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Methods and Algorithms of Heterogeneous Interference Filtration with The Use of Artificial Intelligence Systems in The Tasks of Manipulation of Data of Earth's Remote Sensing.

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ABSTRACT

This article deals with the principal component analysis and independent component analysis means performing a preliminary patterns processing to reduce the dimensionality of the classified space and therefore reduce the time and resources spending to realization of the preliminary patterns processing. The use of autoencoder for solving the problems of classification of patterns is reasonable. The results of experiments demonstrating the expediency of the use of aforesaid methods for the task are given.
Keywords: neural network, principal component analysis, independent component analysis, autoencoder, Kullback–Leibler divergence.

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INTRODUCTION

At the present stage of development of society, involving intensive and often irrational use of natural resources with a variety of technological tools that have a negative ecological impact on the environment, the task of environmental management comes to the forefront. It implies more efficient use of natural resources while reducing the harmful influence exerted by human [1]. One of the components of the solution of the aforesaid problem is the monitoring of natural resources through the analysis of Earth's remote sensing (ERS), received from the spacecraft (SC) [2]. Finally one of the methods of Earth's remote sensing data analysis is the automated construction of electronic cards by means of which other application tasks of environmental management and improving the ecological situation in specific areas are solved in the future [3].

Independent Component Analysis

Independent Component Analysis (ICA) was first suggested in 1986 in Utah, (USA), at a conference on the study of neural networks as a model that could separate a mixture of independent signals on the basis of data on the implementation of the observation vector. ICA can be regarded as an extension of principal component analysis (PCA). This method in contrast to the PCA requires the statistical independence of individual components of the output vector Y and it is unrelated to the requirement of orthogonality. The model used in the Independent Component Analysis may take the form of (1):
(1):

$$Y = H \cdot X, \qquad (1)$$

where X - n - dimensional random vector with independent components, Y - m - dimensional random vector, H - a reversible transformation of the unknown. ICA task is formulated as a task of finding a projection of the vector Y on linear space of vectors X, which components would be statistically independent. With that only some random statistical sample of vector Y values is available for this analysis. [4].

To simplify the independent component analysis series of restrictions are assumed:

-Output signals are statistically independent, in other words the value of one of them does not affect the probability of the values of others;
-Independent components do not have a Gaussian distribution or permissible that only one of the components is normally distributed;
-Reversibility and quadratic matrix matching, i.e. the number of independent components is equal to the number of mixed signals observed.

Traditional methods of linear ICA are constructed by the variational principle:

$$X = \arg\min \cup \max(Q(A \cdot Y)), \qquad (2)$$

where A is matrix of m * n, Q is functional of matrix, which has the meaning of independent component criterion.

For nonlinear ICA the task is uncertain, because the imagery view of H is often unclear in the formula (1). A possible solution to the problem of ICA in this case is a clear definition of the transformation of component independence.

As a criterion of statistical independence mutual information $I(Y_j;Y_i)$ between random variables Y_i and Y_j that are components of the output vector Y can be selected. In the ideal case the information is zero, therefore the corresponding components Y_i and Y_j are statistically independent. This effect is achieved by minimizing the mutual information between all pairs of random variables constituting the vector Y.

This target is equivalent to minimizing the Kullback-Leibler divergence (3) between the probability density function $f_y(y, W)$, parameterized by the W, and the corresponding distribution of the factorial:

$$f_Y(y, W) = \prod_{i=1}^{m} f_{Y_i}(y_i, W), \qquad (3)$$

where $f_Y(y, W)$ is the boundary probability density of function Y_i. Expression (3) can be considered as one of the limiting imposed on the learning algorithm of the neural network.

Minimizing the Kullback-Leibler divergence is used as one of algorithms for searching weight coefficients increment for the implementation of unidirectional neural network.
An alternative to using the algorithm of searching weight coefficient increment based on minimizing the Kullback-Leibler divergence, can serve an algorithm based on natural gradient [4]. There are several advantages of this algorithm:

- Simplicity of implementation;
- Component separation process does not depend on the ratio of the amplitudes of the input signals.

