Processing the Multispectral Satellite Images Using RBF-based Neural Network

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Abstract

The method and instrumental toolkit based on radial basis function neural network to process multispectral satellite images are presented. Experimental testing of network has been carried out using images received from Landsat 7 ETM+ satellite. These images include all the bands of Enhanced Thematic Mapper: 0.45-0.52, 0.52-0.60, 0.63-0.69, 0.76-0.90, 1.55-1.75, 10.4-12.5, and 2.08-2.35 micrometers. All the layers of multispectral image were processed as aggregate. Using the histogram instead of raster representation of a multi-bands fragment to be supplied on network's inputs has allowed to increase efficiency of classification of objects via tone criterion.

Keywords: Multispectral Satellite Image, Neural Network, Machine Vision.

1 Introduction

Neural networks are widely used to process multispectral satellite images [Haykin, 1998], [Atkinson and Tatnall, 1997], [Heerman and Kjazenic, 1992], [Lee and Landgrebe, 1997], [Landgrebe and Schowengerdt, 1978], [Landgrebe, 2005], [Tilton et al., 1999], starting from segmentation and finishing forecasting of change of objects [Maier and Dandy, 2000].

The neural network to be applied consists of a layer of Radial Basis Function cells and a layer of neurons with sigmoid threshold function [Orr, 1996]. The network has been designed so that the data from all the layers of multispectral image were processed as aggregate.

The image has been broken into set of fragments during processing (they can be both overlapped and not depending on the purpose of experiment). The method of allocation of more informative area in a processable fragment has been applied due to use of a mask, applied to every image submitted on an input of a neural network.

There is a lot of methods of preliminary data processing, images enhancement, features extraction to classify the objects on multispectral satellite images [Sadykhov and Podenok, 2005]. The developed network has been modified to apply the histogram analysis instead of raster representation of a multi-bands fragment on network's inputs. It gave ability to increase efficiency of classification of objects via tone criterion. The used method of recognition is completely insensitive to a textural component of processed fragment.

2 Statement of a task

The task to be fulfilled was the evaluation of capabilities of radial basis function (RBF) based neural network to select and classify different land cover types. Experimental testing of proposed network has been carried out using images of Myadel district of Belarus received from Landsat 7 ETM+ satellite. These images include all the bands of Enhanced Thematic Mapper: 0.45-0.52, 0.52-0.60, 0.63-0.69, 0.76-0.90, 1.55-1.75, 10.4-12.5, and 2.08-2.35 micrometers. The data intended to test the classifier were prepared in the following way. Five areas of multispectral image corresponding to different land cover types have been selected. Then trainig and verifying sets were generated from these data. The training samples have been represented by 10 samples from every area using all the spectral bands. The dimension of the sample was 20×20 pixels. To verify the network classifier 2000 samples of each class were picked from different areas as shown at fig. 1.

