The Effect of the Spectral Band Selection Method on Hyperspectral Images Segmentation Accuracy

Ali Bakhshi, Mohammad Hassan Ghassemian, and Alireza Ahmadifard

***Abstract*—In recent years, the image processing intelligent based systems has been the subject of interest for many researchers. In this manner, interpretation of urban aerial hyperspectral textured images is lionizing due to special features of this images. Image segmentation is the first step to reach this aim and extract features of these images. The correct selection of spectral bands is very important, because of multiplicity of spectral bands in this images and variety of texture in each of spectral bands. Since not all spectral bands include useful information, taking into account all of spectral bands decreases the speed of processing and accuracy of segmentation. In this paper, several dimension reduction or in other words spectral band reduction approach studied. In addition, the effect of each dimension reduction algorithms on accuracy of segmentation represented.**

***Index Terms*—Hyperspectral image, dimension reduction, extended mathematical morphology, region growing.**

I. Introduction

Image segmentation is one of the most important steps in image analysis and interpretation. In this way, hyperspectral image segmentation becomes interesting subject of many researches because of special properties of these images. The precision of segmentation in these images is depending on many parameters that one of most important parameters is proper spectral band selection. Suitable spectral band selection is important because of existing information in each band (e.g. texture) is different with other bands also none of spectral bands is contained of useful information. Therefore, spectral bands that contain more information must be select. There are many dimension reduction algorithms such as independent component analysis (ICA), principal component analysis (PCA) and discrete wavelet transform (DWT) [1].

All of existing approaches work depending on best band selection. Then, for processing, we need different approach when we are going to use several bands and using one band was not sufficient for segmentation. We use extended mathematical morphology for feature extraction. Image segmentation is one of the most critical tasks in automatic image analysis because the segmentation results will affect all the subsequent processes of image analysis, such as object representation and description, feature measurement and even the following higher-level tasks such as object classification and scene interpretation [2]. As mentioned before, discrimination of textures in different spectral bands is example of these features. On the other hand, we have different texture in various spectral bands.

In general, this is considerable that none of segmentation algorithms is applicable at different application of image processing. Hence, propose different algorithm for any special application.

With increasing number of algorithms for image segmentation, evaluation of performance of algorithms in studies is necessary. By take into account different hampers for image segmentation, proper algorithm selection is very important.

However, texture characterization is particularly complex when the image data is composed of several spectral bands at different wavelengths, as in the case of remotely sensed hyperspectral images, in which hundreds of spectral bands are often available. Such images have two domains that can be analyzed: the spectral domain and the spatial domain. In this paper, we use joint direction and spectral features for hyperspectral image segmentation. By taking into account the complementary nature of spatial and spectral information in simultaneous fashion, it may be possible to alleviate the problems related to each of them taken separately and improve segmentation and classification results in urban analysis scenarios [3].

Under study image segmentation process, consists of three following stages:

1) Extracting of spectral and direction features and constructing feature image, using extended mathematical morphology.
2) Applying a suitable threshold on feature image, and create a binary image.
3) Finally using region growing algorithm and consider to spectral similarity between adjacent pixels, image segmentation is accomplished.

The rest of this paper organized as follows. Section II describes extended mathematical morphology definition. In section III, we study several spectral band reduction (dimension reduction) algorithms. Experiment results discussed in Section IV and conclusions are given in Section V.

II. Mathematical Morphology

A. Review Stage

In this section, we describe a new methodology for the

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Ali Bakhshi is with the Electrical Engineering Department, Shahrood Branch, Islamic Azad University, Shahrood, Iran (e-mail: a_bakhshi@iau-shahrood.ac.ir).

Mohammad Hassan Ghassemian is with the Electrical Engineering Department, Tarbiat Modares University, Tehran, Iran (e-mail: ghassemi@modares.ac.ir).

Alireza Ahmadifard is with the Electrical Engineering Department, Shahrood University of Technology, Shahrood, Iran (e-mail: ahmadyfard@shahroodut.ac.ir).

classification of urban hyperspectral images. We should mention that used mathematical morphology in 2D images is not applicable in the case of hyperspectral images because of various spectral bands in these images. The greatest challenge in the task of extending morphology operations to hyperspectral images is the definition of a vector ordering relation that allows for the determination of the maximum and minimum elements in any family of N-D vector [4]. In this manner, we introduce spectral angle mapper as a scale of spectral similarity. Then, we utilize an algorithm for feature extraction from hyperspectral images based on morphological operators. Finally, by using correlation and similarity between image pixels in feature image, segmentation is performing.

