *f (x)* on the analysed fragment $X_i \subseteq X$ of the definition area *X*. Preferably, if the different θ_ρ of function *p (x)* corresponds to the different θ_f of function *f (x)*. This can be achieved by selecting the appropriate artificial neurons with various differents θ_{vi}.

3. SPECTRAL METHOD OF THE NOISE FILTER CONSTRUCTION

In a generalised form, the synthesis of noise filters ρ is performed by cyclic repetition of several operations, starting with the first member of the series (1). Thus, after performing spectral analysis of the original function *f* and by applying the spectral algorithm (Sychev, 2011) of artificial neuron ν_1^{α} synthesis to it, the analysis of the derivative of $f_1^{\nu}(x) = f(x) \oplus \nu_1^{\alpha}(x)$ should be performed. Further, the following two procedures are repeated cyclically:

1. In relation to the derived function $f_i^{\nu}(x)$, $i = 1, 2, \ldots, m-1,$ formed at the i^{th} step the corresponding spectral algorithm (Sychev, 2011) determines the component $(i+1)$ of the noise filter – artificial neuron ν_{i+1}^{α}.
2. The $(i+1)$ derived function $f_{i+1}^{\nu}(x) = f_i^{\nu}(x) \oplus \nu_{i+1}^{\alpha}(x)$ is computed

The synthesis procedure is carried out before the formation of the last, m^{th} filter component ν_m^{α} of filter ρ. Then, according to (1), the function $\rho(x)$ of a common filter ρ is determined and its approximating capacity with respect to a given function $f(x)$ is checked .

Similarly, a sequence of computations of components is performed for series (2)

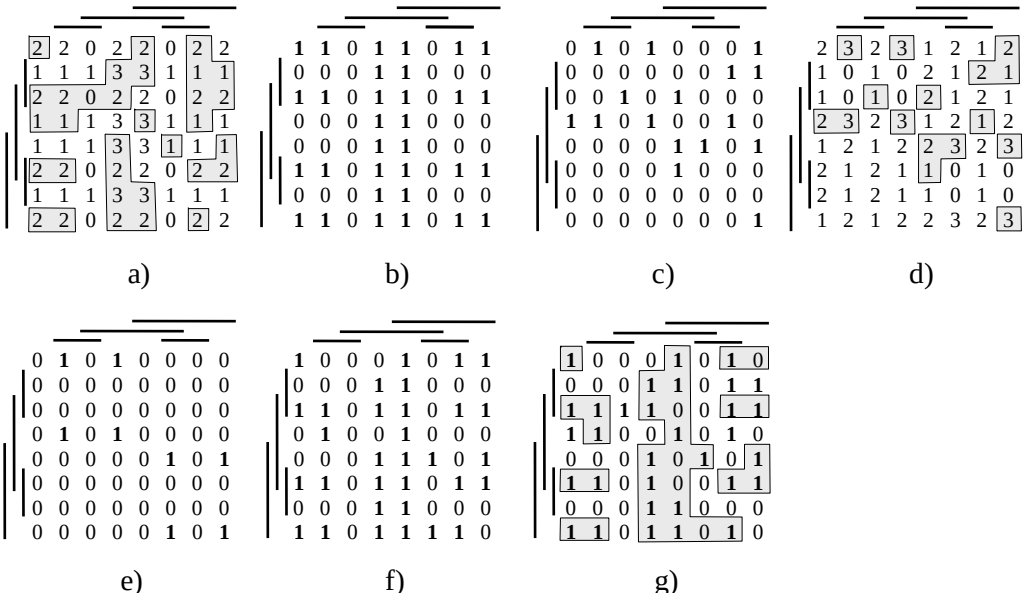
$$\varphi_{i+1} \text{ и } f_{i+1}^{\varphi}(x) = f_i^{\varphi}(x) \oplus \varphi_{i+1}(x).$$

