Image processing for GIS applications supported by the use of artificial neural networks.[*]

Tomasz Kubik[†] Witold Paluszyński[†]
Adam Iwaniak[‡] Przemysław Tymków[‡]

[†] Institute of Cybernetics Engineering, Wrocław University of Technology,
Janiszewskiego 11/17, Wrocław 50-372, Poland
E-mail: {tkubik|Witold.Paluszynski}@ict.pwr.wroc.pl
[‡] Agricultural University of Wrocław
Norwida 25/27, Wrocław 50-372, Poland
E-mail: iwaniak@ar.wroc.pl, przemyslaw.tymkow@wp.pl

Keywords: image processing, neural networks, GIS

Abstract

This paper presents techniques that can be used as a part of data processing in the remote sensing applications. The techniques proposed employ artificial neural networks for automatic recognition and classification of individual land cover classes, such as forests of some type, buildings, etc. Various quantitative measures have been applied to evaluate the quality of the results. Apart from this a simple Bayesian classifier has been proposed. Presented solutions can be applied for processing of satellite images and aerial images as well.

1 Introduction

A basic problem for any country or region in economic planning, environmental studies, or resource management is availability of accurate, current information. In highly developed countries over 70% of administrative decisions is made on the basis of data related to the earth surface. One significant method for providing current, reliable surface information is remote sensing.

Remote sensing relies on detecting and measuring of electromagnetic energy (usually various spectral fractions of light are measured) emanating from distant objects made of various materials, so that they can identified and categorized by class or type, substance, and spatial distribution. Nowadays this kind of data is mainly acquired in form of satellite images.

Satellite images are an invaluable source of information. Initially providing a resolution of 1x1 km, now commercially available satellite images go down do 60x60 cm. While this is still not as good as the finest resolutions provided by aerial photographs, satellite images can be acquired much faster.

An information system that is designed to work with data referenced by spatial or geographic coordinates is GIS (Geographic Information System). GIS should posses ability of automatic capturing, retrieval, analysis and displaying of spatial data. Because satellite images provide a wealth of information, there is a growing demand for automatic routines that can be applied in GIS. Therefore image processing methods and models targeted at satellite images are being developed.

For uniform areas reflectance measured is enough to perform proper objects classification. However this approach fails for areas with a high heterogeneity of spectral response, such as urban areas. Texture processing algorithms can be applied in this case. These algorithms are usually divided into three major categories: structural, spectral and statistical. Structural methods consider texture as a repetition of basic primitive patterns with a certain rule of placement. Spectral methods analyze the power spectrum. Statistical methods are based mainly on local statistical parameters (entropy, fractal dimension, local variance, variogram, etc. [1, 2, 3, 4, 5, 6, 7, 8, 9].) Other methods make use of artificial neural networks [7, 10, 11, 12].

2 Image processing

The images used in the experiments described in this paper were received from Landsat satellite and produced by the TM (Thematic Mapper) scanner. The TM sensor records reflected electromagnetic energy from the visible to thermal infrared regions of the

[*]This research was supported in part by the Committee for Scientific Research through grant 5T12E02924

spectrum in 7 bands. The spatial resolution of TM images is 30x30 m for all bands except the thermal, which has 120x120 m resolution. In our case the problem of image processing has been transformed into the problem of classification defined as follows:

Given: 1) a reference image, consisting of points represented by the set of corresponding pixels intensities in n spectral channels, together with a correct points classification into K classes; 2) a test image, consisting of points represented by the set of corresponding pixels intensities in n spectral channels.
Find: correct classification of points in a test image.

The reference images were produced with the aid of CORINE Program (*Coordination of Information on the Environment*) database and an expert knowledge. The CORINE classification consists of twenty-two classes of land use. After conducting some initial experiments, it turned out that this material is insufficient and does not represent correctly physical features, such as: leafy forests, and parks within a city. Therefore, an improved reference classification map was hand-created by an interpreter. The resulting reference map contained only 12 different classes of land use.

