UDC 528.72:621.391.822 **doi: 10.32620/reks.2019.4.04**

V. V. LUKIN, G. A. PROSKURA, I. K. VASILYEVA

National Aerospace University "Kharkiv Aviation Institute", Ukraine

COMPARISON OF ALGORITHMS FOR CONTROLLED PIXEL-BY-PIXEL CLASSIFICATION OF NOISY MULTICHANNEL IMAGES

*The **subject** of this study is the pixel-by-pixel controlled classification of multichannel satellite images distorted by additive white Gaussian noise. The paper **aim** is to study the effectiveness of various methods of image classification in a wide range of signal-to-noise ratios; an F-measure is used as a criterion for recognition efficiency. It is a harmonic mean of accuracy and completeness: accuracy shows how much of the objects identified by the classifier as positive are positive; completeness shows how much of the positive objects were allocated by the classifier. **Tasks**: generate random valuesof the brightness of the noise components, ensuring their compliance with the accepted probabilistic model; implement the procedures of element-wise controlled classification according to the **methods** of support vectors, logistic regression, neural network based on a multilayer perceptron for images distorted by noise; evaluate and analyze the results of objects bezel-wise classification of noisy images; investigate the effect of noise variance on classification performance. The following **results** are obtained. Algorithms of pixel-by-pixel controlled classification are implemented. A comparative analysis of classification efficiency in noisy images is performed. **Conclusions** are drawn. It is shown that all classifiers provide the best results for classes that mainly correspond to areal objects (Water, Grass) while heterogeneous objects (Urban and, especially, Bushes) are recognized in the worst way; classifiers based on the support vector machine and logistic regression show low recognition accuracy of extended objects, such as a narrow river (that belongs to the wide class of "water"). The presence of noise in the image leads to a significant increase in the number of recognition errors, which mainly appear as isolated points on the selected segments, that is, incorrectly classified pixels. In this case, the best value of the classification quality indicator is achieved using neural networks based on a multilayer perceptron.*

Keywords: *classification; additive white Gaussian noise; pixel-by-pixel controlled classification; the probability of correct classification.*

Introduction

Reliability of decisions carried out in analysis of remote sensing (RS) images is considerably determined by quality of original (acquired) images. The reasons why RS images can be of low quality include: low image contrast; noise, interference and blur; insufficient or excessive illumination of a scene; too small dimensions of objects to be recognized, etc. [1].

One of the main factors that reduces quality of the source data in multichannel (multispectral, hyperspectral) remote sensing is noise that can be quite intensive. It is especially noticeable in homogeneous image areas. Moreover, the noise not only reduces visual quality of images, but also worsens the reliability of their classification [2, 3]. Additive noise is often used as the simplest noise model for optical images and some other types of images. In many practical situations, noise is considered white and Gaussian with a mathematical expectation (mean) equal to zero and a variance σ_n^2 that is approximately constant for entire image. In addition, it is often assumed that the values of additive noise are spatially uncorrelated (independent for neighboring pixels, and, especially, pixels that are placed far from each other). With an eight-bit image representation, additive noise becomes visually noticeable for $\sigma_n^2 \geq 6...10$ or slightly larger values of noise variance. The influence of noise is manifested in deterioration of image classification results [4]. Meanwhile, negative influence of the noise depends also on other factors as what classifier is used, what are its parameters and how these classifiers was trained (designed); what features are used and so on. **The aim of this paper** is to study the classification efficiency of multichannel images distorted by additive white Gaussian noise (AWGN) using several well-known pixel-by-pixel controlled classification methods: Support Vector Machine (SVM), Logistic Regression (LGR), Multilayer Perceptron (MLP) [5].

1. Algorithms for pixel-by-pixel controlled classification of multichannel images

1.1. Support Vector Machine

The support vector method is one of the most popular learning methods that are used to solve classifica-

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

tion and regression problems. It belongs to the family of linear classifiers. The main idea of the method is to construct a hyperplane separating the objects of a data sample in the most efficient (optimal) way. The algorithm works under the assumption that the larger the distance (gap) between the separating hyperplane and the objects of the shared classes, the smaller the average error of the classifier. Therefore, the method is also known as classification method with maximum clearance [6, 7].

The expression for the separating hyperplane has the form:

$$\mathbf{w}\cdot\mathbf{x}-b=0, \tag{1}$$

where $\mathbf{w}$ is the perpendicular to the dividing hyperplane;

b is the distance from the hyperplane to the origin.

The problem of constructing an optimal dividing hyperplane reduces to minimizing $\|\mathbf{w}\|$. This is a quadratic optimization problem, which can be written as

$$\begin{cases} \|\mathbf{w}\|^2 \to \min, \\ c_i(\mathbf{w}\cdot\mathbf{x}_i - b) \ge 1, \quad 1\le i\le n, \end{cases} \tag{2}$$

this corresponds to the case of linear separability of classes. Since in practice it is not possible to guarantee the linear separability of points into two classes in the general case, a set of additional variables $\xi_i \ge 0$ characterizing the magnitude of the error on objects x_i is introduced to construct the support vector machine.