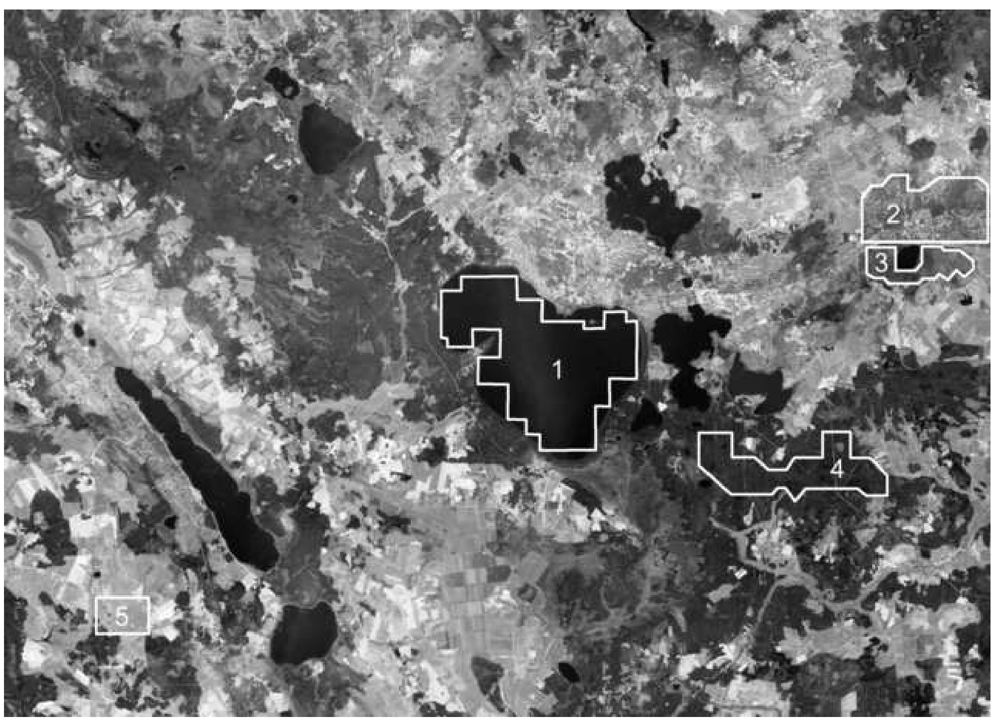


Figure 1: Region of interest. Areas picked to form verifying sets are outlined and marked.

3 The neural network: construction and training

The RBF based neural network has been chosen to implement the classifier. Each cell of a layer plays a role of a cluster center and corresponds one of the image object. Typical representatives of areas chosen for classification of multispectral image have been established as training samples.

The task of classification of objects of the stage belonging five allocated areas were put in spent experiments. It caused presence of five outputs in neural network (five neurons in output layer). Value 1 is formed on each of them in case of ranking of a fragment submitted on an input of a network to corresponding class and 0 in otherwise.

Each neuron of a hidden layer accepts 20×20 pixels fragment of multiband source image. As the result neural network (as well as each neuron of hidden layer) has $20 \times 20 \times 8 = 3200$ inputs. When the histogram instead of raw raster was used the quantity of inputs of network has been decreased down to 2048. That is resulted in reduction of expenses of time required for processing a portion of data with the use of neural network, despite of necessity of creation the histogram in real time.

Functioning of RBF cell of an input layer can be presented as follows:

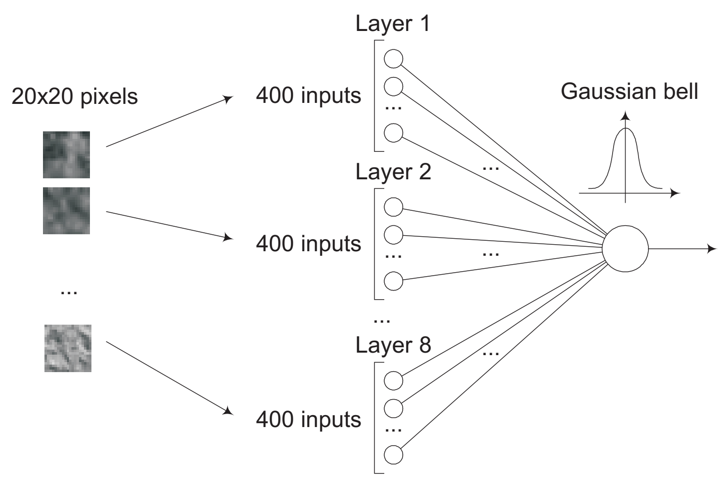


Figure 2: RBF cell functioning.

Each cell receives 3200 input values. Further the search of distance between an input fragment and the center of cluster, corresponding to a concrete cell is fulfilled. Output value in an interval $[0, 1]$ is formed as

$$NET = e^{-\frac{\|x_i - c_i\|^2}{\sigma^2}} = e^{-\frac{1}{\sigma^2}\sum_{i=0}^{n-1}(x_i - c_i)^2} \tag{1}$$

where x_i - vector, submitted on inputs of a cell, c_i - center of a cell, σ - radius of a cell, n - dimension of feature space, NET - value, formed on output of a cell.

Adjustment of centers and radiuses of RBF cells is made during training this layer. For this purpose the centers of cells were rigidly established in symbols of training set corresponding to them, and radiuses were selected experimentally.

