

IMPLEMENTATION OF BOOLEAN FUNCTIONS BY ONE GENERALIZED NEURAL ELEMENT

Summary. *Present article considers the neural elements (NE) with generalized threshold activation function and represents criterion of Boolean functions implementation on such neural elements.*

Keywords: *characteristic vector, neural element, activation function, vector structure, recognition, spectrum, character of group.*

Introduction

Development of suitable methods for processing and solving the problem of digital signals and images recognition is actual and practically important task. As we know [1-5], selection of basis for representation of discrete signals and images is an important stage during their processing and formation of indicators for recognition problem.

Surfaces which are defined by neural elements with conventional threshold activation functions and are used for separation of objects classes, are built by means of hyperplanes. Neural elements with generalized threshold activation function define nonlinear surfaces and by means of these surfaces the complex surfaces are generated, which can be successfully used for solving problems of classification and recognition of objects, defined by sets of Boolean vectors.

Thus, development of effective methods verifying the implementation of logical algebra functions by one neural element with generalized threshold activation function is actual and important while solving problems connected with objects recognition and data compression.

Neural elements with generalized threshold activation function

Let $H_2 = \{-1, 1\}$ – is a cyclic group of 2-nd order, $G_n = H_2 \otimes \dots \otimes H_2$ – is a direct product of n cyclic group H_2 and $X(G_n)$ – is a group of characters [6-8] of group G_n over the field of real numbers R . Let's define function on the set $R \setminus \{0\}$:

$$R \operatorname{sign} x = \begin{cases} 1, & \text{if } x > 0, \\ -1, & \text{if } x < 0. \end{cases} \quad (1)$$

Let $i \in \{0, 1, 2, \dots, 2^n - 1\}$ and (i_1, \dots, i_n) – is its binary code, that is $i = i_1 2^{n-1} + i_2 2^{n-2} + \dots + i_n$, $i_j \in \{0, 1\}$. The value of character χ_i on element $g = ((-1)^{\alpha_1}, \dots, (-1)^{\alpha_n}) \in G_n$ ($\alpha_j \in \{0, 1\}, j = 1, 2, \dots, n$) is defined as follows:

$$\chi_i(g) = (-1)^{\alpha_1 i_1 + \alpha_2 i_2 + \dots + \alpha_n i_n}.$$

Let us consider 2^n -dimensional vector space $V_R = \{\varphi \mid \varphi: G_n \rightarrow R\}$ over the field R . Elements χ_i ($i = 0, 1, 2, \dots, 2^n - 1$) of group $X(G_n)$ form orthogonal basis of space V_R [6]. Boolean function in the alphabet $\{-1, 1\}$ sets definite indication $f: G_n \rightarrow H_2$, that is $f \in V_R$. Consequently, arbitrary Boolean function $f \in V_R$ definitely could be written as follows:

$$f(g) = s_0 \chi_0(g) + s_1 \chi_1(g) + \dots + s_{2^n-1} \chi_{2^n-1}(g).$$

Vectors $s_f = (s_0, s_1, \dots, s_{2^n-1})$ is named the spectrum of Boolean function in system of characters $X(G_n)$ (in system of basis functions of Walsh-Hadamard [9]).

From different characters $X(G_n)$, except the main one, we will build m -element set $\{\chi_{i_1}, \dots, \chi_{i_m}\}$ and relating the chosen systems of characters we will consider the following mathematical model of neural element:

$$f(x_1(g), \dots, x_n(g)) = R \operatorname{sign} \left(\sum_{j=1}^m \omega_j \chi_{i_j}(g) + \omega_0 \right), \quad (2)$$

where vector $w = (\omega_1, \dots, \omega_m; \omega_0)$ is named as vector of neural element structure and $g \in G_n$.

Let $w(g) = \omega_1 \chi_{i_1}(g) + \dots + \omega_m \chi_{i_m}(g) + \omega_0$. If $w = (\omega_1, \dots, \omega_m; \omega_0)$ is a vector of NE structure relating to system of characters $\{\chi_{i_1}, \dots, \chi_{i_m}\}$ of group G_n over R , which implements Boolean function $f: G_n \rightarrow H_2$, then from (1) and (2) immediately follows that

$$\forall g \in G_n \quad w(g) \neq 0. \quad (3)$$

Further we will consider only such neural elements, vector structures of which

satisfy the condition (3). Set of all such $m+1$ -dimensional real vectors that satisfy the condition (3), we will mark by means of $W_{m+1} = W_{m+1}(\chi_{i_1}, \dots, \chi_{i_m})$.

It is obvious, that the neural element relating to the system of characters $\{\chi_1, \chi_2, \chi_4, \dots, \chi_{2^{n-1}}\}$ coincides with the threshold element [10].

Theorem 1. *Boolean function $f: G_n \rightarrow H_2$ is implemented by one neural element relating to system of characters $\{\chi_{i_1}, \dots, \chi_{i_m}\} \subset X(G_n)$ with vector of structure $w \in W_{m+1}$ only in case, when*

$$\forall g \in G_n \quad f(g)w(g) = |w(g)|, \quad (4)$$

where $|x|$ – when module of number $x \in R$.