Then the quadratic optimization problem has the following form:

$$\begin{cases} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \to \min_{\mathbf{w},b,\xi_i}, \\ c_i(\mathbf{w}\cdot\mathbf{x}_i - b) \ge 1-\xi_i, \quad 1\le i\le n, \\ \xi_i \ge 0, \quad 1\le i\le n. \end{cases} \tag{3}$$

This version of the algorithm is called the soft-margin SVM. The coefficient C is a method setting parameter that allows adjusting the relationship between maximizing the width of the dividing strip and minimizing the total error. According to the Kuhn – Tucker theorem, this problem is equivalent to the dual problem of saddle point of the Lagrange function finding.

For SVM classification of data with more than $n = 2$ classes, hyperplanes are usually constructed between all pairs of classes. The decision to assign an unknown feature vector to one or another class is made on the basis of a decision rule based on dividing the tasks into binary ones according to the One-vs-Rest scheme.

The main advantages of SVM are the following:

– the problem of convex quadratic programming is well studied and has a unique solution;

– the support vector machine is equivalent to a two-layer neural network, where the number of neurons in the hidden layer is automatically determined as the number of support vectors;

– the principle of optimal dividing hyperplane leads to maximization of the width of the dividing strip, and, therefore, to a more confident classification.

The disadvantages of SVM classifies include:

– noise instability: outliers in the source data become reference intruder objects and directly affect the construction of the separating hyperplane;

– general methods for constructing kernels and rectifying spaces that are the most suitable for a specific problem are not described;

– the need to select the constant C using cross-validation.

1.2. Logistic Regression

Logistic regression is used to predict the likelihood of a certain event from the values of many features. For this purpose, a dependent variable is introduced, taking values 0 and 1, and a set of independent variables, based on the values of which it is necessary to calculate the probability of acceptance of one or another value of the dependent variable. In the logistic regression, a linear classification algorithm $a: X \to Y$ is constructed [8]

$$a(x,w) = \mathrm{sign}(\sum_{j=1}^{n} w_j f_j(x) - w_0) = \mathrm{sign}\langle x, w\rangle \tag{4}$$

where w_j is the weight of the j-th feature;

w_0 is the decision threshold;

$w = (w_0, \ldots, w_n)$ is the weight vector;

$\langle x, w\rangle$ is the scalar product of the feature description of the object by the weight vector.

It is assumed that a null attribute has been artificially introduced:

$$f_0(x) = -1.$$

The task of training a linear classifier is to configure the vector of weights w for the training sample $X_m = \{(x_1, y_1), \ldots, (x_m, y_m)\}$ representing the "object-response" pairs. In logistic regression, the task of minimizing the empirical risk with a loss function of a special kind is solved for this:

$$Q(w) = \sum_{i=1}^{m} \ln\left(1+\exp\left(-y_i\langle x_i, w\rangle\right)\right) \to \min_u . \tag{5}$$

After the solution w is found, it becomes possible not only to calculate the classification $a(x) = \mathrm{sign}\langle x, w\rangle$ for an arbitrary object x, but also to evaluate the posterior probabilities of its belonging to the classes:

$$P\{y \mid x\} = \sigma(y\langle x, w\rangle), \quad y \in Y, \tag{6}$$

where $\sigma(z) = \dfrac{1}{1+e^{-z}}$ is the sigmoid function.

1.3. Multilayer Perceptron (MLP) Neural Network

The mathematical model of a neural network is a polynomial that calculates the output of the network based on input data and polynomial coefficients [9]. The degree of the polynomial is equal to the size of the sample supplied to the input of the network. The main task is the selection of polynomial coefficients – the so-called training of the neural network.

MLP neural network is a system of interconnected layers of neurons. Each neuron is characterized by an activation function that converts the input signal of the neuron to the output. Connections of neurons with other neurons are characterized by coefficients – the so-called connection weights.

The learning process is an iterative procedure of calculating the output signal of the network and subsequent adjustment of the weights of the links. As an algorithm for adjusting weights in MLP networks, the back propagation algorithm is usually used [10]. This algorithm belongs to the class of gradient algorithms, i.e., changes in connection weights are made in the direction of minimizing the error gradient.

The forecast error during network training is equal to the difference of the signal at the network output y_i and the reference value of the output d_i corresponding to the input data [11]:

$$e_i = (y_i - d_i). \qquad (7)$$

Network training has to be performed until the average error for one training epoch is reduced. Further training usually leads to deterioration in the analytical capabilities of the neural network. Each neuron of such a network has a smooth (everywhere differentiable) nonlinear activation function.

