Algorithms of the Objects' Identification According to Hyperspectral Shooting of the „Resource-P" Spacecraft

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Abstract. The identification algorithms, which carry out the objects' identification of the Earth's surface by means of their hyperspectral features' analysis, received on the base of the processed space images from the „Resource-P" spacecrafts with application of the similarity measures, have been considered. The identification algorithms on the base of the Euclidean distance similarity measure, the angular similarity measure and the fuzzy similarity measure have been applied. The use expediency of the fuzzy linear regression in the algorithm of objects' hyperspectral features' identification has been shown. The results of the hyperspectral information processing with using of the offered algorithms have been presented.

1 Introduction

The problem of processing and analysis of hyperspectral information formed on the base of hyperspectral images of the Earth's surface presented by a big set of pictures of the same scene in the narrow adjoining spectral ranges received from a board of the spacecraft is one of the actual tasks solved by systems of Earth remote sensing. So, in particular, the russian „Resource-P" spacecrafts No. 1 – 3 with the hyperspectral equipment (HSE) on the board started respectively in 2013 – 2016, give out sets of pictures in 130 narrow adjoining ranges of visible area of spectrum which form a hyperspectral image (HSI) [1]. When processing GSI much attention is paid to the questions of the objects' identification of the Earth's surface, using their hyperspectral features (HSF).

Object's HSF in a graphic form can be presented as display of interrelation between the wavelength and values as spectral brightness coefficient (SBC), and spectral reflection coefficient (SRC) of the analyzed object. However at the solution of a problem of object's identification on its HSF use of SRC dependence on wavelength is more preferable as this brightness characteristic doesn't depend on shooting conditions in such degree as SBC. Besides, unlike SBC, for obtaining SRC values the standard reflecting surface in sight of the analyzed object isn't necessary.

Object's identification on its HSF can be carried out by means of comparison with application of some similarity measures of the analyzed object's HSF with some standard HSFs united in special spectral libraries [2–4]. Thus the analyzed and standard HSFs must have identical units of measure, spectral range and permission of data [5].

The analysis of works [6–10] testifies that for the problem solution of objects' identification of the Earth's surface on their HSFs the following approaches are most often used: algorithms on the base of similarity measures; method of a spectral corner; artificial neural networks; algorithm of k-averages; method of maximum likelihood.

The materials of experimental studies, received with application of the above approaches testify that we haven't algorithms which provide the demanded quality of objects' identification on their HSF in the prevailing majority of cases. Thus, the development problem of identification's algorithms of objects' HSF of the Earth's surface with application of various reasonably chosen similarity measures, and also of the aggregation algorithm of identification's private results of objects' HSF received when using several identification's private algorithms of objects' HSF is actual [11–16].

For the solution of identification's problem of objects on its HSFs it is offered to use at the same time four algorithms of HSF identification based on Euclidean distance similarity measure, angular similarity measure and two fuzzy similarity measures for the purpose of the subsequent aggregation of identification's private results of objects' HSF.

The choice of Euclidean distance similarity measure can be proved by high efficiency of application of the given measure at the solution of various applied problems of identification (classification), including problems of identification when processing space images. The choice of angular similarity measure assuming realization of spectral corner method (Spectral Angle Mapper – SAM), can be proved by that this measure provides good identification's results of objects' HSF having similar values of points' brightness of the

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image in all spectral ranges even when on initial images effects of a flare are observed. This fact is explained by that the spectral corner method doesn't consider brightness values of image points. Application expediency of fuzzy similarity measures [5, 6] can be proved by that the analyzed HSF of object can belong at the same time to different classes of objects while algorithms of «rigid» identification which are algorithm on the base of Euclidean distance similarity measure and algorithm on the base of angular similarity measure, will unambiguously carry the analyzed object's HSF to any one unambiguously certain class that can be not always true. The algorithms of „soft" identification based on application of fuzzy similarity measures will allow to solve flexibly a problem of object's identification using HSFs.