Presence of additional layer of neurons with sigmoid transfer function is required to transform and process values formed on outputs of a layer of RBF cells. Weights of this layer should be trained to transform results of classification (clustering) by RBF layer to five target signals. Value of each of target signals should be laid in an interval $[0, 1]$. Weights of an output layer have been adjusted proceeding from the following rule

$$w_{\substack{i\in[0;4]\\ j\in[0;49]}} = \begin{cases} -2, & j < iN_z \cup j \geq (i+1)N_z; \\ 2, & iN_z \leq j < (i+1)N_z, \end{cases} \tag{2}$$

where i - index of neuron, j - index of input weight to be corrected, N_z - quantity of neurons in RBF layer responsible for each area of the initial image.

Neuron of output layer is functioned according to the following rule

$$NET = \sum_{i=0}^{N-1} w_i \cdot x_i, \qquad OUT = \frac{1}{1 + e^{-NET}}, \tag{3}$$

where x_i - vector of input values, w_i - vector of neuron weights, N - count of neurons in hidden layer (RBF cell layer), OUT - the weighted sum of values acting on inputs of neuron and it's weights, NET - value formed on an output of neuron after compression using sigmoid transfer function.

The structure of the developed network consists of two layers as shown on fig. 3

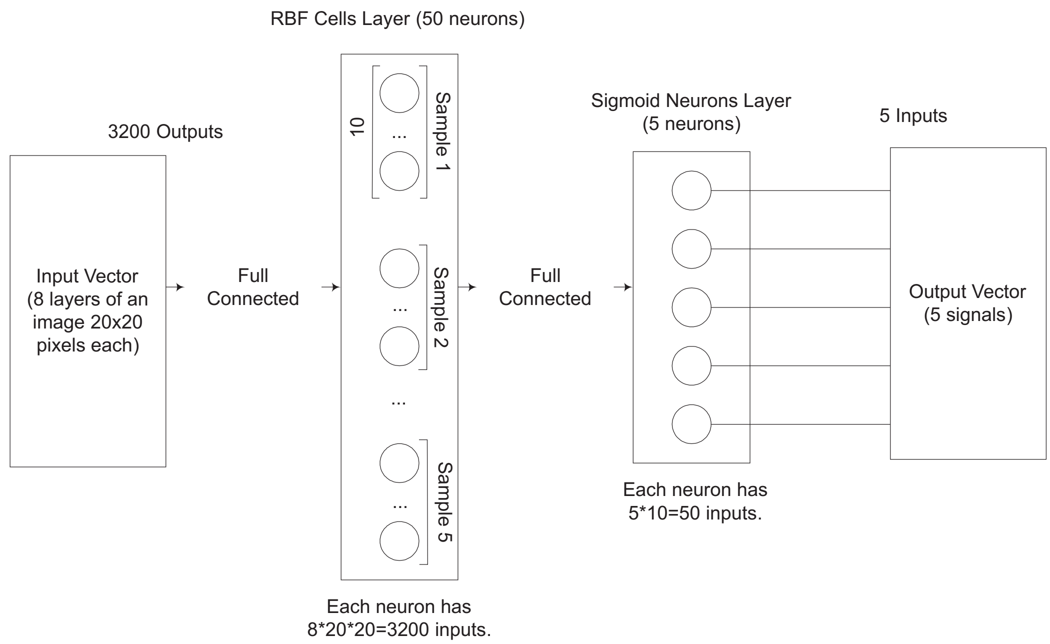


Figure 3: Complete network architecture.

The network has the following characteristics:

- 3200 inputs. The quantity of inputs has been determined by dimension of data used for training and verification of the network (fragments of eights bands of the image in the size of 20 per 20 pixels).
- 50 RBF cells in the input layer. 10 images for each class of objects have been used for training (5 classes have been allocated.
- 5 neurons with sigmoid transfer function in an output layer. The quantity of neurons in this layer has been determined by quantity of object classes. This layer is full connected with input layer of RBF cells.