3 Neural network based classifier

The design of artificial neural network based classifier involved the following: 1) preparing data sets and patterns from images, 2) building and training a network, 3) processing and visualizing results, 4) estimating the classification error.

The patterns files were usually made up of all Landsat spectral images and one reference image. The reference images was partitioned into two parts: the training set and the testing set, for result evaluation.

We used traditional feed-forward, multi-layer neural networks trained in a supervised mode. The architecture and size of a particular network was dependent on classification problem currently defined.

For classification per pixel an input layer of a neural network consisted of as many neurons as the number of spectral channels used. The output level consisted of the number of classes the neural network was expected to be sensitive for. Thus the training pattern was build from the intensity values of the corresponding pixels in all spectral channels and the reference image (classification results for different architectures are shown in Fig. 2.)

For classification per parcel training patterns were created moving a square mask within a reference image (for which the results of classification were known). The size of the mask was an odd number, the center of the mask was a subject of classification. In this case neural networks were design in that way, that input level of a particular network matched a mask of predefined size, but the output level was made of one neuron. Different neural networks were created for different kinds of objects and different masks.

The results of experiments were evaluated by comparing images segmented by the neural networks with corresponding reference images (see Fig. 1.) For this purpose we involved the measures described in the section 5.

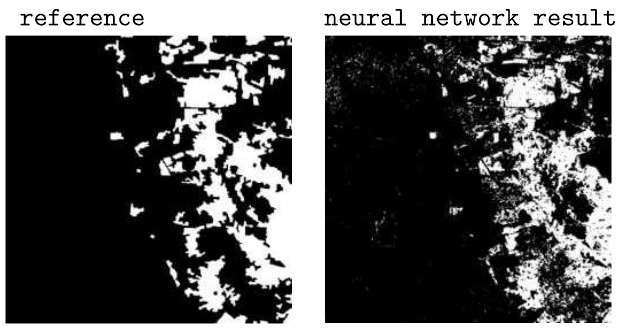

Figure 1: The reference map and the image obtained with a neural network trained to recognize coniferous forests (3 input neurons, 24 hidden neurons, 1 output neuron), $\kappa = 0.945$.

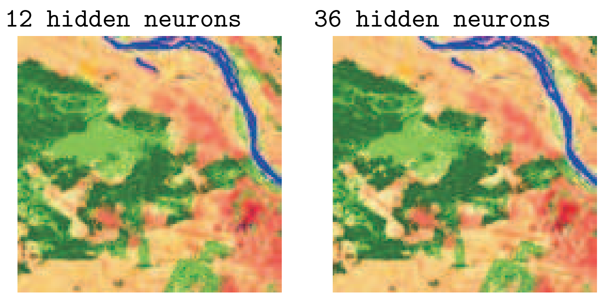

Figure 2: Classification results for different neural network architectures (3 input neurons, 12 output neurons.)

4 Naive Bayes classifier

Naive Bayes classifier combines probability model with a decision rule. Usually the rule is specified as the choice of hypothesis which is the most probable.

This rule is called maximum a posteriori rule. Corresponding classifier is defined by the function $\mathcal{B}$:

$$\mathcal{B}(\bar{x}) = \arg\max_{c_k} P(C=c_k) \prod_{i=1}^{n} P(X_i=x_i|C=c_k) \quad (1)$$

where: $\bar{x} = [x_1, \ldots, x_n]$ – vector of features x_i (in the case of multispectral image these are pixels intensities for one point in n spectral channels); c_k – classes labelled with $k = 1, \ldots, K$; $P(C=c_k)$ – probability, that observed case belongs to the class c_k; $P(X_i = x_i|C = c_k)$ – conditional probablitities (that intensity of a pixel X_i equals given x_i in a channel i, when it is known that corresponding point is of the class c_k).