Feature extraction approach depends on extended mathematical morphology and spectral adjustment concepts. With take into account hyperspectral image by f at N Dimensional space, spectral angle mapper between two pixel vectors f (x, y) and f (i, j), i.e., two N-D vectors at discrete spatial coordinates (x, y) and $(i, j) \in Z^2$, defined as follows [4]:

$$SAM\left(f(x,y), f(i,j)\right) = \cos^{-1}\frac{f(x,y) * f(i,j)}{\left\|f(x,y)\right\| . \left\|f(i,j)\right\|} \tag{1}$$

Now, by definition of cumulative distance between a pixels vector f(x, y) and all the pixel vectors in the spatial neighborhood given by B (B-neighborhood), we will have [5]:

$$D_B\left[f(x,y)\right] = \sum_i \sum_j SAM\left[f(x,y), f(i,j)\right] \tag{2}$$

where (x, y) refers to spatial coordinates in the B-neighborhood. Now according to aforementioned definitions, we can define two standard morphological operations called erosion and dilation respectively as below [3], [6]:

$$\begin{aligned}&\left(f \otimes B\right)(x,y) = \\ &\arg\min_{(s,t)\in Z^2(B)} \sum_s \sum_t SAM\left(f(x,y), f(x+s, y+t)\right)\end{aligned} \tag{3}$$

$$\begin{aligned}&\left(f \oplus B\right)(x,y) = \\ &\arg\max_{(s,t)\in Z^2(B)} \sum_s \sum_t SAM\left(f(x,y), f(x-s, y-t)\right)\end{aligned} \tag{4}$$

Using the above operations, the opening filter is defined as erosion followed by dilation and the closing filter is defined as dilation followed by erosion that represented as follows respectively:

$$\left(f \circ B\right)(x,y) = \left[\left(f \otimes B\right) \oplus B\right](x,y) \tag{5}$$

$$\left(f \bullet B\right)(x,y) = \left[\left(f \oplus B\right) \otimes B\right](x,y) \tag{6}$$

Then, the following vector gives the spatial/spectral profile at f (x, y):

$$\begin{aligned}p(x,y) = &\left\{SAM\left(\left(f \circ B\right)^{\lambda}(x,y), \left(f \circ B\right)^{\lambda-1}(x,y)\right)\right\} \\ &\cup \left\{SAM\left(\left(f \bullet B\right)^{\lambda}(x,y), \left(f \bullet B\right)^{\lambda-1}(x,y)\right)\right\}\end{aligned} \tag{7}$$

Here, the step of the opening/closing series iteration at which the spatial/spectral profile provides a maximum value gives an intuitive idea of both the spectral and spatial distribution in the B-neighborhood [5]. In our experiment, we select $\lambda = 2$. After construction of feature image, we transform feature image to binary image by applying some rules on existing pixels of image. Then, we perform image segmentation by using of region growing algorithm and by taking into account the similarity between adjacent pixels. The authors of the accepted manuscripts will be given a copyright form and the form should accompany your final submission.

III. Dimension Reduction Algorithms

As mention before, none of spectral bands are containing of useful information. On the other hand, speed of processing increased because of spectral bands reduction and reducing the volume of calculations. Suitable bands selection can be perform in various approaches that we study some of them. In the first algorithm, spectral similarity between various bands calculated. In this method, a pixel vector with same and constant coordinate on each spectral band considered, and then spectral similarity between each band with others by using spectral angel mapper (SAM) calculated. After that all of spectral angels calculated, those bands that have most similarity select for processing. In the next algorithm, at the first step we calculating signal to noise ratio (SNR) that define as means of pixels to standard deviations of pixels for all of spectral bands and then spectral similarity between the band that has biggest SNR with others calculated. Afterwards, those bands selected that have most spectral similarity with reference band (the band with biggest SNR).

Finally, at the tertiary algorithm, same as second approach at the first step SNR for all of spectral bands calculated but those bands selected that have biggest SNR. That is, we do not consider the spectral similarity between bands. We should mention that, for suitable comparison between different approaches, the number of selected bands in all of algorithms is equal. As regards we need some similarity scales for heterogonous regions discriminations, the applied algorithm is somehow complex. It should be note that, we could also use feature image to extract the boundaries, but in this case, similarity scale definition would be more complicated.

IV. Experimental Results

In this section, we will discuss about simulation results for the algorithms defined in sections III for hyperspectral image segmentation. For this reason, we introduce hyperspectral image. Then, simulation results will be shown in Fig 2 to Fig 4 It should be mentioning that, all simulations implemented with Matlab software.

The hyperspectral image were acquired during a flight campaign over Pavia, northern Italy (45°11’ N, 9°9’ E), on the 8th of July 2002 from 10:30 a.m. to 12:00 noon. This image acquired by ROSIS_03 (Reflective Optics System Imaging Spectrometer) spectrometer of DLR. The data set acquired from ROSIS sensor does not fully cover the areas of interest, due to the narrower field of view w.r.t. DAIS instrument on which the flight lines were designed. Data are atmospherically corrected but not geometrically corrected. The number of spectral bands is 102 and Geometric resolution is 1.3 metres.

The processor that is used in this simulation is a Centrino Duo T7200, 2GHz with 2GB of memory. Fig. 1 shows the RGB image of the used hyperspectral image.