In this paper, the function of hyperbolic tangent is used as an activation function [8]:

$$y = F(S) = \mathrm{th}(CS) = \frac{e^{CS} - e^{-CS}}{e^{CS} + e^{-CS}}, \qquad (8)$$

where S is the weighted sum of the input signals;

C is the slope of the function.

Advantages of the multilayer perceptron consist in the following:

– the ability to conduct training on non-linear models;

– the ability to conduct model training in real time (online training).

The disadvantages of the multilayer perceptron include:

– MLPs with hidden layers have a non-convex loss function where there is more than one local minimum. Therefore, different initializations of a random weight can lead to different accuracy checks;

– MLP requires tuning a number of hyperparameters, such as the number of hidden neurons, layers, and iterations;

– the network is sensitive to scaling objects.

The methods under consideration have parameters that can be adjusted in the learning process from known data, and parameters that must be set manually (hyperparameters). The optimal combinations of parameters for each classifier have been chosen by optimizing the performance of the classifiers for the training dataset. The best classification accuracy is provided by the following parameters: for the linear support vector machine $C = 0{,}001$, for the logistic regression $C = 100$, for the multilayer perceptron $C = 100$, the number of hidden layers is 17.

2. Formation of a multichannel image distorted by additive white Gaussian noise

To study the classification efficiency of noisy multichannel remote sensing images by the considered methods, we used a real image of the Earth's surface in conventional colors R, G, B, formed according to the data of three spectral channels of the Landsat-TM satellite with wavelengths of 0,66 μm, 0,56 μm and 0,49 μm. The image size is 512×512 (Fig. 1). The image has been distorted by artificially added pure additive white Gaussian noise. In this paper, the classical probabilistic model of noise has been adopted – the normal distribution $N(0, \sigma)$, where σ is the standard deviation (SD).

It is assumed that the noise does not depend on spatial coordinates (i, j) and does not correlate with the image. Noise samples were independently generated for each component {R, G, B} of the image: $\{n_R\}_{ij}$, $\{n_G\}_{ij}$, $\{n_B\}_{ij}$. Statistical estimates of the normalized correlation coefficients between the noise components did not exceed 10^{-4}.

Since the pixel values for raster images are integers (in particular, for an eight-bit image, the brightness interval is limited to values from 0 to 255), for a noisy AWGN image, the pixel values with coordinates (i, j) were determined by the rule:

$$\{I_C^*\}_{ij} = \{I_C\}_{ij} + \{n_C\}_{ij}, \quad C \subset \{R, G, B\}, \qquad (9)$$

$$\text{if } \{I_C^*\}_{ij} > 255 \text{, then } \{I_C^*\}_{ij} = 255;$$

$$\text{if } \{I_C^*\}_{ij} < 0 \text{, then } \{I_C^*\}_{ij} = 0.$$

Fig. 2 shows the investigated image distorted by AWGN with $\sigma = 10$.

To study the influence of the noise intensity on classification results, the noise SD σ was varied in the range of 2…10.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Fig. 1. Test image (Landsat TM image)

Fig. 2. Additive mixture of image (Fig. 1) and Gaussian noise ($\sigma = 10$)

3. Image classification results

For the formation of training samples (fragments of the initial noisy image containing objects of only one class), we used color masks constructed by highlighting clearly distinguishable, homogeneous areas representing each class of objects of natural and anthropogenic origin [6]: 1 (red) – “soil”, 2 (green) – “grass”, 3 (blue) – “water”, 4 (yellow) – “urban”, 5 (cyan) – “bushes”; classes 3 and 4 contained both area and linear objects: class “water” = {lake, river}, class “urban” = {buildings, roads}. F-measure was used as a criterion for recognition quality. This is a harmonic mean of accuracy and completeness (accuracy shows how much of the objects identified by the classifier as positive are indeed positive; completeness shows how much of the positive objects was identified by the classifier). The harmonic mean has an important property – it is close to zero if at least one of the arguments is close to zero. The recognition results for the original image (the absence of noise is conventionally designated as $\sigma = 0$) and images distorted by the AWGN for various values of noise variance using these methods are shown in Fig. 3 - 5.