To build classifier $\mathcal{B}$ at first step the probability $P(C = c_k)$ should be approximated. This can be done as follows:

$$P(C=c_k) = \frac{N_k}{\sum_{k=1}^{n} N_k} \quad (2)$$

N_k - amount of points of the reference image classified to the class k (sum of all N_k equals total number of points of the reference image). Next conditional probabilities should be approximated by the normal distributions:

$$P(X_i=x_i|C=c_k) \cong f(x_{k,i}) = \frac{1}{\sigma_{k,i}\sqrt{2\pi}} e^{\frac{-(x_{k,i}-\mu_{k,i})^2}{2\sigma_{k,i}}} \quad (3)$$

where $x_{k,i}$ - pixel intensity level for class k and for spectral channel i.

Approximation of $\sigma_{k,i}$ can be expressed by the standard deviation of case:

$$S_{N_k-1,i} = \sqrt{\frac{1}{N_k - 1} \sum_{j=1}^{N_k} (x_{k,i,j} - \bar{x}_{k,i})^2} \quad (4)$$

where: $x_{k,i,j}$ - intensity level of pixel j from channel i, for which corresponding point has been assign to class k (according to the provided reference image classification).

Approximation of $\mu_{k,i}$ is given by:

$$\bar{x}_{k,i} = \frac{1}{N_k} \sum_{j=1}^{N_k} x_{k,i,j} \quad (5)$$

5 Quality measures

A number of experiments have been conducted resulting in many classification maps generated. They have been evaluated by human experts and found to be very valuable, readily comparable to the human-processed CORINE map and in some areas more accurate. To quantify the quality of the results in an automatic manner several statistical measures have been considered. For the confusion matrix $A = [a_{ij}]$ where a_{ij} is the number of sample pixels from the jth class that have been classified as belonging to the ith class, the following measures have been proposed[13, 14]:

– the users accuracy of class i: $\frac{a_{ii}}{a_{ri}}$, where $a_{ri} = \sum_i a_{i.}$ (sum of ith row entries);

– the producers accuracy of class i: $\frac{a_{ii}}{a_{ci}}$, where $a_{ci} = \sum_i a_{i.}$ (sum of ith column entries);

– the overall accuracy of the method: $\sum_i a_{ii}/a_t$, where a_t is the total number of pixels;

– simple Kappa coefficient:

$$\hat{\kappa} = \frac{P_o - P_e}{1 - P_e} \quad \text{where} \quad \begin{array}{l} P_o = \sum_i aii/a_t \\ P_e = \sum_i a_{ri}a_{ci}/a_t^2 \end{array} \quad (6)$$

– weighted Kappa coefficient:

$$\hat{\kappa}_w = \frac{P_{ow} - P_{ew}}{1 - P_{ew}} \quad \text{where} \quad \begin{array}{l} P_{ow} = \sum_i \sum_j w_{ij} \frac{a_{ij}}{a_t} \\ P_{ew} = \sum_i \sum_j w_{ij} \frac{a_{i.}a_{.j}}{a_t^2} \end{array} \quad (7)$$

The weights w_{ij} are constructed so that $0 <= w_{ij} < 1$ for all $i \neq j$, $w_{ii} = 1$ for all i, and $w_{ij} = w_{ji}$.

6 Conclusions

Because of the limitations not all of the results obtained had chance to be presented here. Nevertheless the experiments performed proved that satellite images can be processed automatically by supervised learning with a neural network. The best results of classification per-pixel were obtained for areas such as those in the Fig. 1. But sometimes the results for urban areas were only barely acceptable. In such cases the improvements were done by applying per-parcel classification. There information about neighborhood of a pixel (pixels values within moving mask) helped in proper classification. Presented naive Bayesian classifier is an another option (see Fig. 3.) It can be used, as the other techniques discussed, for satellite and aerial image processing.

References

[1] J. R. Carr: Spectral and textural classification of single and multiple band digital images. *Computers and Geosciences*, 22(8):849–865, (1996).

