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The Neural Network Art which uses the Hamming Distance to Measure an Image Similarity Score

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Abstract: This study reports a new discrete neural network of Adaptive Resonance Theory (ART-1H) in which the Hamming distance is used for the first time to estimate the measure of binary images (vectors) proximity. For the development of a new neural network of adaptive resonance theory, architectures and operational algorithms of discrete neural networks ART-1 and discrete Hamming neural networks are used. Unlike the discrete neural network adaptive resonance theory ART-1 in which the similarity parameter which takes into account single images components only is used as a measure of images (vectors) proximity in the new network in the Hamming distance all the components of black and white images are taken into account. In contrast to the Hamming network, the new network allows the formation of typical vector classes representatives in the learning process not using information from the teacher which is not always reliable. New neural network can combine the advantages of the Hamming neural network and ART-1 by setting a part of source information in the form of reference images (distinctive feature and advantage of the Hamming neural network) and obtaining some of typical image classes representatives using learning algorithms of the neural network ART-1 (the dignity of the neural network ART-1). The architecture and functional algorithms of the new neural network ART which has the properties of both neural network ART-1 and the Hamming network were proposed and investigated. The network can use three methods to get information about typical image classes representatives: teacher information, neural network learning process, third method uses a combination of first two methods. Property of neural network ART-1 and ART-1H, related to the dependence of network learning outcomes or classification of input information to the order of the vectors (images) can be considered not as a disadvantage of the networks but as a virtue. This property allows to receive various types of input information classification which cannot be obtained using other neural networks.

Key words: Image similarity score, neural network Hamming, neural network of adaptive resonance theory, learning algorithms of neural network, classification, information

INTRODUCTION

Problem statement and literature analysis: Neural network ART-1 and the Hamming network have a common property: reference discrete images (typical representatives of images or image classes) are stored in the weights of single neuron connections (Yampolsky, 2015; Fausett, 2006; Dmitrienko *et al*., 2014; Suzuki, 2003; Asadullaev, 2017). However, typical black and white images in the neural network ART-1 are formed in the process of network learning, usually by a variety of training images. In the Hamming network, however, they are set by a teacher (Yampolsky, 2015; Fausett, 2006; Dmitrienko *et al*., 2014; Suzuki, 2003; Asadullaev, 2017). At the same time in the network ART-1 during the process of network learning, the measure of proximity of the input and the formed typical image is determined using a special similarity parameter (Fausett, 2006; Dmitrienko *et al*., 2014). When this parameter is calculated only single components of black and white images are considered. In a Hamming neural network, image similarity is determined using Hamming distance which considers both single and zero components of the input and reference images. The process of typical images forming (or representatives of image classes) using a variety of training images in the process of solving a number of tasks (but not all tasks) looks preferable than reference images setting by a teacher. In addition, the image at the input of the Hamming neural network almost always (Dmitrienko *et al*., 2017) causes a network reaction even if it does not belong to any of the image classes stored in neural network connection weights considering a measure of proximity. Unlike, the Hamming network, the ART-1 neural network has an internal novelty detector based on the image similarity parameter (Yampolsky, 2015; Fausett, 2006). If none of the typical images by the value of the

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similarity parameter doesn't look like an input image then, we have new information at the entrance of the network and in the neural network learning mode the input image must be stored as a representative of the new image (image class). This is possible due to the fact that the ART-1 neural network architecture provides the free neurons which are not used until new information to remember has appeared. Due to this, the ART-1 network has the property of stability-plasticity, so that, it can memorize new information without distorting the existing information (Yampolsky, 2015; Fausett, 2006).

