UDK 004.931

V.V. Hnatushenko, D.K. Mozgovoy, I.Ju. Serikov, V.V. Vasyliev

AUTOMATIC VEGETATION CLASSIFICATION USING MULTISPECTRAL AERIAL IMAGES AND NEURAL NETWORK

Abstract: *The purpose of this work is development of a method of automatic recognition and classification of vegetation in multispectral aerial images with the use of a neural network. The outcome of research carried out for different test areas have confirmed high robustness, accuracy and quick response of the proposed method in comparison with visual recognition performed manually by a human operator, and with ground methods of measurements.*

Keywords: *satellite images, accuracy, classification of vegetation, multispectral aerial image, neural network.*

Introduction

Automated classification of multispectral aerial images has to be able to distinguish between objects on the ground and objects above ground. It is difficult to distinguish between buildings and parking lots or trees and grass. On the other hand, the processing tools have improved. Besides the professional (expensive) software tools nowadays open source software tools (freeware) are available.

Paper overview

Accuracy evaluation of the EOS DA web service [1-3] for automatic classification of vegetation by multispectral aerial images (further referred to as web service) is the final stage of testing of the developed system before putting it into operation. For comparison of the obtained result with other existing ones it is necessary to determine the following:

- how to evaluate correspondence;
- with what data to compare the obtained result;
- how to evaluate the quality of the obtained result (the obtained evaluation of difference includes not only the error proper of the tested result, but also it is stipulated by the error of the test data).

Formulation the problem

The objective of the work is accuracy evaluation of the automatic classification of vegetation using multispectral aerial images and a neural network. The validation of a web service of the automatic classification of multispectral aerial images lies in the defining of the basic indicators of classification quality [4-7]:

- classification accuracy (the percentage of unrecognized and falsely recognized classes)
- reproducibility (the repeatability of results in various test cases)
- sustainability (no significant deviations in the results of the classification of vegetation should appear in the input data or during the setting of a processing procedure).

The basic material

Testing Area. As the source data, multispectral aerial images of Google Candid Imagery of 2015, Marin Municipal Water District, Marin County California, have been taken. As a model, a vector layer of vegetation obtained by surface observations on the same territory has been used. The testing areas (example on Fig.1) have been detected considering the conditions of coverage by using simultaneously the source aerial images of Google Candid Imagery and a vegetation vector layer obtained in result of terrestrial measurements of 2015. As model data used a vector layer of vegetation obtained by surface observations on the same territory.

Fig. 1

Recognizable object classes. The neural network was taught to recognize 5 classes [2]:

Class 1 - high vegetation (deciduous trees and shrubs, coniferous trees).

Class 2 - low vegetation (fields, lawns).

Class 3 - buildings and constructions (single- and multi-storey).

Class 4 - water objects (ponds, pools, etc.).

Class 5 - shadows of tall objects (buildings, trees) – an axillary class that is used to exclude the shadowed areas and aimed to reduce the classification errors, which may appear due to inaccurate recognition of the objects shadowed by trees or buildings.

As soon as the model data was classified only by one common class of vegetation the evaluation of EOS DA classification accuracy has been prepared only for classes 1 and 2 that have been united into one class of vegetation.

Model accuracy evaluation. The results of terrestrial measurements of vegetation, considered as the model, have appeared quite erroneous due to the following reasons:

- a time gap between taking pictures and making terrestrial measurements;
- the complexity of accurate recognition of a projective surface of trees;
- system error of georeferencing for all model data layer (shift arising because of using of custom datum);
- instrumental and methodical errors of measurements.

To reduce these errors, manual correction of the vector vegetation layer (the model data) using satellite shots of the specific area has been accomplished. The evaluation of model accuracy has been accomplished by an expert method. A model accuracy on average has been:

- 3...5% without manual correction of the model data;
- 1...2% with manual correction of the model data.

Methodology of Accuracy Evaluation. The most widely used methods of validation of Earth remote sensing classification outcomes are the following:

- Comparison of results with the results of synchronous surface observations and measurements carried out immediately at the time of imaging;
- Comparison with the results of automatic classification by certified software products for the same purpose;

- Comparison with the outcomes of manual classification carried out by operators and evaluated by an expert group (this method is used for comparatively small volumes of data or for a limited set of test areas, which are to be distributed over the territory of the research as evenly as possible).

Taking into account the above, the accuracy of classification evaluation is accomplished by comparison of automatic classification with manual corrected surface observations results.

The testing diagram is shown in Fig. 2.