The construction of the noise filter of type (1) is considered on the example of the function $f(x)$ presented in Fig.2 (a). To make an adequate comparison of the synthesized filter ρ with the white noise filter β^{σ}, the investigation is restricted by the search for two neural components containing the same number of elementary filters $\lambda_1 \div \lambda_6$ on the inputs as the filter β^{σ}. The following components of the filter ρ are determined: artificial neurons with threshold activation function and affine in the deduction field $\mod 2$ by the transformation of $\alpha = (\sigma, \eta), \quad \sigma \in GL_n(2),$ of the input signal $x : x^{\alpha} = \sigma \otimes x \oplus \eta$. The spectral method of constructing such neurons is presented in the paper (Sychev 2011). For example, the following elementary filters are selected as the first component $\nu_1^{\alpha}(x)$ in relation to the function $f(x)$:

$$\lambda_1(x) = x_2 \oplus x_3, \quad \lambda_2(x) = \overline{x_2 \oplus x_5 \oplus x_6}, \quad \lambda_3(x) = \overline{x_3}.$$

The corresponding weights of the inputs of the neuron $a_1 = a_2 = a_3 = 1$. Each value of the argument x corresponds to the level of excitation of the neuron $w_1(x) = \sum_{i=1}^{3} a_i \lambda_i(x)$.

Fig. 3. Karnaugh table of levels of excitations of neurons, the functions of the linearized neurons, the function of noise filter $\rho(x)$, approximation of function $f(x)$ of the filter $\rho(x)$



The aggregate of values of weighted sums $w_1(x)$ in the function $\nu_1^{\alpha}(x)$ definition area *X* is shown in Fig.3 (a). The weighted sums $w_1(x)$ of the argument *x* values where $f(x)=1$ are highlighted with grey. The distribution of the unit k_1 and zero k_0 function values by neuron $\nu_1^{\alpha}(x)$ excitation levels is shown in the table below (Table 2):

Table 2. Distribution of values of function $f(x)$ according to the levels of excitation of the neuron.

$w_1(x)$	0	1	2	3
$k_1 : f(x)=1$	1	7	18	6
$k_0 : f(x)=0$	7	17	8	2

The purpose of constructing a neuron ν_1^{α} within this task of filter synthesis is not the exact implementation of a given function *f*, but its best approximation, which provides a coincidence of the reaction of the neuron and the values of the function for the relative majority of the argument values *x*. Therefore, a threshold value *p* = 2 should be chosen for ν_1^{α}. Thus, the structural vector of the neuron ν_1^{α} has the value A_1 = (2; 1,1,1), which corresponds to the majority logic element "2 of 3". Its affine mapping α_1 is stipulated by the matrix $\sigma_1 = \begin{vmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{vmatrix}$ and the inversion vector $\eta_1 = (011)$. The function $\nu_1^{\alpha}(x)$ is shown in Fig.3 (b).

Further, the derived function $f_1^{\nu}(x) = f(x) \oplus \nu_1^{\alpha}(x)$ is determined according to the order of the filter ρ synthesis. Karnaugh table for this function is shown in Fig.3 (c).

If to speak about $f_1^{\nu}(x)$, the spectral method (Sychev, 2011) is used for calculating the next component of the noise filter, a linearized neuron ν_2^{α}. The first three elementary filters, coupled with the inputs of the neuron ν_2, are selected $\lambda_1'(x) = x_1 \oplus x_2 \oplus x_3 \oplus x_6$, $\lambda_2'(x) = \overline{x_1 \oplus x_4 \oplus x_6}$, $\lambda_3'(x) = \overline{x_6}$. Therefore, the affine mapping $\alpha_2 = (\sigma_2, \eta_2)$ construct the matrix $\sigma_2 = \begin{vmatrix} 1 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix}$ and inversion vector $\eta_2 = (011)$. The weights of the corresponding inputs are determined as equal by value: $a_1 = a_2 = a_3 = 1$. Karnaugh table of the weighted sums $w_2(x)$ of the neuron ν_2^{α} is shown in Fig. 3 (d) where selected the values $w_2(x)$ for which $f_1^{\nu}(x) = 1$. The distribution of the unit k_1 and zero k_0 values of function $f_1^{\nu}(x)$ by neuron excitation levels is shown in the table below (Table 3):

Table 3. Distribution of values of the derivative function $f_1^{\nu}(x)$ according to the levels of the neuron $\nu_2^{\alpha}(x)$ excitation.

$w_2(x)$	0	1	2	3
$k_1 : f_1^{\nu}(x) = 1$	0	4	5	7
$k_0 : f_1^{\nu}(x) = 0$	8	20	19	1

The optimal approximation of the function is provided by a threshold value p = 3, the corresponding structural vector of the neuron ν_2^{α} is A_2 = (3; 1,1,1). The function $\nu_2^{\alpha}(x)$ is shown by the Karnaugh table in Fig. 3 (e). Essentially, a neuron is a third-order local filter with a function $\nu_2^{\alpha}(x) = \varphi_2(x) = \lambda_1'\lambda_2'\lambda_3'$.