2 Identification of object's hyperspectral characteristics on the base of Euclidean distance similarity measure

Identification of object's HSF on the base of Euclidean distance similarity measure realizes identification of HSF with the use of the Euclidean metrics for calculation of distance between two points in the J-dimensional space [15, 16]:

$$E = \left(\sum_{j=1}^{J} (y_j^A - y_j^S)^2 \right)^{0,5} , \qquad (1)$$

where y_j^A is the SRC value of the analyzed HSF for the j-th hyperspectrometer channel; y_j^S is the SRC value of the standard HSF for the j-th hyperspectrometer channel; $j = \overline{1,J}$; J is the hyperspectrometer channel's number, equal to points' number (measurements) for HSF (for example, $J = 96$).

Wavelength λ_j for j-th hyperspectrometer channel ($j = \overline{1,J}$) is considered as well known value. The SRC values of the analyzed and standard HSFs are put in compliance to wavelengths.

Algorithm of HSF identification on the base of Euclidean distance similarity measure assumes: calculation of Euclidean distance similarity measures (1) for the analyzed HSF and standard HSFs, stored in the database; ordering on increase of the calculated values of Euclidean distance similarity measures; choice as required that standard HSF for which value of Euclidean distance similarity measures (1) is minimum.

3 Identification of object's hyperspectral characteristics on the base of angular similarity measure

Identification of the object's HSF on the base of angular similarity measure assumes use of spectral corner method (Spectral Angle Mapper – SAM) realizing an assessment of similarity of the analyzed and standard HSF, considered as vectors which dimension is equal to number of hyperspectrometer channels, by means of corner's calculation between them [5]:

$$\alpha = arccos \frac{G \cdot G'}{|G| \cdot |G'|} = arccos \frac{\sum_{j=1}^{J} g_j \cdot g_j'}{\left(\sum_{j=1}^{J} g_j^2 \right)^{0,5} \cdot \left(\sum_{j=1}^{J} g_j'^2 \right)^{0,5}} , \quad (2)$$

where G and G' are the spectrums of the analyzed and standard HSFs respectively; g_j and g_j' are the SRC values of the analyzed and standard HSFs respectively for wavelength's value λ_j ($j = \overline{1,J}$); J is the hyperspectrometer channel's number.

Algorithm of HSF identification on the base of angular distance similarity measure assumes: calculation of angular similarity measures (2) for the analyzed HSF and standard HSFs, stored in the database; ordering on increase of the calculated values of angular distance similarity measures; choice as required that standard HSF for which value of angular distance similarity measures (2) is minimum.

Often because of errors of HSE, resulting in inaccuracy of information on the about the analyzed object's HSF and also because of almost total absence of the „pure" analyzed HSF and existence in most cases of the analyzed HSF representing mix from several basic classes [5], it is expedient to consider some standard HSFs having the smallest values of Euclidean distance similarity measure (1) and angular similarity measure (2) as the potentially required. However, despite use at identification of a large number of the standard HSFs, results of identification with application of Euclidean distance similarity measure or angular similarity measure can be unsatisfactory.

In this regard it is expedient to carry out confirmation of identification's result, which, in particular, can be received by means of application of other identification's algorithms of object's HSF with the subsequent aggregation of identification's private results. As show experimental studies, the good aggregating identification's result provides sharing of HSF identification's algorithms on the base of Euclidean distance similarity measure, on the base of angular similarity measure and on the base of fuzzy similarity measures.

4 Identification of object's hyperspectral characteristics on the base of fuzzy similarity measures

Identification of object's HSF can be executed on the base of classical linear regression's equation (CLR) by means of the problem's solution of equation parameters' selection (k and b) for the analyzed HSF and standard HSF (for example, according to method of least squares):

$$y = k \cdot x + b \qquad (3)$$

with the subsequent calculation of root-mean-square deviation (RMSD) for the analyzed HSF and standard HSF, which can be used as the characteristics of uniqueness at HSF identification.