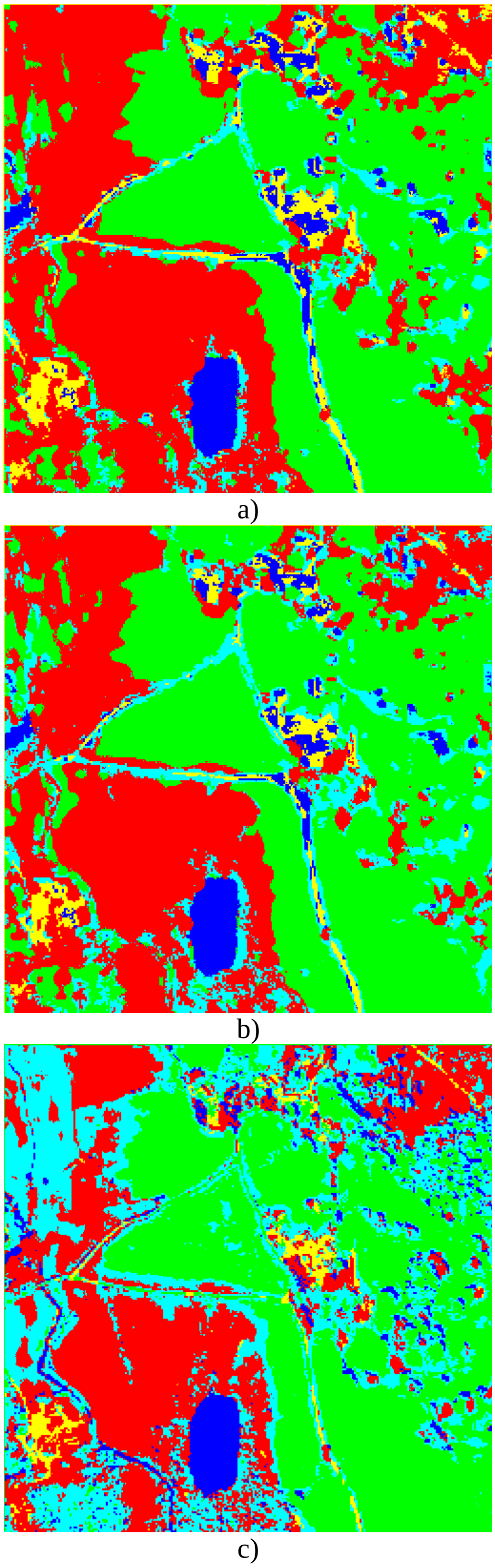
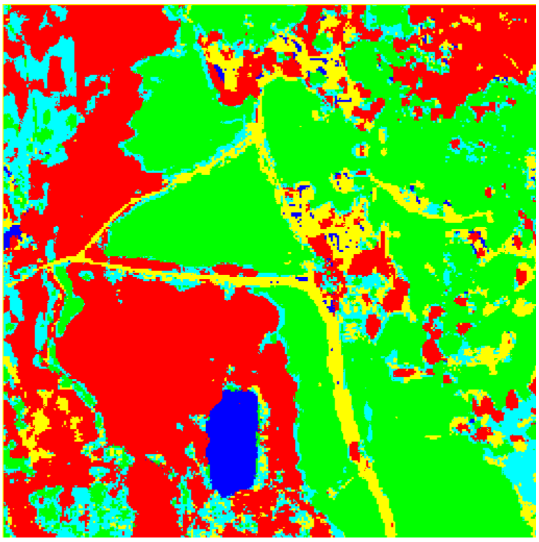
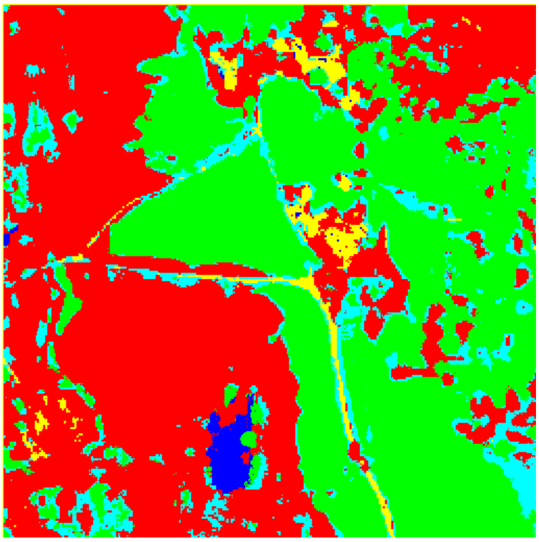


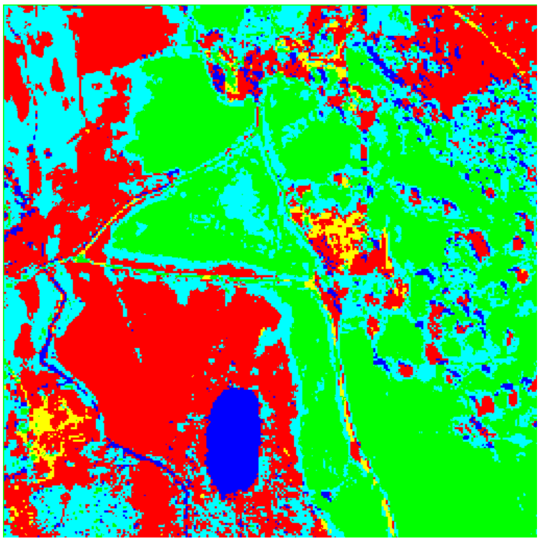
Fig. 3. Class recognition results for $\sigma = 0$ using the methods: a) SVM; b) LGR; c) MLP



a)

