MULTISPECTRAL SATELLITE IMAGES PROCESSING FOR FORESTS AND WETLAND REGIONS MONITORING USING PARALLEL MPI IMPLEMENTATION

Rauf Kh. Sadykhov[1]**, Andrey V. Dorogush**[1]**,**
Yegor V. Pushkin[1]**, Leonid P. Podenok**[2]**, and Valentin V. Ganchenko**[2]

[1]*Computer Systems Departement, Belarusian State University of Informatics*
and Radioelectronics, 6 P. Brovka st, Minsk, Belarus
[2]*Laboratory of System Identification, United Institute of Informatics Problems,*
National Academy of Sciences of Belarus, 6 Surganov st, Minsk, Belarus

ABSTRACT

The effective methods and algorithms based on fuzzy clustering for processing multispectral satellite images have been developed. To enforce discrimination of different land covers and to improve area separation additional channels with fractal characteristics have been evaluated and included into aggregate multichannel image. To significantly reduce time expenses parallel computing technique was used for practical implementation. The classification based on radial basis function (RBF) neural network has been presented. Data preprocessing techniques such as histogram processing and texture features calculation are discussed. The original approximation method based on radial basis functions was developed to create superimposing transform of multispectral images into/from geographical projections. All the software has been implemented as GIS GRASS modules to be runnable in Massive Parallel Processing (MPP) cluster environment using Message Passing Interface (MPI). Experimental testing of developed algorithms and techniques has been carried out using images received from Landsat 7 ETM+ Satellite.

Key words: fuzzy clustering, neural network, .

1. INTRODUCTION

Belarus is the third world gainer after China and United States of forest cover in 1990-2000 [1]. There are many forests in Belarus, Ukraina, and Central Europe. The main problem here is deforestation which is the consequence of two main reasons – agricultural expansion and accidental events. Significant part of forest is damaged by fire, pests, irrational agricultural politics leading to change of ground water level and as result leads to sickness and wreck.

At now it is possible to discriminate forest areas on early stage of damaging using multispectral satellites images of high spatial resolution. Multispectral satellite images are able to bring us information in both visible and invisible spectral bands about vegetation, water temperature and land cover.

Multidimensional cluster analysis, segmentation, classification which are the basic methods in processing the multispectral remote sensing data [2] have high computational complexity. On the other hand development stage of parallel computing has long ago stepped over standardization phase and various implementations of communication procedures and application interface widely known as message passing interface (MPI), are the mandatory component parts of modern operation system. That fact assists in solving the problems related to performance of remote sensing data processing.

To raise the business efficiency of enterprises dealing with satellite data utilizing it is necessary to use novel methods and algorithms of data processing. The specific volume of remote sensing data increases because of spatial and spectral resolution of that data also grows. In this connection necessity appears to provide to end user inexpensive access to high volume remote sensing data warehouses and high performance computational resources. At now such the opportunities can be made available with GRID and MPI technologies which are very fast upcoming. These problems are solved owing to storing the frequently used data in accessible to number of users place and owing to effective parallelization of computation (parallel algorithms).

Some multispectral channels are processed simultaneously and spatial analysis algorithms and multidimensional cluster analysis ones are joined together. Cluster analysis space is usually formed of source image channels or linear combinations of them as in the case of principle components approach. That allows to take in account the spectral relations between pixels of multispectral image only. To take in account spatial relations between pixels that spectral channel space should be appended with other dimensions which can take in consideration spatial metrical relationships. Such the complex construction of the space allows to segment areas where

spectral colors are varied slightly. However clustering the some landscape types which are widespread in Europe (forests, agriculture regions, wetlands) in multispectral colour space even supplemented with spatial dimensions does not allow to make satisfactory segmentation. It is known [3] that good results for the forest and bushes regions are achieved using approaches based on fractal dimension evaluation and textural feature calculation.

The choice of fractal and textural features and characteristics as base to solve forestry and agriculture tasks using multispectral images processing is determined by that fact that segmentation methods based on spectral characteristics does not provide any satisfactory results being applied to such the natural objects as forest, wetland, and agriculture areas.

In spite of fractal theory is developed enough its application to images received with limited spatial resolution is far from completion. From one hand there are strong definition of dimension of fractal set exists, but from other hand real linear or spatial measurements are restricted in resolution and direct implementation of theory to practice is impossible. In this connection every researcher tries to solve the problem of evaluation of fractal characteristics using own methods.