Thus, we can conclude that the ART-1 neural network has certain advantages over the Hamming neural network and inferior to the Hamming network in evaluating the measure of similarity of the input and typical representatives of the image classes. This is because Hamming distance in assessing proximity measures of black and white images uses all image components. Due to this, Hamming distance is widely used in comparing binary vectors and images. In addition, the teacher does not participate in the training of the ART-1 neural network, even in the presence of quality representatives of image classes. This is a disadvantage if you need to solve a number of problems. The purpose of the study is the development of a new network based on the architecture and algorithms of the discrete neural network ART-1 which uses Hamming distance to estimate the image proximity measure. Also, the purpose of the study is to develop network learning algorithms with the participation of a teacher.

Architecture and the functioning algorithms of the neural network ART-1: Neural network ART-1 Fig. 1 and its modifications are described in detail in the literature (Yampolsky, 2015; Fausett, 2006; Dmitrienko *et al.*, 2014; Grossberg, 1987; Carpenter and Grossberg, 1987), therefore, we present only a brief description of its architecture.

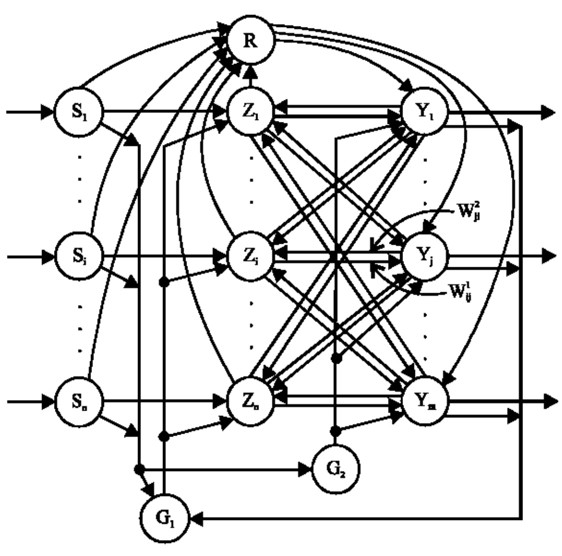

Fig. 1: Neural network ART-1

The neural network has three layers of neurons. Input layer of neurons S_1, ..., S_n, the output of which is fed to the inputs of the decisive neuron R, to the inputs of neurons Z_1, ..., Z_n, interface layer and to the inputs of control neurons G_1 and G_2 putting them into active state while ensuring the functioning of the neurons of the interface layer and the layer of recognition neurons Y_1, ..., Y_m, according to the "two-thirds" rule (Fausett, 2006; Dmitrienko *et al.*, 2014).

MATERIALS AND METHODS

Discrete neural network of adaptive resonance theory that uses Hamming distance: If you compare the architecture of neural network ART-1 Fig. 1 with architecture of discrete neural network ART-1H (architecture is not given because it differs from architecture of network ART-1 only in the lack of connections between the outputs of S-layer neurons and input of the decisive neuron R as well as bias signals of the neurons of the recognition layer which are absent in the network ART-1H), than they are not much different. However, a detailed comparison of the operation algorithms of these networks shows that the networks differences are significant:

- The input vectors of the neural network ART-1H and S-layer neurons are bipolar, rather than binary as in a neural network ART-1
- The connections weights between S and Z layers neurons are changed:

$$w_{S_iZ_i} = 2, i = \overline{1, n}$$

where, s_i, z_i, $(i = \overline{1, n})$, respectively, the neurons of the input and interface layers, n-the number of neurons in the S and Z layers. In the neural network ART-1 these connections weights have a unit weight.

Matrix of connections weights W^1 from Z-layer neurons to the Y-layer neurons at the beginning of the neural network ART-1H learning algorithm has the appearance of $W^1 = \|0, 5\|_{n\times m}$ where, n and m-accordingly, the number of neurons in the interface Z-layer and in the recognition Y-neurons layer. In the neural network ART-1 matrix W^1 at the beginning of the learning algorithm has the form:

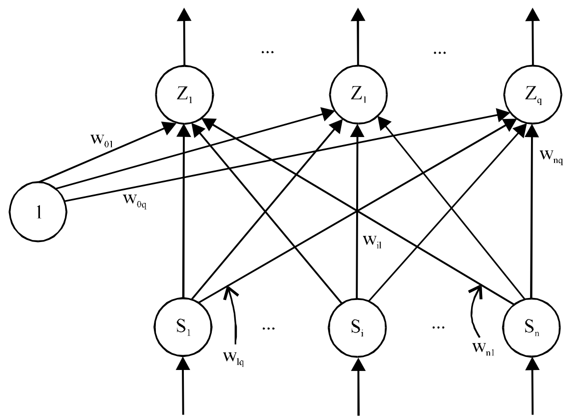

Fig. 2: Hamming network module which calculates a measure of the similarity between the network input vector and the vectors, stored in the weights of Z-layer connections neurons

$$W^1 = \left\| \frac{1}{1+n} \right\|_{n\times m}$$

Figure 2 given the Hamming neural network module (Fausett, 2006; Dmitrienko *et al*., 2017) which calculates the measure of similarity of input vector $S^k = (s_1^k, ..., s_n^k)$ and vectors $W^l = (w_1^l, ..., w_n^l)$, $l = \overline{1, q}$ which are stored in the Z-layer neuron weights is given. The measure of similarity of two vectors S^k and W^l is determined by the scalar product of these vectors:

$$S^k W^l = \sum_{i=1}^{n} s_i^k w_i^l = a_l - d_l \quad (1)$$

where, a_l and d_l, respectively, the number of identical and different bipolar components of the vectors under consideration. Considering that $d_l = n - a_l$, it is easy to get from Eq. 1:

$$a_l = \frac{n}{2} + \frac{1}{2}\sum_{i=1}^{n} s_i^k w_i^l \quad (2)$$

where, a_l is an output signal of Z_l neuron when inputting vector S^k to the neural network. In the Hamming network, the ratio (Eq. 2) is computed using a single neuron, for example, Z_l which has a linear activation function and an input signal U_{inZl}:

$$U_{inZ_l} = w_{0l} + \frac{1}{2}\sum_{i=1}^{n} U_{outS_i} w_{il}, l = \overline{1, q} \quad (3)$$

where, w_{0l} is the neuron $Z_l(l = \overline{1, q})$, connection weight for a single offset signal, $U_{outS_i}(i = \overline{1, n})$, output signals of neuron input layer S; w_{il}-weight of connection between S_i and Z_l neurons, $i = \overline{1, n}$, $l = \overline{1, q}$. In the neural network ART-1H ratio (Eq. 2) is computed using neurons of recognition Y layer.

Matrix of connections weights W^2 from Y-layer neurons to the Z-layer neurons at the beginning of the neural network ART-1H learning algorithm has the appearance of $W^2 = \|-2\|_{n\times m}$. In the neural network ART-1 matrix W^2 at the beginning of the learning algorithm has the appearance $W^2 = \|1\|_{n\times m}$. The rules of the interface layer neurons, recognition neurons layer and decision neuron functioning are changed.

The procedure of connection weights adjustment between the recognition layer and interface neurons layer during distribution of Y-neurons (that is neurons of layer Y which had not been previously involved in the learning process is changed). If neuron-winner Y_J first stands out then its connection weights are given by the source matrices W^1 and W^2. With this, the input image S^k should be stored in connection weights of neuron-winner Y_J by changing the weights of connection which are given by matrices W^1 and W^2. When re-submitting the image S^k the number of different components of the input vector and vector which stores connection weights of neuron Y_J must be equal to zero and the input signal at the input of the neuron Y_J should be maximized:

$$U_{inY_J} = w_{0_J} \cdot 1 + \sum_{i=1}^{n} w_{iJ}^1 U_{outZ_i}$$

This is possible only with the same signs of the factors in all compositions $w_{i_J}^1 U_{outZ_i}, i = \overline{1, n}$. Therefore, when correcting the connections weights of the matrix W^1 new vector components $(w_{1J}^{1*}, ..., w_{nJ}^{1*})$ are determined by the ratio:

$$w_{i_J}^{1*} = \begin{cases} w_{i_J}^1, \text{if } w_{i_J}^1 U_{outZ_i} > 0 \\ -w_{i_J}^1, \text{if } w_{i_J}^1 U_{outZ_i} < 0 \end{cases} \quad (4)$$