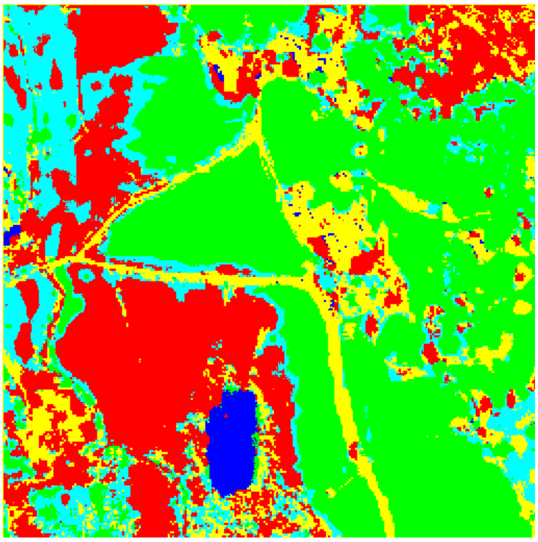


b)

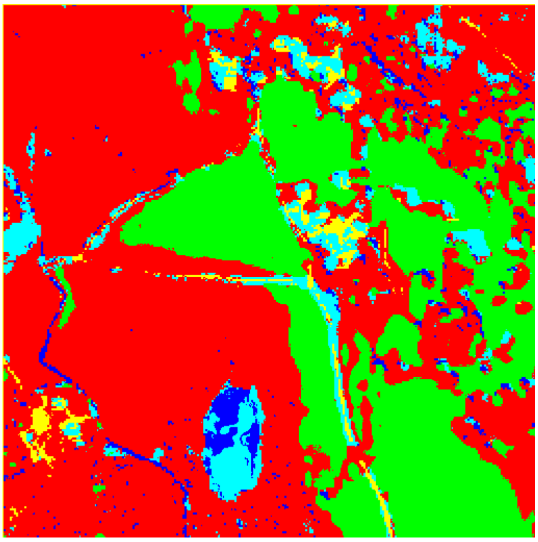


c)

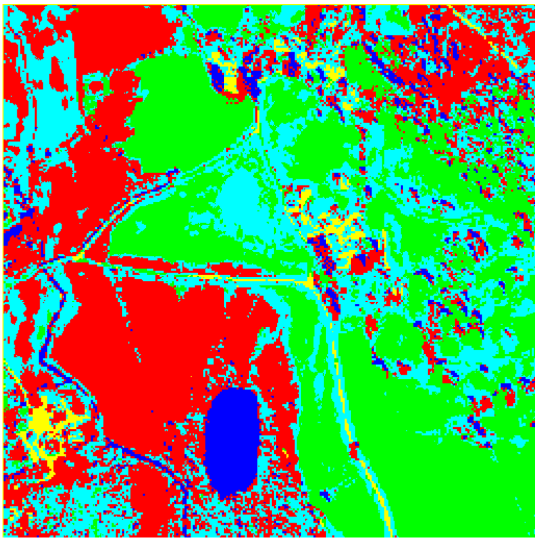
Fig. 4. Class recognition results with $\sigma = 6$ using the methods: a) SVM; b) LGR; c) MLP



a)



b)



c)

Fig. 5. Class recognition results with $\sigma = 10$ using the methods: a) SVM; b) LGR; c) MLP

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Table 1 shows estimates of the probabilities of correct recognition of each class and the total probability P_{corr} for the entire image.

Table 1

Estimates of correct recognition probability

Classifier	Class					P_{corr}
	Soil	Grass	Water	Urban	Bushes	
σ = 0						
SVM	0,73	0,99	0,84	0,71	0,25	**0,8105**
LGR	0,76	0,99	0,85	0,67	0,42	**0,8261**
MLP	0,78	0,96	0,97	0,60	0,54	**0,8345**
σ = 6						
SVM	0,71	0,92	0,65	0,61	0,23	**0,7379**
LGR	0,66	0,97	0,67	0,66	0,17	**0,7530**
MLP	0,75	0,92	0,97	0,55	0,36	**0,7761**
σ = 10						
SVM	0,70	0,86	0,55	0,61	0,20	**0,6909**
LGR	0,57	0,81	0,63	0,60	0,02	**0,6052**
MLP	0,75	0,89	0,96	0,55	0,36	**0,7571**

Analysis of data presented in Figures 3 – 5 and in Table 1 shows the following:

1) all classifiers provide the best results for classes that mainly correspond to area objects ("water", "grass") while heterogeneous objects ("urban" and, especially, "bushes") are recognized in the worst way;

2) it happens some classifiers are the best for one class (e.g., SVM and LGR produce the best results for the class "grass" when noise is absent) whilst another classifier provides the best results for another class (e.g., MLP for "bushes");

3) some classifiers as SVM and LGR fail in recognizing prolonged objects as narrow river (that belongs to the wide class "water") – see, e.g., classification maps in Figures 3,a, 3,b, 4,a and 4,b;

4) noise presence really leads to considerably reduction of classification accuracy, especially for LGR and such heterogeneous class as "bushes";

5) the best classification results are achieved using the MLP classifier;

6) with an increase in the standard deviation of the noise, the number of recognition errors increases, which mainly appear as isolated points, i.e. incorrectly classified pixels.