The novelty of proposed project consists of implementing parallel computing based on GRID and MPI technologies into practice of thematic and processing of the high resolution spatial and multispectral data received remote sensing satellites for end users in GIS environment. The number of methods and algorithms used in processing multispectral images is large enough and so fractal and texture based ones as most effective in respect to thematic processing of forest and agricultural regions and most representative in respect to computation costs are proposed to be realised and tested in the project framework.

2. SEGMENTATION

The effective methods and algorithms for processing multispectral images received from remote sensing satellites to be used for solving the various tasks of the forestry, such the building forest cover maps, evaluation of state of forest health, its fragmentation and biodiversity, detection and post-monitoring the natural and human-induced disturbances and accident forecasting have been developed.

Multi-dimensional cluster analysis and segmentation are base procedures in thematic processing the multispectral images received from remote sensing satellites. There are lot of clustering and segmentation methods which have different benefits and imperfections. The special class of such the methods is represented by fuzzy clustering ones. Three clustering algorithms based on fuzzy methods where developed and utilized as part of segmentation software. There are fuzzy c-means[4] (FCM) and its

variants – Gustafson-Kessel clustering algorithm [5] and Gath-Geva one [6].

FCM is a method of data clustering which allows one data objects to be a member of two or more clusters. It is based on minimization of the following objective function:

$$J = \sum_{i=1}^{N}\sum_{j=1}^{C} \mu_{ij}^{m} \parallel x_i - s_j \parallel, \qquad (1)$$

where m is real number ≥ 0, μ_{ij} – degree of membership of x_i in cluster s_j, x_i is the multi-dimensional data object, s_j is the multi-dimensional center of the cluster, and $\parallel \cdot \parallel$ is any norm expressing the similarity between any measured data and the cluster center.

Fuzzy clustering is carried out through an iterative optimization of the J_m with the update of membership matrix μ_{ij} and the cluster centers s_j using following algorithm:

1. The data set $X = (x_j) = (x_{j1}, x_{j2} \ldots, x_{jp})^T$ given. We choose the number of clusters $1 < c < n$, where p – dimension of data set.

2. Initialize the partition matrix μ_{ij} using random number genetrator in range [0, 1]:

$$\sum_{i=1}^{c} \mu_{ij} = 1, \qquad (2)$$

3. Calculate the cluster centers $s_i = (s_{i1}, s_{i2}, \ldots, s_{ip})^T$ $(i = 1, 2, ..., c)$:

$$s_i = \frac{\sum\limits_{j=1}^{n} \mu_{ij}^2 x_j}{\sum\limits_{j=1}^{n} \mu_{ij}^2}, \qquad (3)$$

4. Calculate the error:

$$E = \sum_{i=1}^{c}\sum_{j=1}^{n} \mu_{ij}^2 (s_i - x_j)^T (s_i - x_j). \qquad (4)$$

If error is small enough, then stop iterations, else go to item 5.

5. Calculate the "new" partition matrix μ_{ij}:

$$\mu_{ij} = \left(\sum_{m=1}^{n} d_{ij}^2 / d_{mj}^2 \right)^{-\frac{1}{2}} \qquad (5)$$

and then go to step 3.

where d_{mj}^2 is similarity measure $\parallel \cdot \parallel$.

Fuzzy c-means, Gustafson-Kessel, and Gath-Geva clustering algorithms are distinguished in the definition of

distance function between the objects to be classified:
Fuzzy C-means:

$$d_{ij}^2 = (s_i - x_j)^T (s_i - x_j), \qquad (6)$$

Simple euclidean distance provides hyper-spherical form of clusters.

Gustafson-Kessel:

$$d_{ij}^2 = (s_i - x_j)^T (det(F_i)^{\frac{1}{2}} F_i^{-1})(s_i - x_j), \qquad (7)$$

Gath-Geva:

$$d_{ij}^2 = \frac{det(F_i)^{\frac{1}{2}}}{\alpha_i} \exp(\frac{1}{2}(s_i - x_j)^T (F_i^{-1})(s_i - x_j)), \qquad (8)$$

where F_i is covariance matrix, that provides ellipsoidal form of clusters and more comprehensive partitioning the multi-dimensional data, α_i is calculated in following manner:

$$\alpha_i = \frac{1}{n} \sum_{j=1}^{n} \mu_{ij}. \qquad (9)$$

Covariance matrix is used to form non-spherical clusters which are more suitable for multi-dimensional data partitioning. That also leads to visible difference in algorithm convergence, effectivity and performance of processing the multispectral images.