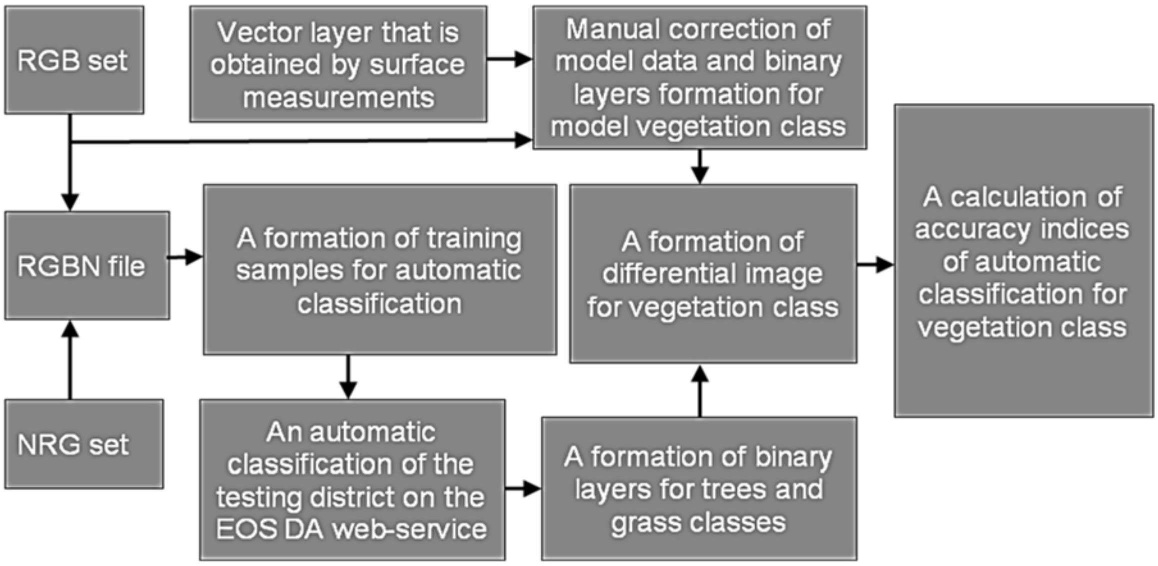

Fig. 2

Applied metrics. The metrics that have been used for the quantifying accuracy of the automatic classification are the following:

- confusion matrix (a number of unrecognized class pixels, a number of falsely recognized class pixel, total result accuracy);

- statistics (Kappa coefficient, a regression or standard error);

- compliancy matrix for several classes (the accuracy can be low due to the transition of class boundaries);

- compliancy matrix with fuzzy boundaries of the class; in this case an algorithm of class boundaries designation may vary.

In this case the following well-known indicators of accuracy classification have been chosen:

- confusion matrix;

- Kappa coefficient.

A confusion matrix is an instrument that applies a cross-tabulation for the evaluation of correlation among the values of matching classes obtained from different sources. The sources are the checked bitmaps (for the automated classification) and a more accurate, supporting data source. (for the manual classification). The class names of the checked data set are indicated on one matrix axe, the model classes used for checking are indicated on another matrix axe.

The main diagonal of the matrix, where the cases of the consistency of calculated classes and actual data are represented. (an accurate classification).

The kappa (κ) coefficient measures the agreement between classification and ground truth pixels. A kappa value of 1 represents perfect agreement while a value of 0 represents no agreement.

$$\kappa = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)},$$

where i is the class number;

N is the total number of classified pixels that are being compared to ground truth;

$m_{i,i}$ is the number of pixels belonging to the ground truth class i, that have also been classified with a class i (i.e., values found along the diagonal of the confusion matrix);

C_i is the total number of classified pixels belonging to class i;

G_i is the total number of ground truth pixels belonging to class i.

Testing Outcomes. A comparative assessment of the accuracy of automatic classification of vegetation using multispectral aerial images and neural network for three testing area has been accomplished.

The indices of classification accuracy of testing area (Fig. 3, 4):

- Kappa Index = 0,76;
- Overall Accuracy = 97,09%.

The above-mentioned indices of automatic classification accuracy of buildings, vegetation, and water objects using multispectral aerial images serve as a proof of the following:

- the used methodology is rather effective;
- the methodology can be used for solving applied tasks.

The biggest advantages of the automated landcover classification compared to manual terrestrial measurements are:

- much faster classification than manual measurements (calculated mainly by the timing of aerial photography);

- any area coverage including closed and hard to get areas;

Fig. 3

Fig. 4

- no expenses for measure operators, transport etc.

- lower price of classification, especially on big territories (determines basically by the cost of aerial imagery);

- more accurate results, absence of man factor (intentional data misrepresentation);

- high level of automatization, the ability to use in pair with existed GIS resources;
- the ability of automated creation, filling an updating spatial databases.

Conclusion

The outcome of research carried out for different test areas have confirmed high robustness, accuracy and quick response of the proposed method in comparison with visual recognition performed manually by a human operator, and with ground methods of measurements.

References:

1. https://eos.com.
2. Мозговой Д.К., Чорненко М.В. Геоинформационные веб-сервисы онлайн обработки спутниковых снимков / Вісник ДНУ. Ракетно-космічна техніка. - 2016. - Вип. 13, т. 24. № 4. – С. 89-95.
3. Мозговой Д.К., Васильев В.В. Мониторинг природных и антропогенных процессов с помощью веб-сервиса Landsat Viewer / Вісник ДНУ. Ракетно-космічна техніка. - 2016. - Вип. 13, т. 24. № 4. - С. 95-101.
4. Iovan C., Boldo D., Cord M., Erikson M. Automatic Extraction and Classification of Vegetation Areas from High Resolution Images in Urban Areas. In: Ersboll B.K., Pedersen K.S. (eds) Image Analysis. SCIA 2007. Lecture Notes in Computer Science, vol. 4522. Springer, Berlin, Heidelberg.
5. Iovan C., Boldo D., Cord M. Detection, segmentation and characterization of vegetation in high-resolution aerial images for 3D city modeling / International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. 37 (Part 3A), pp. 247-252, Pekin, Chine, juillet 2008.
6. Song, C., 2007. Estimating tree crown size with spatial information of high resolution optical remotely sensed imagery. International Journal of Remote Sensing 28(15), pp. 3305–3322.
7. Yao, W., Poleswki, P., and Krzystek, P.: Classification of Urban Aerial Data Based on Pixel Labelling with Deep Convolutional Neural Networks and Logistic Regression, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLI-B7, 405-410, doi:10.5194/isprs-archives-XLI-B7-405-2016, 2016.