UNSUPERVISED CLASSIFICATION OF HIGH RESOLUTION SATELLITE IMAGERY BY SELF-ORGANIZING NEURAL NETWORK

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Abstract
The current paper discusses the importance of the modern high resolution satellite imagery. The acquired high amount of data must be processed by an efficient way, where the used Kohonen-type self-organizing map has been proven as a suitable tool. The paper gives an introduction to this interesting method. The tests have shown that the multispectral image information can be taken after a resampling step as neural network inputs, and then the derived network weights are able to evaluate the whole image with acceptable thematic accuracy.

Keywords: artificial neural network, clustering, high resolution imagery

1. Introduction

Satellite imaging technology has an impressive development in the current years. Geometric resolution as well as the radiometric or spectral ones has been significantly increased: pixels are getting smaller and smaller, the acquired images have larger sizes (higher coverage), sensors have more spectral bands.

The generally used Landsat sensors was firstly launched in 1972 (in that times called Earth Resources Technology Satellite – ERTS), the latest generation, Landsat 7 on April 15, 1999 (The Landsat Program, 2010). This sensor is called Enhanced Thematic Mapper Plus (ETM+); its name suggests the application: thematic mapping. ETM+ has 7 multispectral and one panchromatic bands in the range of visible and non-visible spectrum between 0.45 μm and 12.5 μm. The panchromatic band has a geometric resolution of 15 m, the multispectral ones 30 m, except the thermal infrared channel, where its resolution is 60 m. The swath width is 183 km. This Landsat sensor has a temporal resolution of 16 days. The Ikonos of Satellite Image Corporation (The Satellite Image Corporation, 2010) was launched also in 1999 with 4 multispectral and a pan bands having 3.2 m multispectral and 0.82 m panchromatic geometric resolution. The radiometric resolution is 11 bits, the temporal one 3 days. Swath width takes 11.3 km at nadir, 13.8 km at off-nadir position. The WorldView-2 sensor of the same company has been launched on October 8, 2009 having 8 multispectral bands with 1.8 m geometric resolution and a 0.46 m resolution panchromatic one. The radiometry has 11 bits, swath takes 16.4 km. The revisit time is 1.1 days. The newest planned satellite mission of the company will be launched in 2010-2011 with a 0.25 m geometric resolution!

These technical achievements guaranty more data about the Earth's surface, but this requires more development also in the data processing methodology.

2. Methods

2.1. The Quickbird imagery

As it was mentioned in the Introduction, the new high resolution images have increased geometric and radiometric, as well as temporal resolution. The Quickbird sensor – owned by the Satellite Image Corporation – was launched on October 18, 2001. The revisit frequency lies between 1 and 3.5 days. The radiometric resolution is 11 bits. The sensor has 4 multispectral bands: Red, Green, Blue and a Near-Infrared, and has a panchromatic channel. The former bands have 2.44 m pixel size on the ground, the panchromatic pixel is 0.61 m in size.

We have purchased a multispectral-panchromatic image bundle for Budapest, taken in August 4, 2004. In order to ease the image handle, a cut-off was made from the original image covering the Margaret-Island (Margit-sziget). The cut-off has a size of 721 × 1226 pixels in the visible and infrared bands, and 2885 × 4905 pixels in the panchromatic channel. All pixels have been resampled from 11 bits to 8 bits.

Fig. 1 shows the true-color image composite of the test area.

2.2. Self-organizing maps

The self-organizing (feature) map (abbreviated as SOM) was first described by T. Kohonen in 1982. It belongs to the unsupervised classification (clustering). This artificial neural network is built up of regularly distributed processing elements, the neurons. The neurons are connecting by a regular topology: it can be a rectangular (Fig. 2) or hexagonal grid; in several cases irregular topology is used.