Thus, the noise filter ρ is synthesized with the function $\rho(x) = \nu_1^{\alpha}(x) \oplus \varphi_2(x)$ presented in Fig.3(f). The approximation of the original $f(x)$ with noise filter function $\rho(x)$ of noise filter ρ is shown in Fig.3(g) where the values of $f(x)$ are highlighted in grey where $\rho(x) = 1$.

The function $f(x)$ contains the number of unit values k_1 = 27 and zero values k_0 = 5 in the segment $X_1 = \{x : \rho(x) = 1\}$ on the range of definitions X, $X_1 \subset X$. Therefore, the different $\theta_{f\rho}^1$ on X_1 has the value $\theta_{f\rho}^1 = \log_2(27/5) = 2{,}433$.

For the fragment $X_0 = \{x : \rho(x) = 0\}$, $X_0 \cup X_1 = X$, , respectively: k_1 = 5, k_0 = 27. Different $\theta_{f\rho}^0 = \log_2(5/27) = -2{,}433$ correlates with X_0. By absolute value, these values exceed the corresponding values for the white noise filter $\theta_{f\rho}^1 > \theta_{f\beta}^1$, $|\theta_{f\rho}^0| > |\theta_{f\beta}^0|$.

4. THE WAYS OF INCORPORATING NOISE FILTERS IN THE COMPOSITION OF THE SWITCHING NEURO-STRUKTURES

Switching neuro-structure (Sychev, 2012, 2014) is an ensemble of neurons united by a network of channel switches. The channel switches (PC) are connected in the sets of vertical rows. If the CNS is implemented by a family $\{f_1, f_2, \ldots, f_r\}$ of logical functions, the vertical series contain *r* groups composed of *q* switches. With the input of each PC_{ij}, $i = 1 \div q$, $j = 1 \div r$, certain k^{th} vertical column is associated with a fragment X_{ijk} of the field definitions *X*, $X_{ijk} \subseteq X$, of the family of implemented logical functions. In the case of employing the channel switch of type "1×2" when exposed to the logical control function $u_k(x)$, the fragment X_{ijk} is divided into two sub-fragments X^0_{ijk} and X^1_{ijk}, $X^0_{ijk} \cup X^1_{ijk} = X_{ijk}$, $X^0_{ijk} \cap X^1_{ijk} = \varnothing$, which are associated with the outputs of the switch PC_{ij}. It is necessary to choose such control element u_k which is able to provide the maximum value of the average different of function f_j for two resulting semi-fragments of $(i, j)^{th}$ switch.

For separate function f_j the average different of the pair X^0_{ijk}, X^1_{ijk} is determined by expession

$$\theta^c_{ijk} = \delta^0_{ijk} \cdot \left|\theta^0_{ijk}\right| + \delta^1_{ijk} \cdot \left|\theta^1_{ijk}\right|,$$

where $|\theta|$ is the absolute value of different θ,

$\theta^0_{ijk}, \theta^1_{ijk}$ are differents of function f_j on the semi-fragments X^0_{ijk}, X^1_{ijk} respectively,

$$\delta^0_{ijk} = \frac{\left|X^0_{ijk}\right|}{\left|X_{ijk}\right|}, \quad \delta^1_{ijk} = \frac{\left|X^1_{ijk}\right|}{\left|X_{ijk}\right|},$$

$\left|X_{ijk}\right|, \left|X^0_{ijk}\right|, \left|X^1_{ijk}\right|,$ are the capacities of fragments under consideration.