To eliminate rectangular symmetry of sample data the radial weight mask α_i has been used and output of network is determined as

$$NET = e^{-\frac{1}{\sigma^2}\sum_{i=0}^{n-1}\alpha_i\left(x_i - c_i\right)^2}, \tag{4}$$

where α_i - component of a mask. The following transform has been applied to preserve functional logic of RBF cell

$$NET = e^{-\frac{1}{\sigma^2}\sum_{i=0}^{n-1}\alpha_i\left(x_i - c_i\right)^2} = e^{-\frac{1}{\sigma^2}\sum_{i=0}^{n-1}\left(\tilde{x}_i - \tilde{c}_i\right)^2}, \tag{5}$$

where $\tilde{x}$ and $\tilde{c}$ - modified input vector and center of a cell accordingly.

4 Experimental results

Training and verification data sets have been generated to carry out the experiment. Verification set has been formed from multispectral image using 2000 fragments from 5 areas of interests and consists of 10000 fragments totally. Training set has been selected from verification data set and included 10 fragments for each area, or 50 fragments totally. After training the network all the fragments from verification set including fragments used for training have been exposed to network input. As the result all training fragments have been ranked correctly to corresponding classes. Results of classification of whole verification set are represented in the following table

Table 1. Results of classification.

Area No	1	2	3	4	5
Without input mask, %	100	95.1	100	97.2	100
With input mask, %	100	92.7	100	97.6	100

The percentage ration shows, how many images from the verification set have been ranked to right class. For example, 95.1% of all fragments of area number 2 have been ranked by neural network to class corresponding to this area. Time of processing the single fragment is about 9-10 ms and time of processing whole verification set is about 180 sec when no mask has been used. When radial mask was used the time of whole classification process raised up to 280 sec. Minor alteration of results with and without mask can be explained by the specificity of a problem and sets of data used for training and running tne network.

4.1 Histogram processing

Taking into account specific of the data to be processed, histogram of samples instead of raster has been used to pass on network inputs. The histogram sample consists of eight blocks corresponding to eight bands of the multispectral image.

Process of forming the histogram is displayed on fig. 4. Histogram is presented on figure as set of functions.

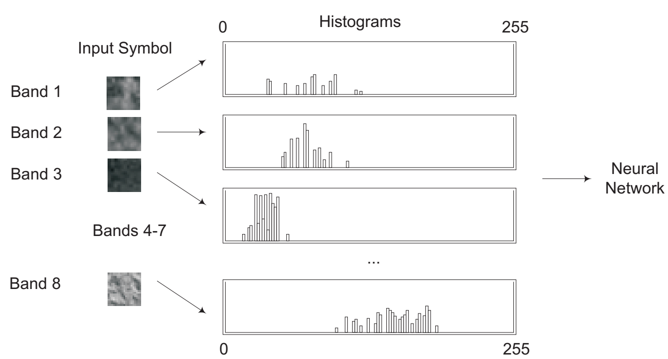
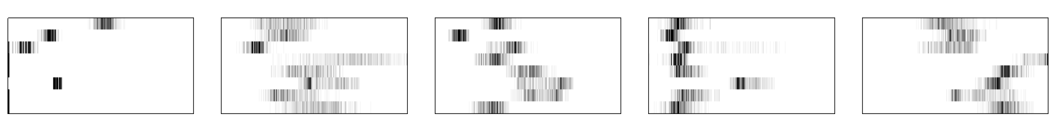


Figure 4: Histogram of sample to be passed to network

Hystograms of different objects of source multispectral image are shown on fig. 5. All the five areas are represented on the figure. The image of hystogram has inversed to provide more readable picture



1) 2) 3) 4) 5)

Figure 5: Histogram of objects from different areas.

Parameters of network are displayed in the table 3. Small increasing of processing performance occures because of reduction of features space dimension.

Table 3. Parameters of network when using hystogram.

Parameter	Value
Network inputs count	$8 \times 20 \times 20 = 3200$
RBF cell inputs count	$8 \times 256 = 2048$
Count of cells in hidden layer (RBF)	50
Count of neurons in output layer	5
One fragment processing benchmark, ms	9
Verification set (2000 fragments) processing benchmark, s	170

The following results of classification using hystogram instead of raw raster have been received at experiment:

Table 4. Results of classification.

Area No	1	2	3	4	5
Classification result, %	100	99.6	99.2	100	99.7

Improvement the quality of classification takes the place because of essential discrimination of processed objects in the chosen features space. It is necessary to take into account that classification was made extremely by criterion of brightness. The textural component of source fragments has been rejected at the stage of creating the histogram.