Fig.1. The test area in the visible range

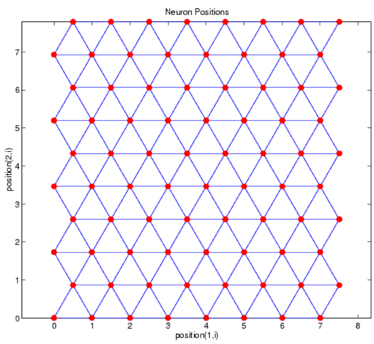


Fig. 2. Hexagonal neuron topology

The algorithm has two blocks (Kohonen 2001): the first is the rough block, called ordering, the second one is the tuning. Both phases have the same steps: first the n-dimensional sample must be shown to the neurons, and then the distance (e.g. Euclidean) between the sample and the neuron weights is calculated.

$$D = \left[\sum_{s=1}^{n} (p_s - w_s)^2\right]^{\frac{1}{n}} \quad (1)$$

where p is the sample vector, w the neuron weight vector.
After this multidimensional distance D one neuron will have the smallest value, this is called as winner. After selecting the winner, the weights must be updated as follows. The neuron weights have to be updated with the factor multiplied by the differences to the sample, for all dimensions:

$$w(q) = w(q-1) + \alpha[p(q) - w(q-1)] \quad (2)$$

This formula is called in the literature as Kohonen learning rule (Kohonen 2001). In the above equation p is the sample multidimensional data vector, w is the neuron weight vector (dimension is the same!), α is a learning factor which follows a monotone decreasing (mostly linear) function. q represents the actual iteration step, where q-1 the former iteration step.

Not only the winner, but its neighboring neurons' weights must be updated. The neighborhood is defined as follow:

$$N_i(d) = \{j, d_{ij} \leq d\} \quad (3)$$

where i is the index of the neuron (practically the winner), j is the index of the other neuron, d is the distance limit (a parameter, which controls the weight update propagation), d_{ij} is the computed distance between the i^{th} and j^{th} neuron. This distance function gives the index of the neighboring neuron, when its distance is less than or equal with the given limit. Considering the neighborhood means, that further neurons' weights are updated.

One can notice that the above described algorithm can manage even n-dimensional data sets, so the suitability of the technique for evaluating of multispectral images is not a question.

3. Results

The tests are started with a 4 × 4 neuron lattice of hexagonal topology. This configuration can bring 16 clusters, as all neurons will "learn" the 16 possible group of pixels. We want to detect the following thematic classes: river, road, meadow, forest, white roof building, red roof building. These 6 classes will be got by aggregating the outcoming 16 clusters. The initial case contained only the visible bands (i.e. RGB), not the infrared, but the low classification quality required the use also the NIR band, so we involved it as the fourth channel.

To accelerate the image processing, we have resampled the test data set, and every 1000 pixel were taken as neural inputs. With this subset we executed the training of the neural net, then all pixels were evaluated with the derived neural network weights.

The number of epochs (training steps during the iteration) was set to 100, the distance function has taken the distances along the neuron links. (Theoretically it can furthermore be Euclidean distance, or any raster distance metrics.) After the training the full image evaluation was run (Fig. 3).