Let's determine the ratio for the connections weights that are stored in the matrix W^2. Image S^k which arrived at the input of the neural network must be stored in the connections neuron-weights of the winner Y_J and the total input signal at the input of any neuron $Z_i(i = \overline{1, n})$, must be equal to zero:

$$U_{inZ_i} = U_{outS_i} w_{S_i Z_i} + U_{outY_J} w_{Y_J Z_i}^2 \quad (5)$$

From the ratio (Eq. 5) the necessary weight of connection between neurons Y_J and Z_i is determined. Since, $w_{S_i Z_i} = 2$ and $U_{outY_J} = 1$, then we get:

$$w^2_{Y_J Z_i} = -2U_{outS_i}$$

In the training mode, the functioning of the neural network ART-1H is determined by the algorithm which coincides in many ways with the neural network ART-1 learning algorithm, however, it also has significant differences. Neural network ART-1H learning algorithm is the following:

Step 1: The neural network parameters and connections weights are initiated, zero signals are set at the inputs and outputs of the network neurons, input training vectors S^1, S^2, ..., S^q set is determined, the conditions for stopping the algorithm are set.

Step 2: Start of calculations, during which from the set of input bipolar vectors S^1, S^2, ..., S^q the vectors are sequentially selected one by one. The initial value of the index k helping to choose the training vector S^k, k = 0 is set.

Step 3: The number of the vector in the input sequence, for which steps 4-12 of the algorithm: k = k+1 will be performed is determined.

Step 4: Input vector $S^k = (s_1^k, ..., s_n^k)$, is fed to the inputs of S-layer elements and the input and output signals of its elements are determined. The output signals of the control neurons are determined:

$$U_{inS_i} = S_i^k, U_{outS_i} = U_{inS_i}, i = \overline{1, n}$$

$$U_{outG_1} = U_{outG_2} = \begin{cases} 1, \text{if } \sum_{i=1}^{n} U_{outS_i} > -n \\ 0, \text{ if } \sum_{i=1}^{n} U_{outS_i} = -n \end{cases}$$

Step 5: Input signals of Z-layer neurons are determined and according to the "two-thirds" rule their output signals are selected (Fausett, 2006; Dmitrienko *et al*., 2014):

$$U_{inZ_i} = U_{outS_i} w_{outS_i, inZ_i} + U_{outG_1} = 2\, U_{outS_i} + U_{outG_1} \quad (6)$$

$$U_{outZ_i} = \begin{cases} 1, \text{ if } U_{inZ_i} > 0 \text{ and } U_{outG_1} = 1, i = \overline{1, n} \\ 0, \text{ if } U_{outG_1} = 0 \\ -1, \text{ if } U_{inZ_i} < 0 \text{ and } U_{outG_1} = 1,\ i = \overline{1, n}. \end{cases} \quad (7)$$

Ratios (Eq. 6 and 7) are selected, so that, when U_{outG1} = 1 then the output signals of Z-layer neurons repeat the output signals of the S-layer neurons.

Step 6: The output signals of Y-layer neurons are determined:

$$U_{outY_j} = \begin{cases} k_1 w_{0j} \cdot 1 + \sum_{i=1}^{n} w_{ij}^1 U_{outZ_i}, \text{ if } U_{outY_j} \neq -1 \text{ and } U_{outG_2} = 1, j = \overline{1, m} \\ -1, \text{ if } U_{outY_j} = -1, j = \overline{1, m} \\ 0, \text{ if } U_{outG_2} = 0 \text{ and } U_{outY_j} \neq -1, j = \overline{1, m} \end{cases} \quad (8)$$

where, w_{0j}-connection weight for the neuron bias signal Y_j, $w_{0j} = n/2, j = \overline{1, m}$; k_1-scale factor that prevents neuron Y_J outputs from having big signals. Unbraked Y-neurons work according to the "two-thirds" rule that is when U_{outG2} = 1.