Distance function for Gustafson-Kessel and Gath-Geva algorithms uses covariance matrix to take into account different metrics (scales) in different dimensions. The large images to be processed might be the reason of weak covariance matrix conditionality that results in heavy losses of aptitude for discrimination for Gustafson-Kessel and overflows for Gath-Geva when fixed digit capacity arithmetics based on atomic numerical types is used. To keep of that problems standard normalization methods and arbitrary (multi-precision) arithmetics are the sufficient efforts. When d_{ij}^2 becomes small the overflow may occure. To prevent that case the distant function is confined from below by some smallest value d_{min}.

Due to source signal noise the some spatial segment granularity occurs. To reduce that granularity the weak non-linear filtering using algorithm [7] was applied to source channels. That algorithm may be used both for edges extraction and for nonlinear filtering. It does not lower the sharpness of transitions of channel brightness the boundaries of cover types remain clear. As a result the boundaries of spatial segments after clustering process also remain legible. Smoothing properties of that filter can be widely varied using brightness threshold and spatial parameters.

Algorithm works with values of brightness and pixels' coordinates simultaneously. To form the homogeneous areas or search the edges on the gray-scale image a round mask is used. Usually the mask's radius is 3.4 pixels which gives mask of 37 pixels size. The mask is placed at each point of the image and the brightness of each pixel of the mask is compared with the brightness of the mask central pixel.

$$c(\mathbf{r}, \mathbf{r}_0) = \begin{cases} 1, I(\mathbf{r}) - I(\mathbf{r}_0) \leq t \\ 0, I(\mathbf{r}) - I(\mathbf{r}_0) > t, \end{cases} \qquad (10)$$

where $I(\mathbf{r}_0)$ – the brightness value of the mask's center, $I(\mathbf{r})$ – the brightness value of the mask pixel, t specific threshold.

The result of the comparisons is sum:

$$n(\mathbf{r}_0) = \sum_{\mathbf{r}} c(\mathbf{r}, \mathbf{r}_0). \qquad (11)$$

where n is the quantity of pixels in the USAN (Univalue Segment Assimilating Nucleus). Then that sum should be minimized, so the algorithm is called SUSAN (Smallest USAN). Parameter t means the maximum of ignored noise. Then n is compared with it's thresholding value g, which is $3n_{max}/4$, where n_{max} – maximum value which could be assigned to n.

3. FRACTAL CHARACTERISTICS

The segmentation of some land cover types on multispectral satellite images based on fuzzy clustering might be enforced if fractal properties of objects would be taken into account [8]. Such land cover types are the forests and wetlands.

To calculate (evaluate) fractal signature of grayscale image intensity value $g(i, j)$ is discretized using scale ϵ. Then two surfaces $U^\epsilon(i, j)$, $L^\epsilon(i, j)$ are built. All the discretized values $g^\epsilon(i, j)$ are located between these surfaces. Upper surface U^ϵ consist of points values of which upper then $g^\epsilon(i, j)$ on ϵ and Lower surface L^ϵ consist of points values of which lower then $g^\epsilon(i, j)$ on ϵ. Both the surfaces at zero scale ($\epsilon = 0$) are determined as $U^0(i, j) = L^0(i, j) = g(i, j)$.

The conctructed cover formed by $U^\epsilon(i, j)$ and $L^\epsilon(i, j)$ has thickness equal to 2ϵ. It's surface is volume of cover divided by 2ϵ. Square of intensity surface $A(\epsilon)$ at evaluating window R is calculated as

$$A(\epsilon) = (\sum_{i,j \in R} U^\epsilon(i, j) - L^\epsilon(i, j))/2\epsilon = V(\epsilon)/2\epsilon. \qquad (12)$$

Fractal dimension is determined using slope of function $\log A(\epsilon)$ of $\log \epsilon$. Fractal dimension $D(i, j)$ for pixel (i, j) is calculated as weighted sum of local fractal dimensions $F\epsilon(i, j)$ as

$$D(i, j) = (\sum_\epsilon C_\epsilon F_\epsilon(i, j))/(\sum_\epsilon C_\epsilon) \qquad (13)$$

when $C_\epsilon = (\log \epsilon - \log(\epsilon - 1))/\log 2$; $F_\epsilon = (\log A(i, j, \epsilon) - \log A(i, j, \epsilon - 1)]/[\log \epsilon - \log(\epsilon - 1))$.