[2] M. Tuceryan and K. Anil: *The handbook of Pattern recognition and computer vision*, chapter 2.1

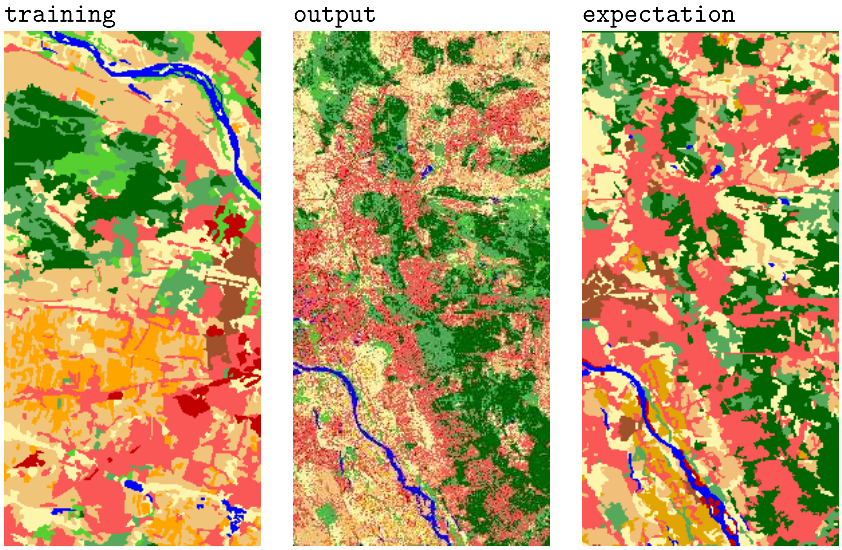

Figure 3: Classification results for naive Bayes classifier build on data coming from three spectral channels (not shown). `training` is a reference image used for classifier building, `output` shows classification results, `expectation` is a reference image showing expected classification results.

Texture Analysis, pp. 207–248 World Scientific Publishing Co., 2nd edition, (1998).

[3] S. Berberoglu, C. Lloyd, P. Atkinson, and P. Curran: The integration of spectral and textural information using neural networks for land cover mapping in the Mediterranean. *Computers and Geosciences*, 26(4):385–396, (2000).

[4] J. Keuchel, S. Naumann, M. Heiler, and A. Siegmund: Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data. *Remote Sensing of Environment*, 86(4):530–541, (2003).

[5] Q. Cheng: Multifractality and spatial statistics. *Computers and Geosciences*, 25(9):949–961, (1999).

[6] M. Chica-Olmo and F. Abarca-Hernndez: Computing geostatistical image texture for remotely sensed data classification. *Computers and Geosciences*, 26(4):373–383, (2000).

[7] X.-H. Liu, A. Skidmore, and H. Van Oosten: Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, 56(4):257–268, (2002).

[8] J. Ju, E. D. Kolaczyk, and S. Gopal: Gaussian mixture discriminant analysis and sub-pixel land cover characterization in remote sensing. *Remote Sensing of Environment*, 84(4):550–560, (2003).

[9] G. M. Foody: Estimation of sub-pixel land cover composition in the presence of untrained classes. *Computers and Geosciences*, 26(4):469–478, (2000).

[10] G. W. H. German and M. N. Gahegan: Neural network architectures for the classification of temporal image sequences. *Computers and Geosciences*, 22(9):969–979, (1996).

[11] D. M. Miller, E. J. Kaminsky, and S. Rana: Neural network classification of remote-sensing data. *Computers and Geosciences*, 21(3):377–386, (1995).

[12] J. Ruiz-del Solar: TEXSOM: Texture segmentation using self-organizing maps. *Neurocomputing*, 21:7–18, (1998).

[13] L. Hubert-Moy, A. Cotonnec, L. Le Du, A. Chardin, and P. Perez: A Comparison of Parametric Classification Procedures of Remotely Sensed Data Applied on Different Landscape Units. *Remote Sensing of Environment*, 75(2):174–187, (2001).

[14] G. M. Foody: A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, 20:37–46, (1960).