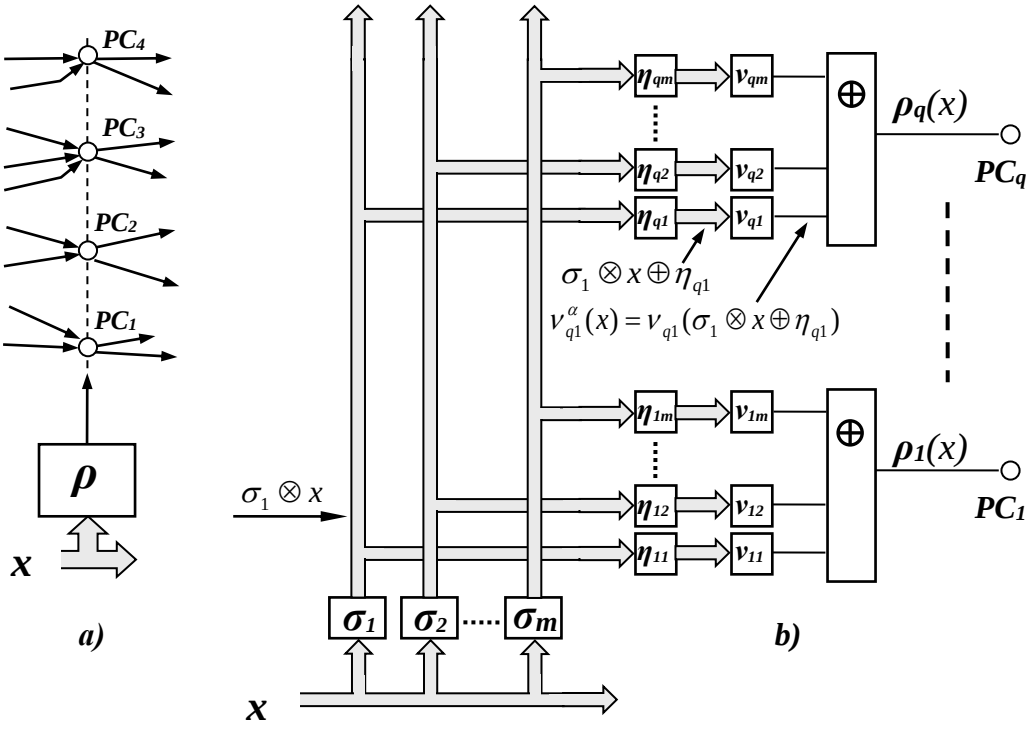
Similar processes happen for the whole family of functions $\{f_1, f_2, \ldots, f_r\}$. Since the segmentation is carried out in all fragments *q* of each group *r*, it is necessary to maximize the value

$$\theta^c_{k\Sigma} = \sum_{i=1}^{q} \sum_{j=1}^{r} \left(\delta^0_{ijk} \cdot \left|\theta^0_{ijk}\right| + \delta^1_{ijk} \cdot \left|\theta^1_{ijk}\right| \right).$$

The various options of using the filters as control elements u_k and switches of channel neural structure can be proposed for achieving this goal. For example, the easiest-to-use method is shown in Fig.4(a). However, as is easy to notice, it will be difficult to effectively split simultaneously all input fragments X_{ijk}, $i = 1 \div q$, $j - 1 \div r$, switches of k^{th} column with a single noise filter. Family functions $\{f_1, f_2, \ldots, f_r\}$ on different fragments X_{ijk} have different combinations of values, and therefore the selected control function u_k for some phrases seems to be non optimal. As a result, the CNS, which implements a family of complex functions, will contain a significant number *t* of vertical columns, and it is desirable to reduce this number. Nevertheless, the ease of managing the neural network can be the preferred factor. In this case, the calculation and selection of simple filters λ included in the noise filter ρ composition must be performed according to (Sychev 2014) by analyzing the total spectrum.

$$S_{\Sigma}(\omega) = \sum_{j=1}^{r} \left| \sum_{i=1}^{q} S_{ij}(\omega) \right|.$$

Fig. 4. Examples of application of noise filters in neural-structures



In Fig.4, symbols ***a)*** and ***b)*** denote the following variants: ***a)*** the control of channel switches of the vertical series with one filter *p*; ***b)*** control of PC on the basis of filters family $\{\rho_1, \rho_2, \ldots, \rho_q\}$, formed by the variants of affine mapping of argument.

Reduction of the required number *t* of vertical series of switches can be achieved by applying affine mappings of argument *x* on the inputs of control noise filters.