Step 7: Until neuron Y_J which connections weights vector is closest in Hamming distance to input binary vector S_k hasn't been found, the algorithm performs the steps 8-10.

Step 8: In the layer of Y-neurons neuron Y_J is exuded the output signal of which satisfies the inequalities:

$$U_{outY_J} \geq U_{outY_j}, j = \overline{1, m} \quad (9)$$

If there are several such neurons then the element with the lowest index is selected. Neuron Y_J is moved into the state with a single output signal. All the other Y-neurons (except inhibited) are moved into inactive state $(U_{outY_j} = 0)$. Single output signal of element Y_J resets control neuron G_1 to zero and proceeds to the inputs of the Z-layer elements.

Step 9: The signals at the inputs and outputs of the interface elements layer are determined:

$$U_{inZ_i} = U_{outS_i} w_{S_i Z_i} + U_{outY_J} w^2_{Y_J Z_i}$$

$$U_{outZ_i} = \begin{cases} 1, \text{ if } U_{inZ_i} \neq 0 \\ 0, \text{ if } U_{inZ_i} = 0 \end{cases}$$

Output signals of Z-layer neurons arrive at the inputs of the decisive neuron R.

Step 10: Decisive neuron R calculates Hamming distance R_H between the input vector S^k and the vector which is stored in Y_J neuron connections weights:

$$R_H = \begin{cases} \sum_{i=1}^{n} U_{outZ_i}, \text{ if } \sum_{i=1}^{n} w^2_{Y_J Z_i} \neq -2n \\ 0, \text{ if } \sum_{i=1}^{n} w^2_{Y_J Z_i} = -2n \end{cases}$$

If $R_H = \sum_{i=1}^{n} w^2_{Y1Z1} \neq -2n$ then, the neuron Y_J has already been distributed. If at the same time $R_? \leq R_{HD}$ where, R_{HD} Hamming distance wherein the vectors belong to the same class it is necessary to adjust the weights of the connections between the neuron Y_J and Z-layer of the neuron, moving on to the next step of the algorithm. If $R_? > R_{HD}$, then, the input image and the image which is stored Y_J neuron connections weights, belong to different classes. The unit output signal which inhibits neuron $Y_J(U_{outYJ} = -1)$ appears at the output of the neuron R. Then the algorithm switches back to step 7 and the search for a new winning neuron in input vector S^k begins again.

If $\sum_{i=1}^{n} w^2_{Y_J Z_i} = -2n$ then, the neuron Y_J has not yet been distributed and can store the input image. Transition to the next step of the algorithm is made. If $R_H = 0$ and $\sum_{i=1}^{n} w^2_{Y_J Z_i} \neq -2n$ then, the input image matches the image which is stored in weights of the connections neuron Y_J. It is not necessary to adjust Y_J neuron connections weights. Go to step 12 of the algorithm.

Step 11: Y_J winning neuron connections weights are configured/adjusted basing on ratios (Eq. 4) and (5).

Step 12: The criteria of the end of the neural network learning era are checked: (the last input training vector "k = q?" is filled). If the operation is not complete successfully the algorithm switches to step 3. If the condition k = q is true then the transition to the next step of the algorithm is performed.

Step 13: The criteria for the ending of the learning process are checked. The criteria may be either the absence of a change weights of connections $w^1_{ij}, w^2_{ij} \left(i = \overline{1,n}, j = \overline{1,m}\right)$ neural network during the training era or achieving a given number of learning epochs, etc. If the criteria are not met the algorithm switches to step 2, otherwise to step 14.