7) with an increase in the standard deviation of noise to 10, the classification quality in terms of overall probability P_{corr} reduces by 15 % for the support vector machine, 27 % for logistic regression, and 9 % for a neural network based on a multilayer perceptron.

Conclusions

Studies have shown that the presence of noise in the RS data complicates the recognition task, therefore, with the pixel-by-pixel classification of images, a large number of errors arise when objects either are not allocated or belong to another class. The effectiveness of various classification algorithms has been studied on a real satellite image, to which spatially uncorrelated white Gaussian noise was added with σ in the range 2…10. As the criterion for the effectiveness of the studied algorithms, statistical estimates of the total probability of correct recognition P_{corr} and the probabilities of correct recognition for each class have been taken. It is shown that an increase in the standard deviation of noise to 10 leads to a decrease in P_{corr} by 9…27 % compared with the classification of the noise-free image. The best classification of noisy images is ensured by the use of MLP classifier. The direction of further research is to evaluate and forecast the effectiveness of the application of post-classification processing of multichannel images distorted by various types of noise, both signal-dependent and signal-independent, to improve classification accuracy.

References

1. Современные методы интеллектуальной обработки данных ДЗЗ [Текст] / Н. С. Абрамов, Д. А. Макаров, А. А. Талалаев, В. П. Фраленко // Программные системы: теория и приложения. – 2018. – Т. 9, No. 4(39). – С. 417-442. doi: 10.25209/2079-3316-2018-9-4-417-442.

2. Modeling and estimation of signal-dependent noise in hyperspectral imagery [Text] / J. Meola, M. T. Eismann, R. L. Moses, J. N. Ash // J. Appl. Opt. – 2011. – Vol. 50. – P. 3829-3846.

3. Adaptive DCT-based filtering of images corrupted by spatially correlated noise [Text] / V. Lukin, N. Ponomarenko, K. Egiazarian, J. Astola // Proc. SPIE Conference Image Processing: Algorithms and Systems VI. – 2008. – Vol. 6812. – 12 p.

4. Афанасьев, А. А. Гибридные методы автоматизированной идентификации изменений ландшафтного покрова по данным дистанционного зондирования Земли в условиях шумов [Текст] / А. А. Афанасьев, А. В. Замятин // Компьютерная оптика. – 2017. – Т. 41, No. 3. – С. 431-440. doi: 10.18287/2412-6179-2017-41-3-431-440.

5. Proskura, G. A. Improvement of Multichannel Image Classification by Combining Elementary Classifiers [Text] / G. Proskura, V. Lukin, I. Vasilyeva // Problems of Infocommunications. Science and Technology : Proc. Internat. Scientific-Practical Conf., Kyev, Ukraine, 8-11 Oct. 2019. – Kyev, 2019. – 5 p.

6. Hsu, Chih-Wei A practical guide to support vector classification [Electronic resource] / Chih-Wei Hsu, Chih-Chung Chang, Chih-Jen Lin. – Access mode : https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf. – 9.10.2019.

7. Bach, Francis Non-Asymptotic Analysis of Stochastic Approximation Algorithms for Machine Learn-

ing [Text] / Francis Bach, Eric Moulines // Advances in Neural Information Processing Systems 24 : Proc. 25th Annual Conf., Granada, Spain, 12-14 Dec. 2011. – Granada, 2011. – P. 451-459.

8. A library for large linear classification [Text] / Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh et al. // Journal of Machine Learning Research. – 2008. – No. 9. – P. 1871-1874.

9. Venkat, N. Computational Analysis and Understanding of Natural Languages: Principles, Methods and Applications [Text] / N. Venkat, C. R. Gudivada // Handbook of Statistics. – 2018. – Vol. 38. – P. 2-515.

10. Alsmadi, M. S. Propagation Algorithm: The Best Algorithm Among the Multi-layer Perceptron Algorithm [Text] / M. S. Alsmadi, K. B. Omar, S. A. Noah // IJCSNS International Journal of Computer Science and Network Security. – 2004. – Vol. 9. – No. – P. 378-383.

11. Deep learning classification of land cover and crop types using remote sensing data [Text] / N. Kussul, M. Lavreniuk, S. Skakun, A. Shelestov // IEEE Geoscience and Remote Sensing Letters. – 2017. – Vol. 14(5). – P. 778-782. doi: 10.1109/LGRS.2017. 2681128.