If for object's HSF identification we use only one characteristic of uniqueness – such as RMSD, in some cases objects' HSF, having approximately equal values of RMSD, can be carried to one class in spite of the fact that the form of curve for objects' HSF will be various. In this regard for identification of object's HSF it is offered to use additional characteristics of uniqueness which can be received on the base of fuzzy linear regression (FLR) equation. These characteristics can be used for calculation of fuzzy similarity measures.

In [6] it is shown that is most expedient to use FLR equation with asymmetric fuzzy parameters as it (unlike FLR equation with symmetric fuzzy parameters) provides calculation of the uniqueness characteristic's value – RMSD, which is equal or close to the value received by means of CLR equation:

$$Y(x) = A_1 \cdot x + A_0 , \qquad (4)$$

where $A_1 = (a_1, c_1, d_1)$ and $A_0 = (a_0, c_0, d_0)$ – triangular fuzzy numbers (TFN), corresponding to parameters k и b of CLR equation (3), represented by means of the triangular membership functions, and considered as the asymmetric fuzzy parameters of FLR equation (4).

When algorithms' developing of object's HSF identification on the base of fuzzy measures various fuzzy similarity measures [6] can be used. Thus identification algorithms will have identical stages of realization.

At the first stage of algorithm parameters (namely TFN) the FLR equation of the analyzed HSF are defined. Therefore the problem of square programming (PSP) formulated as follows [7] is solved:

$$F_{\text{ЗКП}} = k_1 \cdot \sum_{j=1}^{J} (y_j - \sum_{i=0}^{n} a_i \cdot x_{ji})^2 +$$
$$= k_2 \cdot (1-\alpha) \cdot \sum_{j=1}^{J} \sum_{i=0}^{n} (c_i + d_i) \cdot x_{ji} + \xi \cdot \sum_{i=0}^{n} (c_i^2 + d_i^2) \to \min_{a,c,d} \qquad (5)$$

and

$$\sum_{i=0}^{n} a_i \cdot x_{ji} + (1-\alpha) \cdot \sum_{i=0}^{n} d_i \cdot x_{ji} \geq y_j ; \qquad (6)$$

$$\sum_{i=0}^{n} a_i \cdot x_{ji} - (1-\alpha) \cdot \sum_{i=0}^{n} c_i \cdot x_{ji} \leq y_j ; \qquad (7)$$

$$c_i \geq 0; d_i \geq 0 \ (j = \overline{1,J}; \ i = \overline{0,n}; \ n = 1) , \qquad (8)$$

where j is the ordinal number of hyperspectrometer channel ($j = \overline{1,J}$); J is the hyperspectrometer channel's number; i is the ordinal number of TFN (if $n = 1$ then $i = \overline{0,1}$); $x_{j0} = 1$ ($j = \overline{1,J}$) – parameter b of CLR equation (2); x_{j1} – wavelength value for the j-th hyperspectrometer channel; y_j is the SRC value for wavelength x_{j1} ($x_{j1} = \lambda_j$); α is a value of TFN level, characterizing FLR corridor's width ($\alpha \in [0,1]$); k_1, k_2

are the weight coefficients characterizing a contribution of the first and second items in the objective function (5); ξ is a small positive number such that $k_1, k_2 \gg \xi$ (the third item is entered into criterion function in order that it had a square type and that at the search of TFN values could formulate the PSP [17]).

At the solution of PSP (5)–(8) it is supposed that $k_1 = k_2 = 1$ (in [7] it is shown that the choice of parameters' values k_1, k_2 has no strong impact on the problem solution); $\xi = 0,001$. Let $a_0 = z_1$; $c_0 = z_2$; $d_0 = z_3$; $a_1 = z_4$; $c_1 = z_5$; $d_1 = z_6$; $x_{j1} = \lambda_j$; $y_j = g_j$.

