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Comparison of Spectral-Spatial Classification Methods for Hyperspectral Images of High Spatial Resolution

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This paper reviews three methods of spectral-spatial classification for hyperspectral images of high spatial resolution: 1) pixelwise classification with post-filtering of resulting class map; 2) spectral-spatial classification based on geometric moments; 3) spectral-spatial classification based on segmentation. The paper provides the results of experimental comparison of these methods. The experiments are based on classification of images obtained by airborne hyperspectral sensor.

Keywords: hyperspectral images, local context, spectral-spatial classification.

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Сравнение методов классификации гиперспектральных изображений высокого пространственного разрешения по спектральным и пространственным признакам

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В работе рассматриваются три метода классификации гиперспектральных изображений высокого пространственного разрешения: 1) попиксельная классификация с последующей фильтрацией получаемой картосхемы, 2) спектрально-текстурная классификация на основе геометрических моментов и 3) спектрально-текстурная классификация на основе предварительной сегментации. Приводятся результаты экспериментального сравнения указанных методов на данных, полученных с помощью авиационного гиперспектрометра.

Ключевые слова: гиперспектральное изображение, локальный контекст, спектрально-текстурная классификация.

Introduction

In the field of aerospace remote sensing there is active development of hyperspectral systems, providing images in visible and infrared regions of the spectrum [1]. Now there is a potential to use highly informative hyperspectral images (HSI) for a wide range of scientific and practical problems. However, a significant limitation to such usage is the lack of suitable tools for automated analysis of hyperspectral images.

Among the main features of the HSI are high spectral resolution (of the order of a few nanometers) and a large number (up to several hundreds) of spectral channels, which raises the problem of the so-called "curse of dimensionality", due to which many of the traditional classifiers become unusable. In addition, pixelwise classification of high spatial resolution HSI often results in fragmented noisy maps, which are difficult to interpret and to use [2].

This report presents the results of experimental comparison of three HSI classification methods that take into account both spectral and spatial characteristics: 1) pixelwise classification followed by spatial filtering of a resulting classified image, 2) spectral-textural classification based on geometric moments and 3) spectral-textural classification based on preliminary segmentation. For the experiments, we used two images taken in 2011 by aerial hyperspectrometer developed by NPO "Lepton" (Zelenograd-based company) [3]. Before the classification a selection of uncorrelated systems of spectral features as created by applying Principal Component Analysis (PCA) method and its modification, Minimum Noise Fraction (MNF) method. These methods are well established in the area of HSI processing and allow to reduce the number of spectral features by an order of magnitude without compromising the quality of the classification [4].

Description of the HSI classification methods

The first classification method used in the experiments is described in detail in [4]. The method consists of pixelwise classification of the HSI and then spatial filtering of the resulting classified image with Majority Filter (MF). Each pixel is assigned a class to which the majority of pixels in a predetermined surrounding area belong. For pixelwise classification, method of Maximum Likelihood (ML) and Support Vector Machine (SVM) were used.

The second and third classification methods are based on the use of information about image texture. There is no universally accepted definition of texture but in the area of multi- and hyperspectral imagery, texture of an object can be interpreted as the characteristic of the distribution of spectral brightness vectors of the image region occupied by an object, which is caused by the regular arrangement of non-uniform elements of the object.

The second method of classification consists of extracting textural features by using geometric moments and subsequent classification of obtained feature vectors. Geometric moments are widely used to determine the textural characteristics of the objects on monochrome images [5]. Geometrical moment $m_{p,q}$ of the order p, q of the digital image $I(i, j)$ (with size $M \times N$) is defined as $m_{p,q} = \sum_{i=1}^{M} \sum_{j=1}^{N} i^p j^q I(i, j)$. In the area of texture analysis geometric moments are calculated for a window (of size $l \times l$) surrounding the pixel in question. For hyperspectral images calculation of moments for multiple sets of p, q significantly increases the number of features, thereby only intensifying the “curse of dimensionality”. Therefore, in this study only one moment $m_{0,0}$ was used, which is the sum of the spectral brightnesses of pixels in the window of size $l \times l$ (in this case for each pixel the feature value is determined by the formula $Avg(i, j) = m_{0,0}(i, j) / l^2$). As in the first method, the classification of resulting feature vectors was performed by ML and SVM methods.

The third method of classification is described in [6] and is based on the pre-segmentation of HSI based on spectral features. The basic idea of this method is as follows. Using only spectral features for texture classification will lead to a fragmented noisy classified image. However, in a given area of the image covered by one object the percentage of pixels of different clusters will approximately be the same while for different objects this characteristic will differ. This pattern holds for most of the textures corresponding to objects of natural origin (e.g. forest, swamp, tundra). This approach has been successfully used for textural segmentation of multispectral images based on grid clustering algorithms [7]. The advantage of this method is that it does not require a large amount of training samples; it is sufficient to provide only a few samples for each class.