The proof follows immediately from (2) and from equality: $(R \text{ sign } x) \cdot x = |x|$, where $x \in R \setminus \{0\}$.

Theorem 2. *Boolean function $f: G_n \rightarrow H_2$ is implemented by one neural element relating to system of characters $\{\chi_{i_1}, \dots, \chi_{i_m}\} \subset X(G_n)$ with vector of structure $w \in W_{m+1}$ only in case, when*

$$\sum_{g \in G_n} f(g)w(g) = \sum_{g \in G_n} |w(g)|. \quad (5)$$

Proof. Sufficiency. Indeed, when function f is not implemented by one NE relating $\{\chi_{i_1}, \dots, \chi_{i_m}\}$, then such elements exist $g_1, \dots, g_k \in G_n$ for which the equality (4) is not true, that is:

$$\forall g_j \in \{g_1, \dots, g_k\} \quad f(g_j)w(g_j) = -|w(g_j)|$$

and

$$\sum_{g \in G_n} f(g)w(g) = \sum_{g \in G_n \setminus \{\chi_{i_1}, \dots, \chi_{i_m}\}} |w(g)| - \sum_{j=1}^k |w(g_j)|. \quad (6)$$

Hence on the basis of (5) we have

$$2 \sum_{j=1}^k |w(g_j)| = \sum_{g \in G_n} |w(g)| - \sum_{g \in G_n} f(g)w(g) = 0.$$

Consequently, $\forall g_j \in \{g_1, \dots, g_k\} \quad w(g_j) = 0$, that contradicts the condition $w \in W_{m+1}$. The necessity follows directly from theorem 1.

Let us write the left side of equality(5) in expanded form:

$$\begin{aligned}\sum_{g \in G_n} f(g)w(g) &= \sum_{g \in G_n} f(g)(\omega_1 \chi_{i_1}(g) + \dots + \omega_m \chi_{i_m}(g) + \omega_0) = \\ &= \omega_0 \sum_{g \in G_n} f(g) + \sum_{j=1}^m \omega_j \left(\sum_{g \in G_n} f(g) \chi_{i_j}(g) \right) = \omega_0 b_0 + \sum_{j=1}^m \omega_j b_{i_j},\end{aligned}$$

where $b_f(X) = (b_{i_1}, \dots, b_{i_m}; b_0)$, $(b_{i_1} = 2^n s_{i_1}, \dots, b_{i_m} = 2^n s_{i_m}, b_0 = 2^n s_0)$ – is a characteristic vector of Boolean function f relating to the system of characters $X = \{\chi_{i_1}, \dots, \chi_{i_m}\}$.

Using the concept of characteristic vector of Boolean function f relating to the system of characters $X = \{\chi_{i_1}, \dots, \chi_{i_m}\}$ theorem 2 could be written as follows:

Theorem 3. Boolean function $f: G_n \rightarrow H_2$ is implemented by one neural element relating to the system of characters $X = \{\chi_{i_1}, \dots, \chi_{i_m}\} \subset X(G_n)$ with vector of structure $w \in W_{m+1}$ only in case, when its characteristic vector $b_f(X)$ satisfies the condition

$$(w, b_f(X)) = \sum_{g \in G_n} |w(g)|,$$

where $(w, b_f(X))$ – is a scalar product of vectors w and $b_f(X)$.

Conclusions

It derives from theorem 3 that Boolean function, which is implemented by one neural element relating to system of characters $X = \{\chi_{i_1}, \dots, \chi_{i_m}\} \subset X(G_n)$, is definitely determined by its $m+1$ -dimensional characteristic vector $b_f(X) = (b_{i_1}, \dots, b_{i_m}; b_0)$, and functions, which are not implemented by one neural element, are definitely determined in spectral region only by its spectrum $s_f = (s_0, s_1, \dots, s_{2^n-1})$. Consequently, compression coefficient of Boolean function f , which is implemented by one neural element in spectral area is set by the ratio $2^n / (m+1)$. This means that characteristic vectors of such Boolean functions could be successfully used for data compression. Maximization of data compression coefficient is reduced to minimization of parameter

$m = m^*$, that is to finding out such minimum system of characters $X^* = \{\chi_{i_1}, \dots, \chi_{i_{m^*}}\}$ relating to which the corresponding functions of logic algebra are implemented by one neural element.

If neural element with vector of structure $w \in W_{m+1}$ relating to system of characters $X = \{\chi_{i_1}, \dots, \chi_{i_m}\}$ implements the Boolean function f , then from theorem 3 and equality (6) follows that for Boolean function $h: G_n \rightarrow H_2$ ($h \neq f$) the following inequality is true

$$(w, b_f(X)) > (w, b_h(X)).$$

The last inequality could be used for construction of iterative procedure of neural elements synthesis with generalized threshold activation function relating to system of characters X .

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