Then PSP (5) – (8) can be written as:

$$F_{\text{ЗКП}} = \sum_{j=1}^{J} (g_j - z_1 - z_4 \cdot \lambda_j)^2 + \sum_{j=1}^{J} (z_2 + z_5 \cdot \lambda_j + z_6 \cdot \lambda_j) + \\ + 0,001 \cdot (z_2^2 + z_3^2 + z_5^2 + z_6^2) \to \min_{z_1, \dots z_6} \qquad (9)$$

and

$$\begin{cases} z_1 + z_3 + z_4 \cdot \lambda_j + z_6 \cdot \lambda_j \geq g_j; \\ z_1 - z_2 + z_4 \cdot \lambda_j - z_5 \cdot \lambda_j \leq g_j; \\ z_2 \geq 0; \\ z_3 \geq 0; \\ z_5 \geq 0; \\ z_6 \geq 0. \end{cases} \qquad (10)$$

For the solution of PSP in the form of (8) at restrictions (9) the method of Lagrange uncertain multipliers can be used. In view of the fact that the solution of PSP by this method is very labor-consuming problem, use of the existing mathematical packages allowing to solve minimization problems with restrictions is expedient. In particular, can be solved in system of engineering and scientific calculations of MATLAB with application of the built-in function „quadprog" [18].

FLR equation (3) for the analyzed object's HSF is formed on the base of PSP solution (9) – (10). Thus on the base of the calculated TFNs $A_1 = (a_1, c_1, d_1)$ и $A_0 = (a_0, c_0, d_0)$ of FLR equation (4) for values of waves' lengths $x = \lambda_j$ ($j = \overline{1,J}$) characteristic points of the CLR equation $Y_{FLR}^{CLR}(\lambda_j)$ is defined:

$$Y_{FLR}^{CLR}(\lambda_j) = a_0 + a_1 \cdot \lambda_j , \qquad (11)$$

Also the equations of the upper $Y_{FLR}^{UP}(\lambda_j)$ and lower $Y_{FLR}^{LOW}(\lambda_j)$ borders of FLR corridor of the analyzed characteristic are defined:

$$Y_{FLR}^{UP}(\lambda_j) = a_0 + d_0 + (a_1 + d_1) \cdot \lambda_j , \qquad (12)$$

$$Y_{FLR}^{LOW}(\lambda_j) = a_0 - c_0 + (a_1 - c_1) \cdot \lambda_j . \qquad (13)$$

The FLR equation (3) for the standard HSF, and also the CLR equation, the upper $Y_{FLR}^{UP}(\lambda_j)$ and lower $Y_{FLR}^{LOW}(\lambda_j)$ borders of FLR corridor, defined according to (11), (12) and (13), are formed similarly.

Herewith, all calculated values of FLR for the standard HSF are stored in the database.

The FLR corridors of the analyzed HSF and standard HSF are asymmetric (fig. 1) because of TFN's $A_1 = (a_1, c_1, d_1)$ and $A_0 = (a_0, c_0, d_0)$ asymmetry.
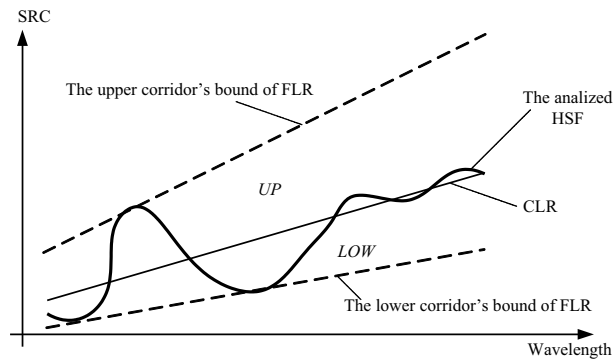

Fig. 1. The HSF representation in FLR corridor.

In this regard the HSF points can be broken into 2 subsets: a subset of the points lying in the upper part of FLR corridor (between the line of upper bound of FLR corridor and the CLR line, determined respectively by the equations (12) and (11)), and a subset of the points lying in the lower part of FLR corridor (between the line of the lower bound of FLR corridor and the CLR line, determined respectively by the equations (13) and (11)).