Experimental results

In the experiments two images with sizes of 600×420 and 1000×350 pixels were used. Each image contained 87 spectral channels in the range 404–1016 nm. RGB composites of the images are shown in Fig. 1*a* and 2*a*. The spatial resolution was around 1 m. The images show areas of Savvatevskoe forestry in Tver Oblast region.

Ground-truth reference maps obtained from the surveys of forest taxation were available for areas that are presented on these images. The ground-truth maps contained classes corresponding to species and age composition of forest stands. However, reference maps were several decades older than

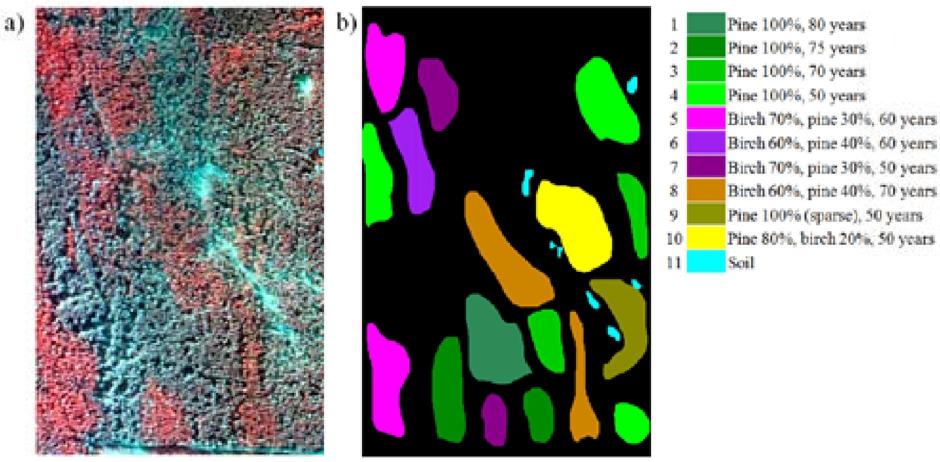

Fig. 1. RGB-composite (channels 81, 19, 10) (a) and reference map (b) of image 1

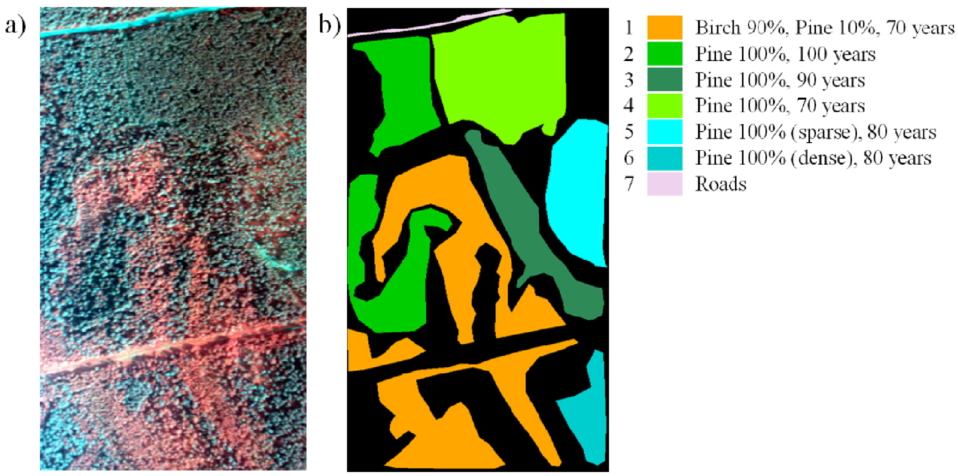

Fig. 2. RGB composite (channels 81, 19, 10) (a) and reference map (b) of image 2

the images, so reinterpretation by visual analysis of the images was performed by experts (resulting reference maps are presented in Fig. 1*b* and 2*b*). Doubtful pixels on the boundaries of the classes were assigned to the background (shown as black) and were not taken into account in the assessment of classification accuracy.

Control samples were used to assess the quality of the classification. 1000 randomly selected points of each class were used for training of classifiers. The classification results were averaged over five independent runs (with different training sets). We used the majority filter (MF) with window size of 5×5 pixels, and for calculating $Avg(i, j)$ texture features we used a window of 21×21 pixels.

