Implementation of a multi-layer hamming network in problems for recognition dry areas of agricultural crops

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Abstract. The article discusses the possibilities of using the mathematical and instrumental enhancement of the multilayer Hamming network in the tasks of recognizing aerial photographs, in particular, the advantages of the neuromodel for implementing further research to solve the problems of increasing crop yield based on monitoring and segmentation of dry crop areas are highlighted.

1. Introduction
Work on artificial neural network (INS) models has a long history. The development of detailed mathematical models began more than 70 years ago with the work of F. Rosenblatt et al. The renewed interest is due to the development of new topologies and algorithms, the emergence of new methods for implementing analog ultra-large integrated circuits, some interesting presentations, as well as a growing interest in studying the functioning of the human brain [1-2]. INS are widely used for pattern recognition, classification problems, optimization problems, forecasting, data analysis, decision-making and adaptive management, as well as recognition of aerial photographs.

2. Materials and methods
The idea of the Hamming network functioning is to issue one of the reference samples that is closest to the image supplied to the input of the neural network. The neural network works as a classifier, comparing the vector that entered the input with the reference vectors stored in memory. The Hamming distance is used as a comparison measure. The set of reference images and the image that is fed to the network input are specified as binary vectors. The Hamming distance between two vectors of the same dimension is determined by the number of non-matching components in these vectors (Fig. 1) [3]. Vectors with bipolar components are received at the input of the Hamming INS.
The Hamming network consists of four layers of neurons, some sources describe that the network consists of two or three layers, such a contradiction arises due to the fact that the input and output layers are considered conditional and belong to another layer, so they may not be designated [4-5]. The mathematical apparatus of the network is implemented in two layers.

The number of neurons of the input layer \( n \) corresponds to the number of binary features of the images under consideration. In the first and second layers of the INS, the number of neurons is equal to \( m \), the number of images stored in the network. For example, to search in a neural network of thousands of products, layers with a dimension of a thousand neurons will be used. The number of neurons of the output layer is also equal to the number of stored reference images [6-8].

Figure 3 shows in more detail the device of the first layer involved in the calculations.
where \( f(s) \) is the activation function of the neuron, \( s \) is the state of the neuron, and \( F \) is the activation threshold of the neuron.

The first layer of the neural network is used to calculate the Hamming distance, the number of components of the input vector that differ from the components stored in the image database is taken into account. The smaller the Hamming distance, the stronger the signal is obtained. The state of the neurons of the first layer is calculated using the formula (2). The superscript indicates the number of the layer in the neural network.

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S^{(1)}_j = \frac{1}{2} \sum_{i=0}^{n-1} w_{ij} x_i + T,
\]

where \( S^{(1)}_j \) is the state of the \( j \)-th neuron of the first layer, \( j = 0, \ldots, m-1, m \) is the number of stored images, \( n \) is the number of components of the input vector, \( w_{ij} \) is the weight coefficient of the \( i \)-th component, \( j \)-th image, \( x_i \) is the \( i \)-th component of the input vector, \( T \) is the offset, according to the formula, \( a \) is the number of identical components of vectors.

Feedback in the Hamming neural network forms associative memory. Associativity consists in strengthening the connection with those reference images that are most similar to the vector supplied to the network. Figure 4 shows the second computational layer of the Hamming neural network in more detail. This layer implements the MAXNET neural network, which finds the neuron with the largest signal. Each neuron is connected to other neurons by negative synaptic connections, a synapse with a positive signal communicates with its own neuron. Such connections are formed through a special element of the neuron, called the branching point. The difference between this layer and the Hopfield neural network is that the neuron has a connection with its own input.

Figure 4. Structure of the second computational layer of the Hamming neural network

This layer works until there is only one active neuron left in the network, which had the largest signal at the input. During the operation of the second layer of the neural network, weak signals are
gradually reset and become inactive, and only one neuron belonging to the reference image whose vector is closest in Hamming distance to the vector of the image received at the input is activated in the output layer.

3. Conclusion
After considering the structure of the Hamming neural network, it became clear that the Hamming neural network can first produce products that are least similar to a given prototype, gradually approaching the product with the largest signal. Thus, it is possible to put the numbers of images that are gradually being eliminated from calculations into the stack, and the last element in the stack will be the number of the image that is closest to the product that the user is looking for [9-12]. The advantages of the Hamming network are the minimization of iterative learning cycles (the same weight coefficients are always obtained for the same training sample).

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