At the second stage of algorithm for the points of the analyzed HSF and each standard HSF lying in the upper *UP* and lower *LOW* parts of FLR corridors we calculate values of fuzzy similarity measures F^{UP} and F^{LOW}, using one of two fuzzy similarity measures [6]:

$$f_1 = 1 - \frac{\sum_{j=1}^{J} |u_A(\lambda_j, g'_j) - u_S(\lambda_j, g''_j)|}{\sum_{j=1}^{J} |u_A(\lambda_j, g'_j) + u_S(\lambda_j, g''_j)|}, \qquad (14)$$

$$f_2 = \frac{1}{J} \cdot \sum_{j=1}^{J} \frac{min(u_A(\lambda_j, g'_j), u_S(\lambda_j, g''_j))}{max(u_A(\lambda_j, g'_j), u_S(\lambda_j, g''_j))}, \qquad (15)$$

where $u_A(\lambda_j, g'_j)$ is a value of membership function of fuzzy set A of the analyzed HSF to the FLR equation of this HSF for SRC value g'_j, corresponding to wavelength λ_j ($j = \overline{1, J}$); $u_S(\lambda_j, g''_j)$ is a value of membership function of fuzzy set S of the standard HSF to the FLR equation of this HSF for SRC value g''_j, corresponding to wavelength λ_j ($j = \overline{1, J}$); J is the channels' number of the hyperspectrometer equal to points' number in the analyzed (standard) HSF.

These similarity measures were chosen from a set of the fuzzy similarity measures, because they showed the highest quality of identification results for the test data sets described by means of FLR equations. The value of membership function of the some HSF point (λ_j, g_j) to the FLR equation of this HSF can be defined as [7]:

$$u(\lambda_j, g_j) = \begin{cases} 1 - \dfrac{a_0 + a_1 \cdot \lambda_j - g_j}{c_0 + c_1 \cdot \lambda_j}, \text{if} \\ a_0 + a_1 \cdot \lambda_j - c_0 - c_1 \cdot \lambda_j \le g_j \le a_0 + a_1 \cdot \lambda_j; \\ 1 - \dfrac{g_j - a_0 - a_1 \cdot \lambda_j}{d_0 + d_1 \cdot \lambda_j}, \text{if} \\ a_0 + a_1 \cdot \lambda_j \le g_j \le a_0 + a_1 \cdot \lambda_j + d_0 + d_1 \cdot \lambda_j; \\ 0, \text{otherwise}; \end{cases} \qquad (16)$$

where $a_0, c_0, d_0, a_1, c_1, d_1$ are the TFN's parameters calculated at the solution of PSP (9) – (10).

At the finishing third stage of algorithm for the analyzed HSF and each standard HSF at first the calculation of the resultant fuzzy similarity measure, defined as minimum of fuzzy similarity measures F^{UP} and F^{LOW}, is carried out:

$$F = min(F^{UP}, F^{LOW}). \qquad (17)$$

Then all standard HSFs are ordered on decrease of fuzzy similarity measures' values. Thus as the required we choose that standard HSF, for which fuzzy similarity measures' value (17) is maximum.

Taking into account the stages described above it is possible to tell that HSF's identification algorithm on the base of fuzzy similarity measure assumes:
• finding of FLR equation for the analyzed HSF;
• extraction from the database of the calculated FLR values for the standard HSFs and calculation of fuzzy similarity measures' values F^{UP} and F^{LOW} according to (14) or (15) for the analyzed and standard HSFs;
• calculation of fuzzy similarity measures' values (17) for the analyzed and standard HSFs and a choice as required that standard HSF for which value of fuzzy similarity measures' value (17) is maximum.

5 The aggregation algorithm of identification's private results of object's HSF

As it was already noted, for improvement of identification's quality of the analyzed object's HSF the aggregation realization of identification's private results (in one way or another) is necessary.

At application of four identification's algorithms to the analyzed HSF and some standard HSFs four values are calculated: value of Euclidean distance similarity measure E (1); value of angular similarity measure α (2); two values of fuzzy similarity measures and, the formulas (14), (15) F_1 and F_2 (17) calculated according to (14), (15) и (17).