The following formula is used to calculate the increment weighting coefficients.

$$\frac{dW}{dt} = \eta(t)(1 - f(y(t))g^T(y(t))), \qquad (4)$$

where η (t) is the function that characterizes the learning rate of unidirectional neural network. This feature is always non-negative and its value tends to zero as the network training.
The functions f (x) and g (x) may take a different view, but they should never be the same. Most often the functions are selected so that one of them has a concave shape, and another - convex.

Principal component analysis

Principal component analysis (PCA) is one of the main ways to reduce the dimensionality of the data, having lost the minimum amount of information. Sometimes PCA is called Karhunen - Loeve transform or Hotelling transform. PCA is an orthogonal linear transformation of the input vector X of dimension n into an output vector Y of dimension p (Figure 1), where $p < n$, with that components of the vector Y are uncorrelated and the total variance remains unchanged after conversion. The set of input sequences may be represented as a matrix (5):

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{L1} & x_{L2} & \dots & x_{ln} \end{bmatrix}; \quad x^k = (x_{k1}, x_{k2}, \dots, x_{kn}), \qquad (5)$$

where x^k corresponds to the k-th input pattern, L is the total number of patterns [5].

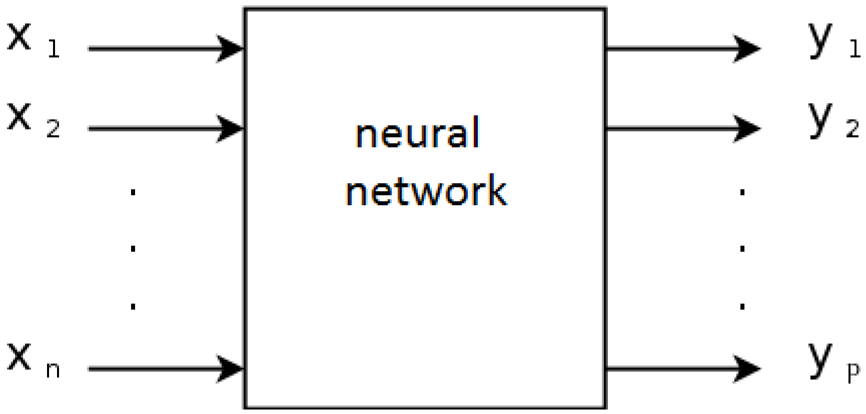

Fig. (1). –PCA network model

Autoencoder

Autoencoder is a special structure of neural networks, allowing use training without teachers using the method of backpropagation. The simplest structure of the autoencoder is shown in Figure 2 - the direct distribution network, without feedback, the most similar to the perceptron and comprising an input layer, an intermediate layer and output layer [6].

The main purpose of training the autoencoder is to ensure that the input feature vector called network response equal to the input vector. So the task of the autoencoder is to find an approximation of such function the response of a neural network would be equal to the value of input signs up to the setpoint error.

To the solution of the problem wouldn't be trivial, the neural network topology must satisfy one of the following conditions:

- The number of neurons in the hidden layer should be less than the dimensionality of the input data (as shown in Figure 2).
Such compression provides a data restriction when transmitting input to the output network. As such the operation of autoencoder resembles the method of Principal component analysis (PCA);

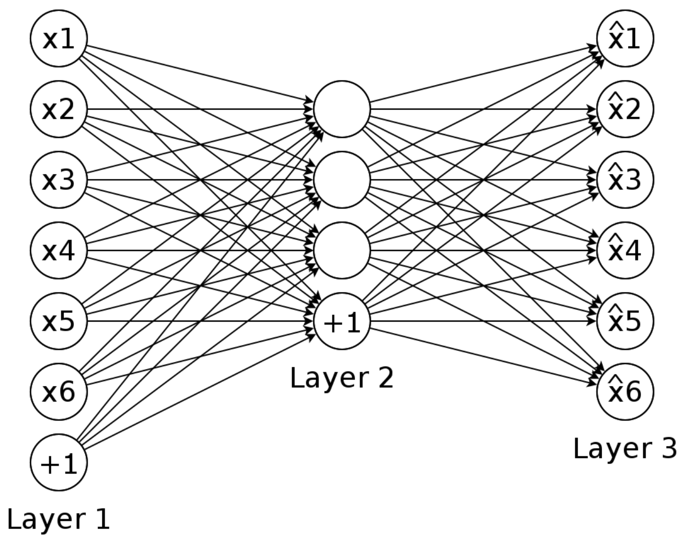

Fig. (2). – Autoencoder structure.