Step 14: Stop. Functional features of the ART-1H neural network in the recognition mode largely coincides with its functioning in the training mode. Regarding to that, the description of the functioning of the neural network in the recognition mode is given in abbreviated form. In case of need, detailed description of the network functionality can be restored with the algorithm of its training. However, only one image is fed to the input of the neural network in the recognition mode and the change winning neuron connections weight is not performed. The algorithm of the recognition of an image $S^k = (S^k_1, \ldots, S^k_n)$ by the neural network is following:

Step 1: Parameters and weights of neural network connections are being defined. Zero signals at the inputs and outputs of the network are set up. Input image $S^k = (S^k_1, \ldots, S^k_n)$ and criteria of the ending of the algorithm are being designated.

Step 2: Input image S^k is passed to the inputs of elements of S-layer. The input and output signals of its elements are determined, output signals of controlling neurons G_1 and G_2 are defined.

Step 3: The input and output signals of Z-layer neurons are determined.

Step 4: The output signals of the Y-layer neurons are determined. The algorithm loops through steps 5-7 until a neuron Y_J with the most close in Hamming distance vector of connections weights to the input of bipolar vector S^K is found.

Step 5: Y_J neuron with output signal which satisfies inequalities (Eq. 9) is emitted in the layer of Y-neurons. If the number of such kind of neurons is more that one, then the element with the lowest index is selected. Neuron Y_J is being set up into a state with single output, all the rest of Y-neurons (except inhibited one) are put on into inactive state. Solitary output neuron signal Y_J resets the controlling neuron G_1 to zero and is passed as the inputs to the elements Z-layer.

Step 6: Input and output signals of Z-layer elements to be entered into the inputs of the decisive neuron R are determined.

Step 7: Decisive neuron R calculates Hamming distance R_H between the input vector S^k and the vector stored in the neuron Y_J connection weights.

If a $R_? > R_{HD}$ then the input image (vector) and the image stored in the neuron Y_J connection weights belong to different classes of images. A solitary signal which inhibits neuron Y_J appears at the output of the neuron R_H. The algorithm moves to step 4 and begins the search for a new neuron-winner for input vector S^k. If a $R_? > R_{HD}$, then the input image and the image stored in the neuron Y_J connection weights, belong to the same class which is indicated by a specific solitary signal of Y_J neuron.

Step 8: Stop.

RESULTS AND DISCUSSION

Usage of ART-1H neural network for classification of vectors: Let's look at the utilization of ART-1H neural network in order to classify the following bipolar vectors:

$$S^1 = (1, 1, 1, -1, -1, -1, -1),\ S^2 = (1, 1, -1, -1, -1, -1, -1)$$
$$S^3 = (-1, 1, 1, -1, -1, -1, -1),\ S^4 = (1, -1, 1, -1, -1, -1, -1)$$
$$S^5 = (1, 1, -1, 1, -1, -1, -1),\ S^6 = (-1, -1, -1, -1, 1, 1, 1)$$
$$S^7 = (-1, -1, -1, -1, -1, 1, 1),\ S^8 = (-1, -1, -1, -1, 1, -1, 1)$$
$$S^9 = (-1, -1, -1, -1, 1, 1, -1),\ S^{10} = (-1, -1, -1, 1, 1, 1, -1)$$

To solve the problem, we use ART-1H neural network with the following parameters: m = n = 7; q = 10, matrix of initial connections weights $W^1 = \|0, 5\|_{7\times7}$, $W^2 = \|-2\|_{7\times7}$, R_{HD}-1 maximum allowable Hamming distance at which binary vectors are considered to be belonging to the same class. Execution of the algorithm gives the following results: the first vector S^1 distinguishes neuron-winner Y_1 and adapts the initial connections weights of matrices W^1 and W^2. The second vector S^2 differs from vector S^1 by unit Hamming distance that's why it adapts the initial connections weights of the neuron Y_1 and as a sequence, new representative of the first class of vectors is remembered by this neuron. The next input vectors S^3 and S^4 distinguish a new neurons-winners that store these images as representatives of two new classes of vectors. The vector S^5 coincides with the representative of the first class of vectors and therefore it belongs to the first class. As a result of all input vector's calculation the, six classes of vectors are obtained, the vectors are:

Class 1: S^1, S^2, S^5; class 2: S^3; class 3: S^4;
class 4: S^6, S^7; class 5: S^8; class 6: S^9, S^{10}

Connections weights matrix W^1 looks like:

$$W^1 = \begin{vmatrix} 0.5 & 0.5 & -0.5 & -0.5 & -0.5 & -0.5 & -0.5 \\ -0.5 & 0.5 & 0.5 & -0.5 & -0.5 & -0.5 & -0.5 \\ 0.5 & -0.5 & 0.5 & -0.5 & -0.5 & -0.5 & -0.5 \\ -0.5 & -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & 0.5 \\ -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & -0.5 & 0.5 \\ -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & 0.5 & -0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \end{vmatrix}$$

ART-1H neural network learning results, similar to neural network ART-1 may depend on the order of images in the input sequence. For example, if the order of the vectors in the input sequence is:

$$S^2, S^5, S^4, S^1, S^3, S^6, S^8, S^7, S^9, S^{10}$$

Then, the following classes are composed:

Class 1: S^2, S^5; class 2: S^4, S^1; class 3: S^3;
class 4: S^6, S^8; class 5: S^7; class 6: S^9, S^{10}

Remark 1: Dependency of learning outcomes (or classification of input vectors) on the order of the vectors in the input sequence is considered a weakness of ART-1 neural network. However, it also can be considered as its string trait, since, the changing order of items in the input sequence gives various types of classification of input information which is unavailable to most of neural networks.

Remark 2: In order to avoid issues related to changing order of items in the input sequence, the teachers may be in use, the same as in Hamming neural network. Using matrices of initial connections weights W^1 and W^2 the teacher sets up vector model templates and prohibits adaptation of connections weights of the vectors with input vectors. Only two template vectors S^1 and S^6 can be specified for given example. In that case the matrix W^1 has a look like the following:

$$W^1 = \begin{vmatrix} 0.5 & 0.5 & 0.5 & -0.5 & -0.5 & -0.5 & -0.5 \\ -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \end{vmatrix}$$

After submitting information to the input of the ART-1H neural network the first five vectors are assigned to the first class and the rest to the second.

Remark 3: ART-1H neural network brings advantages of both the Hamming neural network (like using of teacher's knowledge) as well as ART-1H neural network the possibility of obtaining typical representatives of classes of vectors in the learning process based on input information. In order to achieve the advantages, the vector model templates should be set up by the teacher before the operation of the network starts. In case the teacher sets up not full set of vectors model templates, typical class representatives are created using one of the neural network ART-1 algorithms.

CONCLUSION

New adaptive resonant theory network named ART-1H is tendered in the study. The network calculates the proximity of vectors (images) using Hamming distance. Hamming distance algorithm takes into account all the components of vectors during calculation, unlike the ART-1 neural network that calculates the proximity with use only individual components of binary vectors. In contrast to the Hamming network, the new network allows the formation of typical representatives of vector classes in the learning process, instead of using teacher's information that is not always reliable. The new network can also be used as a Hamming network in which the reference vectors can be set up by the teacher.

The new network can combine the advantages of the Hamming neural network and ART-1 by setting up part of the initial information as reference images with help of the teacher, additionally setting up parts of typical representatives of the classes obtained with ART-1 neural network. ART-1 and ART-1H neural networks feature of calculation learning outcomes or classification of input information depending on the order of vectors (input images) it should be considered rather as an advantage than a drawback, since, it gives ability to get various types of classification of input information.

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