All the layers of multispectral image were processed as aggregate. Fractal dimension and signature evaluation was used to enforce area separation, partitioning of the images, and subsequent classification. The fractal signature layers have been used to as additional dimensions and were included into aggregate multi-channel image being subject to segmentation. These algorithms most appropriate for thematic processing but require high computational costs and can not be implemented for desktop computing directly. Therefore parallel computing technique was used for practical implementation.

4. NEURAL NETWORK TECHNOLOGIES

Neural networks are widely used to process multispectral satellite images [9], starting from segmentation and finishing forecasting of change of objects.

The developed neural network consists of a layer of Radial Basis Function cells and a layer of neurons with sigmoid threshold function. The network has been designed so that the data from all the layers of multispectral image were processed as aggregate.

The image has been broken into set of fragments during processing (they can be both overlapped and not depending on the purpose of experiment). The method of allocation of more informative area in a processable fragment has been applied due to use of a mask, applied to every image submitted on an input of a neural network.

The developed network has been modified to apply the histogram analysis instead of raster representation of a multi-bands fragment on network's inputs. It gave ability to increase efficiency of classification of objects via tone criterion. The used method of recognition is completely insensitive to a textural component of processed fragment.

The task to be fulfilled was the evaluation of capabilities of radial basis function (RBF) based neural network to select and classify different land cover types.

The RBF based neural network has been chosen to implement the classifier. Each cell of a layer plays a role of a cluster center and corresponds one of the image object. Typical representatives of areas chosen for classification of multispectral image have been established as training samples.

The task of classification of objects of the stage belonging five allocated areas were put in spent experiments. It caused presence of five outputs in neural network (five neurons in output layer). Value 1 is formed on each of them in case of ranking of a fragment submitted on an input of a network to corresponding class and 0 in otherwise.

Each neuron of a hidden layer accepts 20×20 pixels fragment of multiband source image. As the result neural network (as well as each neuron of hidden layer) has

Table 1. Results of classification.

Area No	1	2	3	4	5
True samples, %	100	95.1	100	97.2	100

$20 \times 20 \times 8 = 3200$ inputs. When the histogram instead of raw raster was used the quantity of inputs of network has been decreased down to 2048. That is resulted in reduction of expenses of time required for processing a portion of data with the use of neural network, despite of necessity of creation the histogram in real time.

Each cell receives 3200 input values. Further the search of distance between an input fragment and the center of cluster, corresponding to a concrete cell is fulfilled. Adjustment of centers and radiuses of RBF cells is made during training this layer. For this purpose the centers of cells were rigidly established in symbols of training set corresponding to them, and radiuses were selected experimentally.

Presence of additional layer of neurons with sigmoid transfer function is required to transform and process values formed on outputs of a layer of RBF cells. Weights of this layer should be trained to transform results of classification (clustering) by RBF layer to five target signals. Value of each of target signals should be laid in an interval $[0, 1]$.

The used network has 3200 inputs. The quantity of inputs has been determined by dimension of data used for training and verification of the network (fragments of eights bands of the image in the size of 20 per 20 pixels). There are 50 RBF cells in the input layer. 10 images for each class of objects have been used for training (5 classes have been allocated. There are 5 neurons with sigmoid transfer function in an output layer. The quantity of neurons in this layer has been determined by quantity of object classes. This layer is full connected with input layer of RBF cells.

Training and verification data sets have been generated to carry out the experiment. Verification set has been formed from multispectral image using 2000 fragments from 5 areas of interests and consists of 10000 fragments totally. Training set has been selected from verification data set and included 10 fragments for each area, or 50 fragments totally. After training the network all the fragments from verification set including fragments used for training have been exposed to network input. As the result all training fragments have been ranked correctly to corresponding classes. Results of classification of whole verification set are represented in the table 1.

The percentage ratio shows, how many images from the verification set have been ranked to right class. For example, 95.1% of all fragments of area number 2 have been ranked by neural network to class corresponding to this area. Time of processing the single fragment is about 9-

10 ms and time of processing whole verification set is about 180 sec when no mask has been used. When radial mask was used the time of whole classification process raised up to 280 sec. Minor alteration of results with and without mask can be explained by the specificity of a problem and sets of data used for training and running tne network.