References

1. Abramov, N. S., Makarov, D. A., Talalaev, A. A., Fralenko, V. P. Sovremennye metody intellektual'noi obrabotki dannykh DZZ [Modern methods for intelligent processing of Earth remote sensing data]. *Programmnye sistemy : teoriya i prilozheniya – Program Systems : Theory and Applications*, 2018, vol. 9, no. 4(39), pp. 417-442. (In Russian). doi: 10.25209/ 2079-3316-2018-9-4-417-442.

2. Meola, J., Eismann, M. T., Moses, R. L., Ash J. N. Modeling and estimation of signal-dependent noise in hyperspectral imagery. *J. Appl. Opt.*, 2011, vol. 50, pp. 3829-3846.

3. Lukin, V. V., Ponomarenko, N. N., Egiazarian, K., Astola, J. Adaptive DCT-based filtering of images corrupted by spatially correlated noise. *Proc. SPIE Conference Image Processing: Algorithms and Systems VI.*, 2008, vol. 6812. 12 p.

4. Afanas'ev, A. A., Zamyatin A. V. Gibridnye metody avtomatizirovannoi identifikatsii izmenenii landshaftnogo pokrova po dannym distantsionnogo zondirovaniya Zemli v usloviyakh shumov [Hybrid methods of automated identification of changes in landscape cover by Earth remote sensing data in the conditions of noises]. *Komp'yuternaya optika – Computer optics*, 2017, vol. 41, no. 3, pp. 431-440. (In Russian). doi: 10.18287/2412-6179-2017-41-3-431-440.

5. Proskura, G. A., Lukin, V. V., Vasilyeva, I. K. Improvement of Multichannel Image Classification by Combining Elementary Classifiers. *Proc. Internat. Scientific-Practical Conf. on Problems of Infocommunications. Science and Technology*, Kyev, Ukraine, 8-11 Oct. 2019. 5 p.

6. Chih-Wei Hsu, Chih-Chung Chang, Chih-Jen Lin. *A practical guide to support vector classification.* Available at: https://www.csie.ntu.edu.tw/~cjlin /papers /guide/guide.pdf (accessed 9.10.2019).

7. Bach, F., Moulines, E. Non-Asymptotic Analysis of Stochastic Approximation Algorithms for Machine Learning. *Proc. 25th Annual Conf. on Advances in Neural Information Processing Systems 24*, Granada, Spain, 12-14 Dec. 2011, pp. 451-459.

8. Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, Chih-Jen Lin A library for large linear classification. J*ournal of Machine Learning Research*, 2008, no. 9, pp. 1871 – 1874.

9. Venkat, N., Gudivada, C.R., Computational Analysis and Understanding of Natural Languages: Principles, Methods and Applications. *Handbook of Statistics*, 2018., vol. 38, pp. 2-515.

10. Alsmadi, M. S., Omar, K. B., Noah, S. A. Back Propagation Algorithm: The Best Algorithm Among the Multi-layer Perceptron Algorithm. *IJCSNS International Journal of Computer Science and Network Security*, 2004, vol. 9, no. 4, pp. 378-383.

11. Kussul N., Lavreniuk M., Skakun S., Shelestov A. *Deep learning classification of land cover and crop types using remote sensing data*. IEEE Geoscience and Remote Sensing Letters, 2017, vol. 14(5), pp. 778-782. doi: 10.1109/LGRS.2017. 2681128.

Поступила в редакцию 5.09.2019, рассмотрена на редколлегии 10.12.2019

ПОРІВНЯННЯ АЛГОРИТМІВ ПОЕЛЕМЕНТНОЇ КЕРОВАНОЇ КЛАСИФІКАЦІЇ ЗАШУМЛЕНИХ БАГАТОКАНАЛЬНИЙ ЗОБРАЖЕНЬ

В. В. Лукін, Г. А. Проскура, І. К. Васильєва

Предметом вивчення в статті є алгоритми поелементної керованої класифікації багатоканальних супутникових знімків, спотворених адитивним гаусовим шумом. Метою є дослідження ефективності класифікації зображень різними методами в широкому діапазоні значень співвідношення сигнал-шум; у якості критерію ефективності розпізнавання прийнята F-міра – гармонійне середнє точності і повноти: точність показує, яка частка об'єктів, виділених класифікатором як позитивні, дійсно є позитивними; повнота показує, яка частина позитивних об'єктів було виділено класифікатором. **Завдання**: згенерувати випадкові значення яскравостей шумових компонент, забезпечивши їх відповідність прийнятій ймовірнісній моделі; реалізувати процедури поелементної контрольованої класифікації за **методами** опорних векторів, логістичної регресії, нейронної мережі на основі багатошарового персептрона для зображень, спотворених шумом; оцінити результати виділення об'єктів на зашумлених зображеннях; дослідити вплив дисперсії шуму на ефективність розпізнавання. Отримані наступні **результати**. Реалізовано алгоритми поелементної керованої класифікації. Виконано порівняльний аналіз ефективності розпізнавання об'єктів на зашумлених зображеннях. **Висновки**:

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

в результаті порівняльного аналізу показано, що усі класифікатори забезпечують високу точність розпізнавання для класів, що відповідають площинним об'єктам (вода, трава), в той час як різнорідні об'єкти (будови і, особливо, кущі) мають низьку точність розпізнавання; класифікатори на основі методу опорних векторів і логістичної регресії показують низьку точність розпізнавання протяжних об'єктів, таких як вузька річка (яка відноситься до широкого класу «вода»). Наявність шуму на зображенні призводить до значного збільшення кількості помилок розпізнавання, які, переважно, проявляються у вигляді ізольованих точок на виділених сегментах, тобто неправильно класифікованих пікселів. При цьому оптимальне значення показника якості класифікації досягається використанням нейронних мереж на основі багатошарового персептрону.

Ключові слова: класифікація; адитивний гаусів шум; поелементна керована класифікація; ймовірність правильного розпізнавання.

СРАВНЕНИЕ АЛГОРИТМОВ ПОЭЛЕМЕНТНОЙ УПРАВЛЯЕМОЙ КЛАССИФИКАЦИИ ЗАШУМЛЕННЫХ МНОГОКАНАЛЬНЫХ ИЗОБРАЖЕНИЙ

В. В. Лукин, Г. А. Проскура, И. К. Васильева

Предметом изучения в статье являются алгоритмы поэлементной управляемой классификации многоканальных спутниковых снимков, искаженных аддитивным гауссовым шумом. **Целью** является исследование эффективности классификации изображений различными методами в широком диапазоне значений отношения сигнал-шум; в качестве критерия эффективности распознавания принята F-мера – гармоническое среднее точности и полноты: точность показывает, какая доля объектов, выделенных классификатором как положительные, действительно является положительными; полнота показывает, какая часть положительных объектов была выделена классификатором. **Задачи**: сгенерировать случайные значения яркостей шумовых компонент, обеспечив их соответствие принятой вероятностной модели; реализовать процедуры поэлементной контролируемой классификации по **методам** опорных векторов, логистической регрессии, нейронной сети на основе многослойного персептрона для изображений, искаженных шумом; оценить результаты выделения объектов на зашумленных изображениях; исследовать влияние дисперсии шума на эффективность распознавания. Получены следующие **результаты**. Реализованы алгоритмы поэлементной управляемой классификации. Выполнен сравнительный анализ эффективности распознавания объектов на зашумленных изображениях. **Выводы**: в результате сравнительного анализа показано, что все классификаторы обеспечивают высокую точность распознавания для классов, соответствующих площадным объектам (вода, трава), в то время как разнородные объекты (строения и, особенно, кусты) имеют низкую точность распознавания; классификаторы на основе метода опорных векторов и логистической регрессии показывают низкую точность распознавания протяженных объектов, таких как узкая река (которая относится к широкому классу «вода»). Наличие шума на изображении приводит к значительному увеличению количества ошибок распознавания, которые, преимущественно, проявляются в виде изолированных точек на выделенных сегментах, то есть неправильно классифицированных пикселей. При этом наилучшее значение показателя качества классификации достигается использованием нейронных сетей на основе многослойного персептрона.

Ключевые слова: классификация; аддитивный гауссов шум; поэлементная управляемая классификация; вероятность правильного распознавания.

Лукин Владимир Васильевич – д-р техн. наук, проф., зав. каф. информационно-коммуникационных технологий им. А. А. Зеленского, Национальный аэрокосмический университет им. Н. Е. Жуковского «Харьковский авиационный институт», Харьков, Украина.

Проскура Галина Анатольевна – канд. техн. наук, доц. каф. информационно-коммуникационных технологий им. А. А. Зеленского, Национальный аэрокосмический университет им. Н. Е. Жуковского «Харьковский авиационный институт», Харьков, Украина.

Васильева Ирина Карловна – канд. техн. наук, доц., доц. каф. информационно-коммуникационных технологий им. А. А. Зеленского, Национальный аэрокосмический университет им. Н. Е. Жуковского «Харьковский авиационный институт», Харьков, Украина.

Lukin Vladimir – doctor tehn. sciences, professor, Head of the Department of Information-Communication Technologies named after O. O. Zelensky, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine, e-mail: lukin@ai.kharkov.com, ORCID Author ID: 0000-0002-1443-9685.

Proskura Galina – cand. tehn. sciences, associate professor of the Department of Information-Communication Technologies named after O. O. Zelensky, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine, e-mail: g.proskura@khai.edu, ORCID Author ID: 0000-0001-8960-0421.

Vasilieva Irina – cand. tehn. sciences, docent, associate professor of the Department of Information-Communication Technologies named after O. O. Zelensky, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine, e-mail: i.vasilieva@khai.edu, ORCID Author ID: 0000-0002-1378-1104.