The results of classification using different sets of features and classification methods are shown in Fig. 3 and 4. For comparison, the figures also include the accuracy of pixelwise classification based only on spectral features. The accuracy of the spectral-textural segmentation-based classification of image 2 is shown in Figure 5. First 4 principal components were used as spectral features in this experiment.

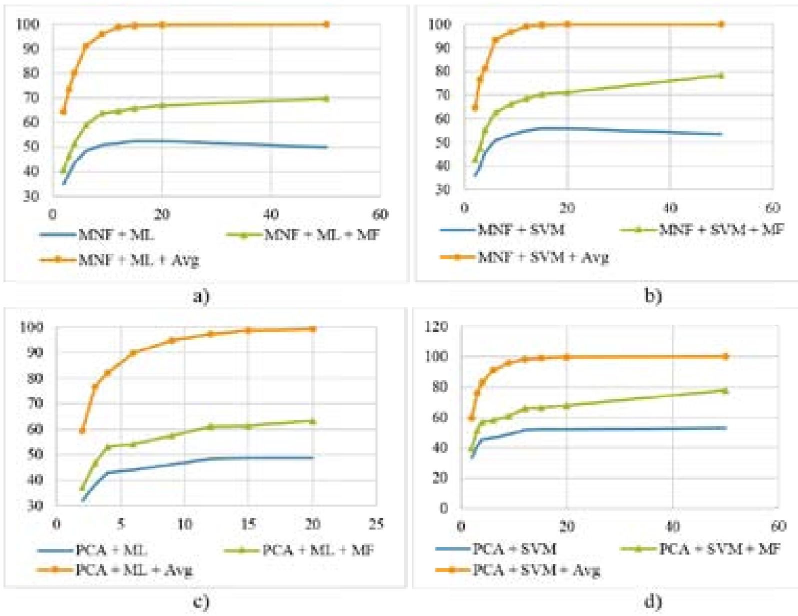

Fig. 3. Classification accuracy of image 1, based on different feature sets and classification methods, depending on number of features

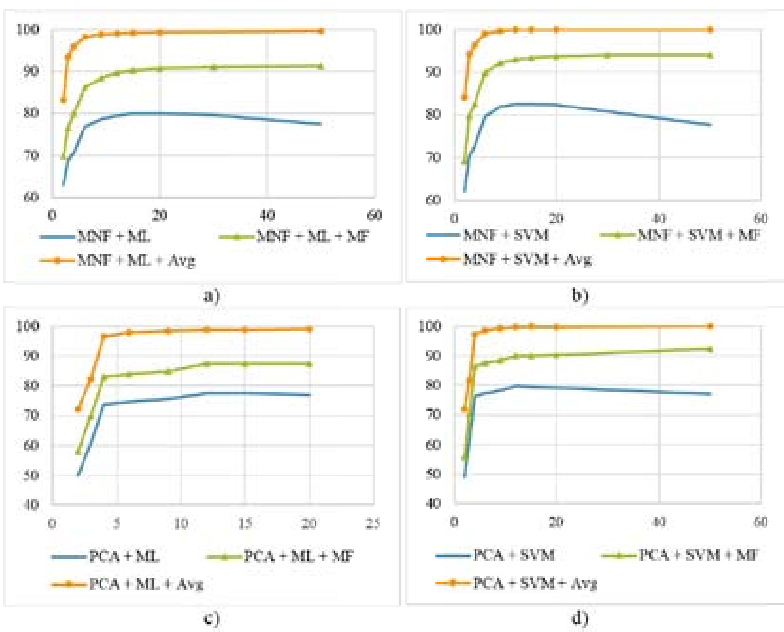

Fig. 4. Classification accuracy of image 2, based on different feature sets and classification methods, depending on number of features

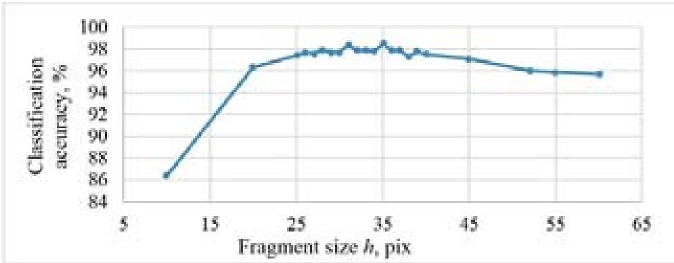

Fig. 5. Accuracy of spectral-textural classification based on pre-segmentation for image 2

Conclusion

Analysis of the results shows that spatial information makes it possible to achieve a significant improvement in the accuracy of classification (by 5–50%) in comparison to pixelwise spectral classification. For the test images used in this research the best results were achieved by classification based on geometric moments, the accuracy approached 100%.

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