4.2 Live experiment 1

Multispectral images processing is one of the most important elements of remote sensing. A couple of experiments in this sphere have been carried out to verify quality of recognition using constructed and trained neural network model. Images of different spectral and spatial resolution have been used in these experiments.

A single band of multispectral image used in the experiment is shown at fig. 1. The neural network has been constructed and trained to perform the experiment. 10 samples of each class were picked from different areas as shown at fig. 1 to train the network classifier.

The main target of experiment is to process the whole multispectral image with the use of trained model and to build joined map of all classes which were used as source areas for picking up fragments during training neural network. Prepared network model accepts 20×20 pixels fragment of multiband source image. The image has been processed with step of 5 pixels (75% compositing between near by fragments). Total time required to process the whole image is 3 hours 27 minutes 10 seconds.

The simplest one model of all described above has been used in this experiment. Centers of RBF cells were rigidly established in symbols of training set corresponding to them, and radiuses were selected using the criterion of mean square deviation applied to the concrete cell and to the nearest cell which belongs to another class.

4.3 Live experiment 2

The next experiment has been applied to the image shown at fig. 7 which represents a fragment of Cheluskincev park (Minsk, Belarus). This image includes all the bands of visible part of spectrum: 0.4-0.5, 0.5-0.6 and 0.6-0.7 micrometers. It has a spatial resolution of 1.38 meters.

Results of classification of whole verification set (2000 sample fragments from each source area) are represented in the Table 5.

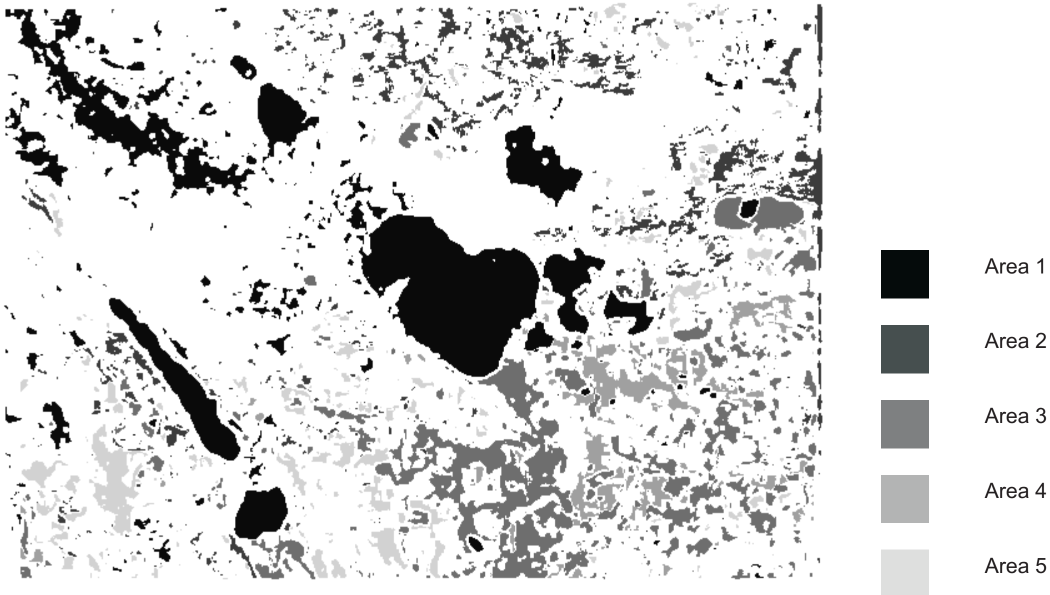


Figure 6: Result map with allocated classes displayed in gradations of gray.

Figure 7: Region of interest. Areas picked to form verifying sets are outlined and marked.

Table 5. Results of classification.

Area No	1	2	3	4	5	6
Classification result, %	97.85	87.3	100	100	100	100

5 Conclusion

Neural Network with Radial Basis Function based layer has shown high performance and efficiency. Using the histogram instead of raster representation of a multi-bands fragment to be supplied on network's inputs has allowed to increase efficiency of classification of objects via tone criterion.

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