5. PARALLEL IMPLEMENTATION

The novel compressing technique based on biorthogonal wavelets and arithmetic coding has been developed to effectively store and recover the high resolution multi-spectral satellites images and its fragments. All the software has been implemented as GIS GRASS modules to be runnable in Massive Parallel Processing (MPP) cluster environment using Message Passing Interface (MPI).

Generalized structural schema of MPP-implementation contains three main parts:

1. Opensource GIS GRASS. It contains database of images, which is used to store images and keeping up integrity of geographical data related to them. Also it provides import/export of images.

2. Control unit. This unit is intended for coordinate calculation, sectioning the source image on to parts, and assembling results.

   Computational cluster which provides executing the parallel implementation of algorithms.

Image processing is realized in the following way: Source image is divided to parts, each of them contains some section of original multispectral image and perhaps surrounding area (phantom points).

After dividing image to parts processing stage follows. At this stage realizes parallel multispectral image processing by parts. Message Passing Interface was selected as basis of parallel calculation. This technology was selected because it allows simple organization of interaction between of calculating processes and synchronization.

6. RESULTS

Experimental testing of developed algorithms and techniques has been carried out using images received from Landsat 7 ETM+ Satellite. Raw output data of developed segmentation software is 2-d vector field over R^N, where N is a number of clusters. Each component of that field is strictly increasing function of probability for pixel to be member of one of N clusters. On presented images one can see some well discriminated land cover types. There are open water, forests, wetlands, bushes and agriculture areas. Figure 1 shows results of segmentation on
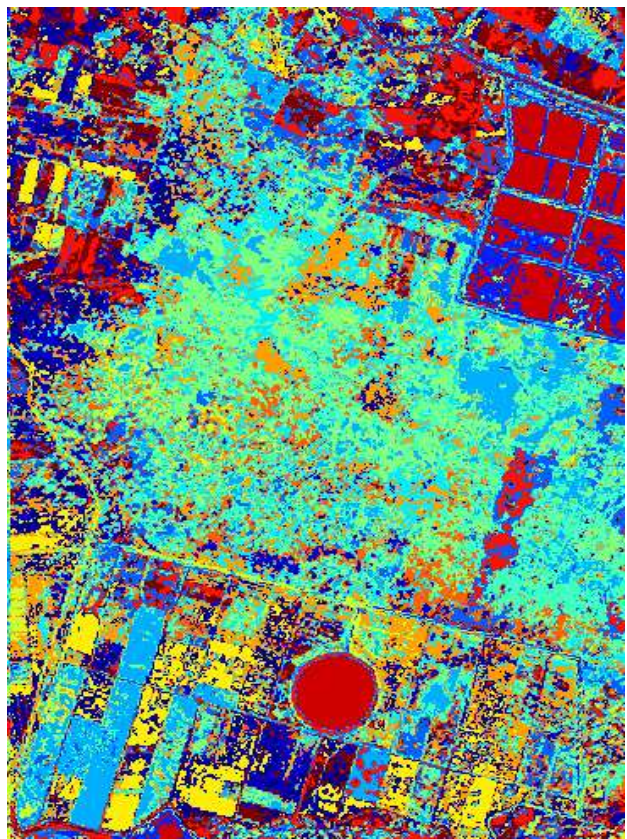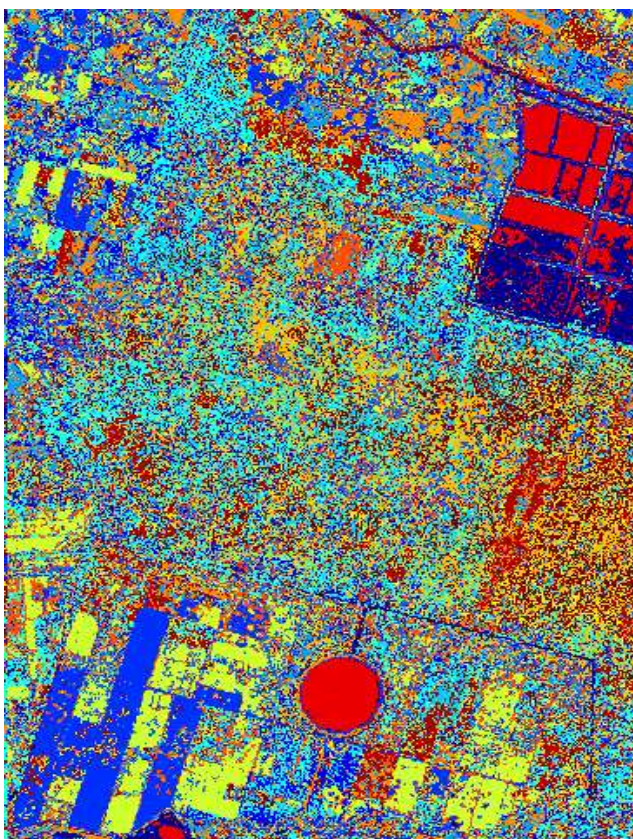