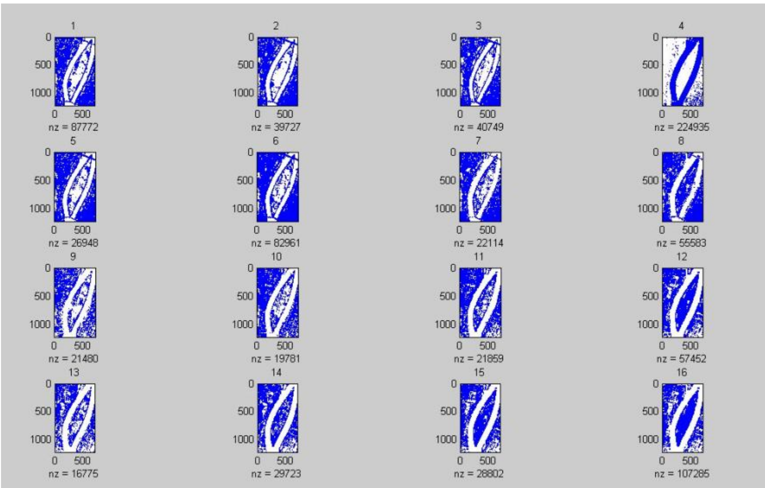
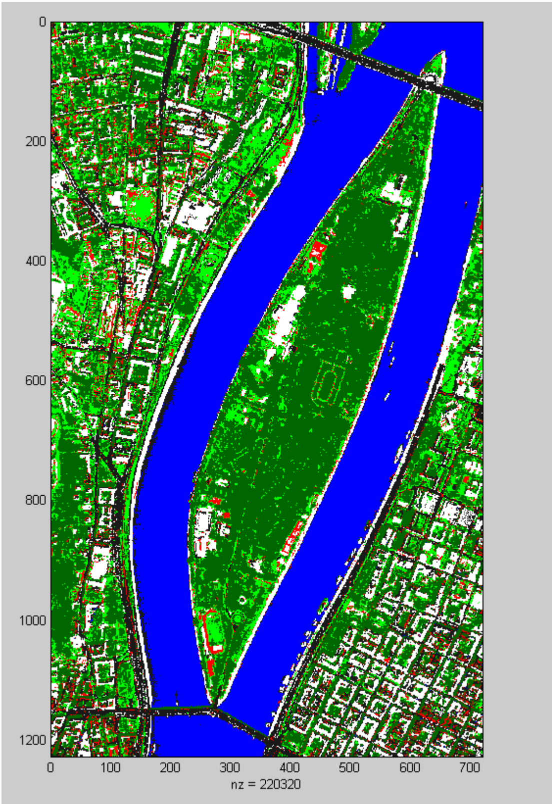


Fig. 3. The clusters as the output of the neurons' training

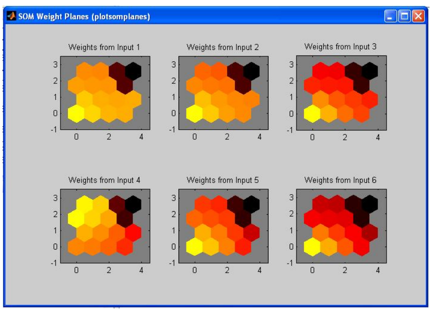
After aggregating the output clusters into a single thematic map, the final classification map can be obtained with right color coding (Fig. 4).

The clustering was performed in Matlab environment. The Neural Network Toolbox gives further analyzing possibilities, like the diagram of the strength of the neurons (weight plane diagram) or the sample hits diagram (Fig. 5). The left diagram shows the "importance" of the current neuron among others, while the right image gives information, how the original pixels were classified into the neurons bins.

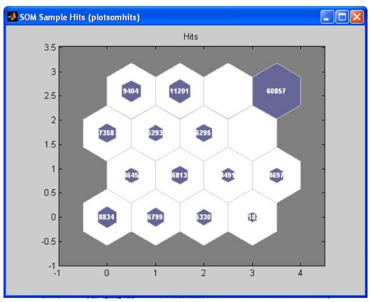


■	River
■	Red roof building
■	Meadow
■	Forest
□	White roof building
■	Road

Fig. 4. Final clustering of the high resolution image subset



a) weight plane diagram



b) sample hits diagram

Fig. 5. Analyzing tools of a trained SOM

4. Discussion

The presented experiment proved that the Kohonen SOM is a suitable tool for analyzing high resolution multispectral satellite images. The test has shown that the method can handle such amount of data (more than 800 000 pixels) in a very fast way, i.e. the training of the subsampled pixels has taken about 30 seconds; the classification with the derived weights was roughly the same time. The choose of the network topology was tested, but no significant differences were experienced. The same was found with the epoch numbers: after a necessary epoch set (~100), the increased training length doesn’t mean quality increase. The method was applied with simulated images, too. The most interesting was a downsampled synthetic image, where the geometric resolution of a Landsat image was derived from our Quickbird imagery. The method has resulted a smooth, “detail-free” view of the study area, where the fine structures, like streets, concrete river coast disappear. The processing of the original Quickbird data set keeps all these information, so the technique can be applied even in larger thematic mapping campaigns.

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