- The activation of neurons of the hidden layer should be sparse.

This requirement lets get a non-trivial results, even when the number of neurons in the hidden layer is greater than the dimension of the input data [7].

Autoencoder as a way of reducing the dimension of the feature space can be used in two ways:

- Using the structure shown in Figure 2, the operation of the autoencoder is similar to a neural network that implements the method of PCA. This approach has the following advantages:
- High accuracy of the results;
- Reducing the number of resources used;
- A high level of parallelism;
- High output;

The structure shown in Figure 2, may be complicated by the addition of one more inner layer (Figure 3).

Adding an additional inner layer in the structure of autoencoder allows dividing the neural network into two subnets after training. Thus autoencoder is divided into two subnets, one of which functions as the encoder and the other as the decoder.

At this rate the classification of patterns will be made between uses of the encoder and the decoder, i.e. not the sets of texture features will be classified directly but their representations in autoencoder. After the decoding procedure the set of already divided into classes patterns will be obtained. [7].

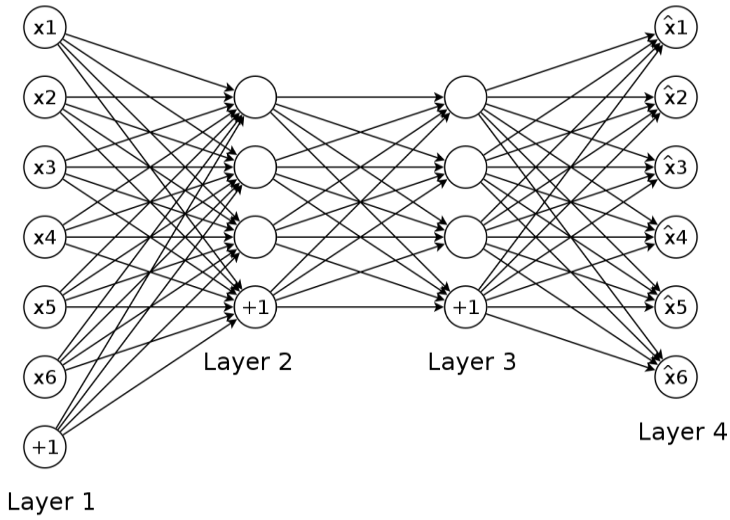

Fig. (3). – Elaborate structure of *autoencoder*

This structure of autoencoder complicates the construction of the classifier and increases the time and resource consumption, but allows reducing dimension of the classified vectors.

CONCLUSIONS

The results of the experimets show:

- The feasibility of independent component analysis to filter the type of "salt - pepper" noise in the one-dimensional and two-dimensional discrete signals (patterns);
- The use of neural network implementations of PCA lets to achieve sufficient accuracy of the result in the solution of problems of classification of remote sensing data in the construction of electronic maps and terrain models;

- The use of PCA neural network implementations allows organizing operative (with minimal delay) process of construction of electronic maps and terrain models;
- Neural network implementation of the PCA is easy to parallelize. That allows creating software and hardware complexes of remote sensing data efficient from a computational point of view and cheap from an economic point of view;
- The use of the autoencoder use in pattern recognition problems for reducing the dimension of the vector space demonstrated the high computational efficiency and accuracy of adjustment sufficient for the application of this method in practice.

SUMMARY

The proposed algorithms can be used in tasks of construction of digital maps and virtual terrain model using the recognition, as well as to build detailed two-dimensional and three-dimensional maps and terrain models.

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