Figure 1. Segmentation results using fuzzy C-means at 15 clusters without any filtering

15 clusters using fuzzy C-means without any preliminary filtering. As we can see there also are fuzzy boundaries of segments on the cluster map going on to "sand" in some places. To diminish such the phenomena one can use filter which will smooth slightly changing areas rather blur clearly discriminated land cover type edges. Most appropriate filter having got such the behavior is the non-linear one described in [7]. Smoothing property of that filter increases with brightness threshold grows. At the same time some part of edges remains sharp. Amount of sharp edges and consequently cluster granularity depend on brightness threshold. Thus we get additional degree of freedom in segmentation process control that could dramatically improve the segmentation results.

Nonlinear filtering lowers intraclass covariance but practically doesn't touches interclass ones, so cluster discrimination doesn't suffer. Smoothing the channels before segmentation allows to eliminate fine granularity of output segment map and to merge the small cluster with large ones. In reality this means disappearance of some real small objects, for example, bushes in wetland areas. Nevertheless, sometimes it is necessary to get generalized segment map. The SUSAN filter allows to fulfil nonlinear processing variyng the threshold in wide region achieveing the smoothing results from neglible small up to very strong.

Figure 2 demonstrates examples of segmentation using non-linear filtering for Gustafson-Kessel clustering algo-
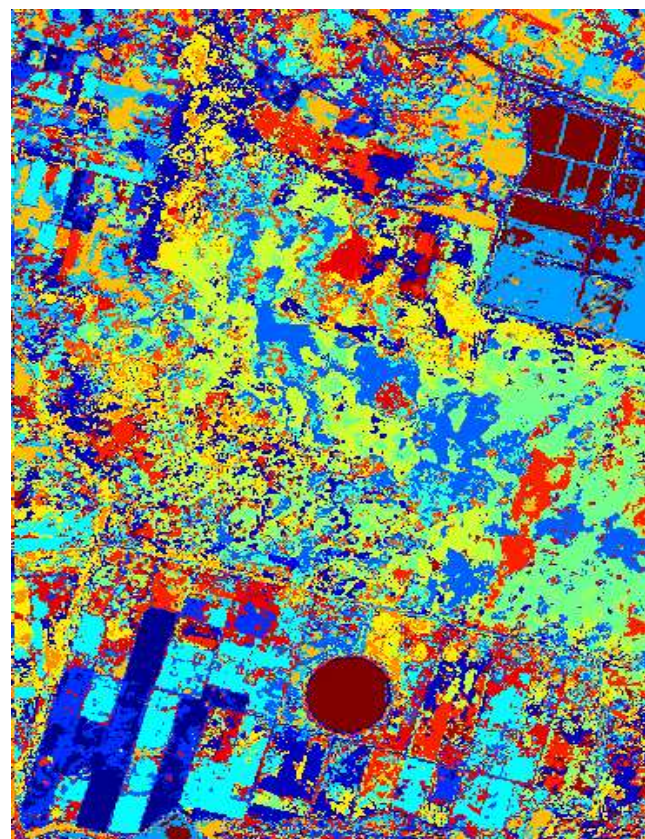
Figure 2. Segmentation results using Gustafson-Kessel algorithm at 20 clusters without any filtering (a) and using filtering with threshold = 20 (b)

rithms. The cluster number was choosen taking into account real diversity of land covers for territory being ivestigated. Actually a lot of experiments with different cluster number were fulfiled. As soon as segmentation become to look stable cluster number was stated.

Obtained results have transformed into scalar field using simple maximal probability solver to get the possibility of visual evaluation and have presented as colour map of spatial partitions. As a result every pixel became a member of one cluster. All pixels of same colour are members of same cluster. No any intelligent algorithm was used to colourize segment map so the same areas on different pictures have different colours.

As one can see the growth of the threshold leads to raising the segment area when target number of clusters is fixed. However it should be pointed that general structure of segment arrangement and its structure in relation with land cover types is not significantly changed.

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