During the work with the database containing information on the standard HSFs for the analyzed object's HSF the four identifying sets will be received. Each set is the application's result of one of four HSF identification's algorithms and contains K values (according to number of the standard HSFs in the database).

Each such identifying set can be ordered on decrease (increase) of values of the used similarity measure. As a result some rating estimates will be appropriated to the standard HSFs in the database (ordinal numbers in a rating): than value of Euclidean distance similarity measure and angular similarity measure are higher and values of fuzzy similarity measures are lower, the number in a rating is less.

Let R_E^k is the rating assessment of the k-th standard HSF for the identification's algorithm on the base of Euclidean distance similarity measure E; R_α^k is the rating assessment of the k-th standard HSF for the identification's algorithm on the base of angular similarity measure α; $R_{F_1}^k$ is the rating assessment of the k-th standard HSF for the identification's algorithm on the base of fuzzy similarity measure F_1; $R_{F_2}^k$ is the rating assessment of the k-th standard HSF for the identification's algorithm on the base of fuzzy similarity measure F_2 ($k = \overline{1, K}$).

The aggregation algorithm of identification's private results of object's HSF assumes:
• the aggregation of identification's private results received with application of Euclidean distance similarity measure E, angular similarity measure α and two fuzzy similarity measures F_1 and F_2 by means of formula:

$$\overline{R}^k = (R_E^k + R_\alpha^k + R_{F_1}^k + R_{F_2}^k)/4; \qquad (18)$$

• the ordering of the standard HSFs from the database on increase of average values of the rating assessments $\overline{R}^k$ ($k = \overline{1, K}$).

Let the aggregating rating assessments R_{ord}^k are defined as numbers in a rating for the average assessments $\overline{R}^k$ ($k = \overline{1, K}$). It is obvious that for the further analysis it is expedient to use the insignificant part of the best standard HSFs from the database (from 5 to 10 standard HSFs) having the smallest values (ordering numbers) of the aggregating rating assessments R_{ord}^k.

After the visual comparative analysis of identification's results of the analyzed object's HSF by means of some best standard HSFs from the database received in the above way and presented both in text and in a graphic form, the software operator can make a final decision on compliance to the analyzed object's HSF of some standard HSFs from the database.

6 The experimental studies

The developed software was used for solving the problem of identification of the anthropogenous objects according to hyperspectral shooting from the „Resource-P" spacecraft (No. 1 and No. 2).

The experiment for assessing the reliability of identification solutions with the use of the developed algorithms on the real hyperspectral data in the amount of 15 pictures, each of which contained more than 100 objects was conducted.

Table 1. The identification results.

No	The algorithm	The false omissions,%	The false detection,%
1	The Spectral Angle Mapper algorithm (SAM, the program complex ENVI)	15,4	5,2
2	The aggregation algorithm (the developed software)	4,5	5,5

The data sampling of 402 HSFs in which 181 characteristics belong to the anthropogenous objects has been made.

The identification was carried out by the algorithms from the developed software, and also by the SAM algorithm which is realized in the program complex ENVI. The results of identification given in table 1 show the increase in reliability of the identification decision for 10,9% in comparison with the SAM algorithm from the program complex ENVI [18].

7 Conclusions

The results of experimental studies confirm expediency of further development of the offered approach to the solution of identification's problem of objects' HSF, based on aggregation of identification's private results objects' HSF, received with application of various reasonably chosen identification's algorithms for the purpose of reliability's increase of classification decision. Further researches can be directed on reasonable attraction of new similarity measures for the solution of identification's problem and improvement of aggregation algorithm of identification's private results of objects' HSF.

Use of the offered approach for developing HSF identification's algorithms will allow to solve objects' identification's problem of the Earth's surface on allocated from the processed space images of the „Resource-P" spacecraft HSF with the subsequent accumulation of the standard HSFs in the database that, in turn, will provide creation of actual domestic spectral library of standards HSFs which can be applied when monitoring a condition of agricultural grounds, forests, water resources, an ecological condition of soils, etc. [19, 20].