Figure 4b) presents the corresponding control block diagram for one of the family functions f_j of the family $\{f_1, f_2, \ldots, f_r\}$. The general construction presupposes the formation of a control noise filter ρ_{ij} with a function $\rho_{ij}(x) = \bigoplus_{n=1}^{m} \nu_{ijn}^{\alpha}(x)$ where $\nu_{ijn}^{\alpha}(x) = \nu_{ijn}(\sigma_n \otimes x \oplus \eta_{ijn})$ for each switch $PC_{ij}, i = 1 \div q,$ of vertical row *k*. Here, the calculation of the matrix of linear transformation σ_n, simple filters λ and inverting vectors η_{ijn} is performed with employment of the total spectrum

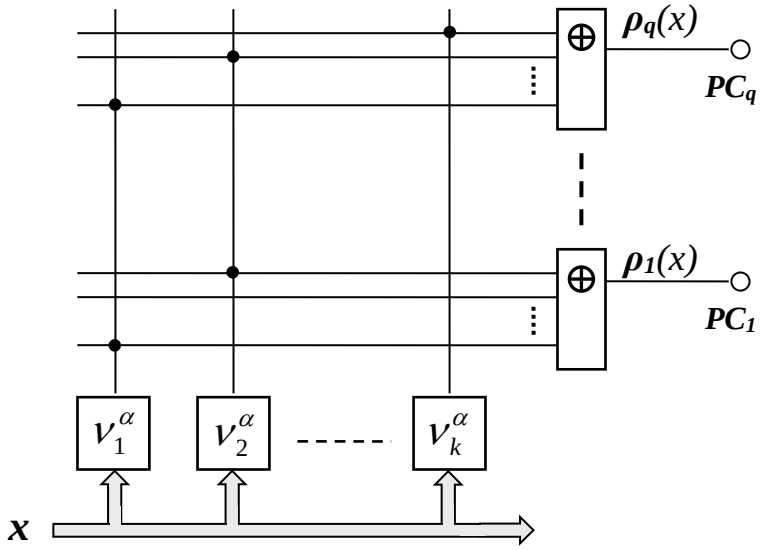
$$S_{\Sigma}(\omega) = \sum_{j=1}^{r} \sum_{i=1}^{q} \left| S_{ij}(\omega) \right|$$

Figure 5 presents the option of application of the noise filters, which is intermediate in complexity and efficiency. It also shows the switch control structure for a single function f_j of family

$\{f_1, f_2, \ldots, f_r\}$. The controlling filter $\rho_i, i = 1 \div q,$ implements a function $\rho_i(x) = \bigoplus_{d \in V} \nu_d^{\alpha}(x)$ with the subset $V \subseteq \{1,2,\ldots,k\}$. Simple filters λ, which are the components of the linearized neurons ν_d^{α}, in this variant for the whole family $\{f_1, f_2, \ldots, f_r\}$ are calculated, as well as in the first variant, by means of the total spectrum

$$S_{\Sigma}(\omega) = \sum_{j=1}^{r} \left| \sum_{i=1}^{q} S_{ij}(\omega) \right|.$$

Fig. 5. Controlling the channel switches by the family of filters $\{\rho_1, \rho_2, \ldots, \rho_q\}$ formed by a combination the linearized neurons $\{\nu_1^{\alpha}, \nu_2^{\alpha}, \ldots, \nu_k^{\alpha}\}$



5. CONCLUSIONS

The theory of communication considers an overlay of pseudorandom sequence on the transmitted signal in order to coordinate the parameters of the signal with the parameters of the communication channel to improve the noise immunity in the process of information transmission. Similarly, the procedure of mixing the output signals of neurons generates the pseudorandom signal, optimally correlated in its binary representation with a given logical function on the considered fragment of the definition.

The sequential computation of the components proposed in the paper allows constructing an optimal neural noise filter with an acceptable approximating ability to a given function. The use of these filters as controlling elements of switches in the CNS will significantly affect the possibility of increasing the average different $\theta_{k\Sigma}^{c}$.

It should be noted that the increase in the number of neural components in filter ρ causes an increment $\theta_{k\Sigma}^{c}$ by a certain amount θ_{Δ}. However, the value θ_{Δ} for each new additional component in the filter becomes smaller than the previous one. Therefore, it is necessary to take this fact into account in the process of computing the optimal filter.

However, if to determine "the utility" of enhanced filters in relation to the previous value $\gamma = (\theta^c_{k\Sigma} + \theta_\Delta)/\theta^c_{k\Sigma}$ for the k^{th} column of the CNS, then, in general for the neuro-structure with *m* vertical rows of switches, the "utility" will increase by γ^m times. Therefore, the value γ can affect significantly the volume of CNS, determined by the number *m* of rows of channel switches.

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