Also, we plan to use the SVM-classifiers in sovling the problem of the HSF identification [21–23]. Herewith, firstly, it is neccassary to create the reprezantative dataset of the HSFs and, secondly, use it to learn the SVM-classifiers. Then, we can identify the new HSF as the HSF of some known class.

References

1. V. Zelentsov, B. Sokolov et al., Resurs-P" Satellite Hyperspectral Data: Preliminary Evaluation of Information Capacities, *Proceedings of the conference Living Planet Symposium*, **740**, 416 (2016)

2. USGS Spectroscopy Lab. http://speclab.cr.us-gs.gov.

3. Jet Propulsion Laboratory, ASTER Spectral Library. NASA. http://speclab.jpl.nasa.gov.

4. A.M. Baldridge, S.J. Hook, C.I. Grove, G. Rivera, *Remote Sensing of Environment*, **113**, 711–715 (2009)

5. C. Yang, J.H. Everitt, J.M. Bradford, *American Society of Agricultural and Biological Engineers*, 51, 729–737 (2008)

6. D. Van der Weken, M. Nachtegael, E.E. Kerre, An overview of similarity measures for images. *Proceedings of ICASSP 2002 (IEEE Int. Conf. Acoustics, Speech and Signal Processing)*, 3317 – 3320 (2002)

7. Lee Haekwan, Tanaka Hideo,. *Journal of the Operations Research Society of Japan*, **42** (1999).

8. J.D. Adams, M.O. Smith, P.E. Johnson, *Journal of Geophysical Research*, **91,** 8090 – 8112 (1996)

9. K. Michael, Su Griffin at al., *Lincoln laboratory journal*, **15** (2005).

10. E.V. Nikulchev, A.P. Kondratov, *Advanced Studies in Theoretical Physics*, **9**, 795-800 (2015)

11. N.N. Astakhova, L.A. Demidova, E.V. Nikulchev, *Applied mathematical sciences*, **9**, 4813–4830 (2015)

12. L.A. Demidova, N.I. Nesterov, Fuzzy and possibilistic segmentation of earth surface images by means of intelligent information technologies. Proceedings *2014 International Conference on Computer Technologies in Physical and Engineering Applications, ICCTPEA 2014*, pp. 35 – 36.

13. L.A. Demidova, *Automation and Remote Control*, **74**, 313–320 (2013)

14. L.A. Demidova, S.V. Truhanov, *Cloud of Science*, **2**, 40–60 (2015)

15. L.A. Demidova, S.V. Truhanov, *Contemporary Engineering Sciences*, **8**(20), 885–900 (2015)

16. J. Dattorro, *Convex optimization & euclidean distance geometry* (Meboo publishing USA, 2005)

17. D.M. Himmelblau, Applied nonlinear programming. (The Univ of Texas, McGraw-Hill Book Company, 1972).

18. S. Attaway, *Matlab A practical introduction to programming and problem solving* (Butterworth Heinemann, 2009).

19. O. Grigorieva, O. Brovkina el al., A complex model for forest ecosystem state assessment based on remote sensing data: case study in Baikalsky Nature Reserve, *The 4th International Workshop on Simulation for Energy, Sustainable Development and Environment, 26-28 September 2016/ Cyprus*, pp. 14-19.

20. V.F. Mochalov, A.V. Markov el al., *Advances in Intelligent Systems and Computing*, **466**, 497-506 (2016)

21. L.A. Demidova, Yu.S. Sokolova, Training set forming for SVM algorithm with use of the fuzzy clustering algorithms ensemble on base of cluster tags vectors similarity matrices, *2015 International Conference "Stability and Control Processes" in Memory of V.I. Zubov (SCP),* 571-572 (2015)

22. L.A. Demidova, Yu.S. Sokolova, E.V. Nikulchev, *International Journal of Advanced Computer Science and Applications*, **7**(5), 294-312 (2016)

23. L.A. Demidova, Yu.S. Sokolova, E.V. Nikulchev, *International Journal of Advanced Computer Science and Applications*, **7**(2) 16-24 (2016)