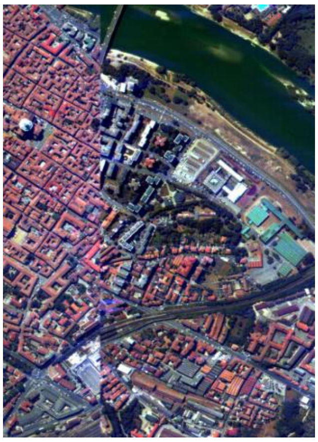
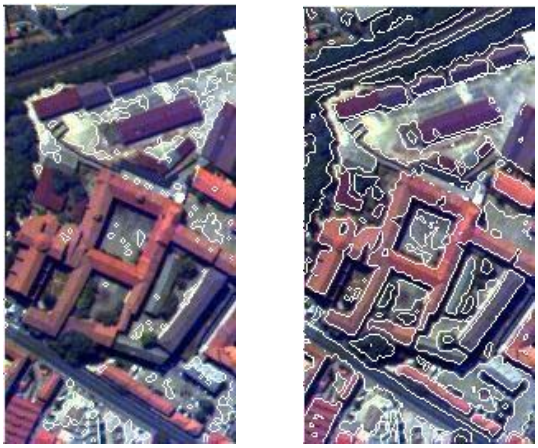


Fig. 1. RGB image of Pavia.

The results of simulations represented on portion of hyperspectral image, with respect to high volume of data. At the first, segmentation results for considering all of spectral bands are represented in Fig. 2(a).

As illustrated in Fig. 2(a) the result of segmentation isn’t appropriate. Indeed, none of image boundaries correctly recognized. As mentioned before, this segmentation occurs because of exist many unsuitable spectral bands in hyperspectral image that contain noisy information. Now, we are applying dimension reduction algorithms that described in previous section. Segmentation result for first dimension reduction algorithm, band selection depending on spectral similarity, represented in Fig. 2(b). It is considerable that, spectral similarity calculated depending on SAM that defined in section 2. That is, with choosing on vector on each band, spectral similarity between it and others calculated. It is clear that, a smaller angel means bigger spectral similarity.

As shown in Fig. 3(a), many of boundaries recognized. But also many points that aren’t boundary recognized.



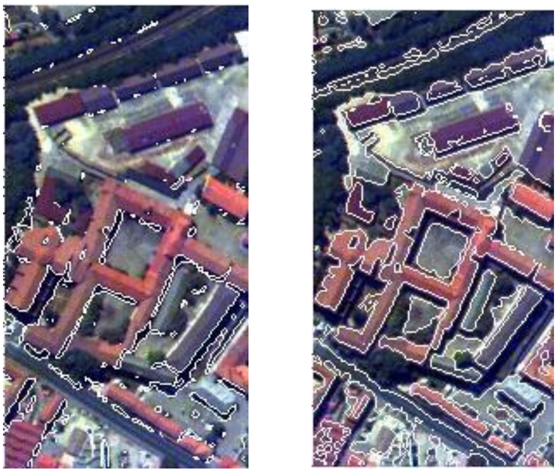
(a) (b)

Fig. 2. (a) The segmented image for all spectral bands (b) the segmentation result for first dimension reduction algorithm

Now, second algorithm portrayed in prior section studied. That is, SNR for each of spectral band calculated. Then, the band with biggest SNR selected as reference band. At the end, those bands that have most spectral similarity into reference band selected. The Results of segmentation for this algorithm are shown in Fig. 3(a).

As shown in Fig. 4 many of boundaries don’t recognize. Though, precision of this algorithm is more than first algorithm. As described in section III, tertiary algorithm worked depends on large SNR criteria. The simulation results for this algorithm illustrated in Fig. 3(b).

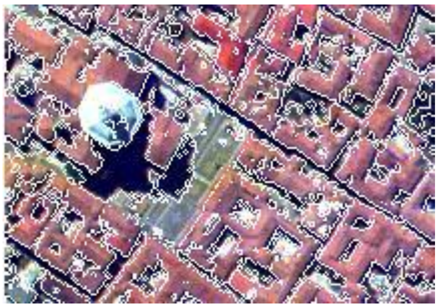
It’s clear that, precision of segmentation increased considerably for this method and boundaries of region recognized more accurate. Here, significant point is that, number of selected spectral bands can effect on improving results. By the way, speed of processing considerably increased if suitable segmentation achieved by a few number of spectral bands.



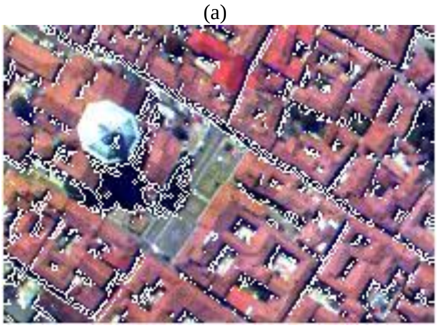
(a) (b)

Fig. 3. (a) The segmentation result for second dimension reduction algorithm; (b) the results of simulations for tertiary

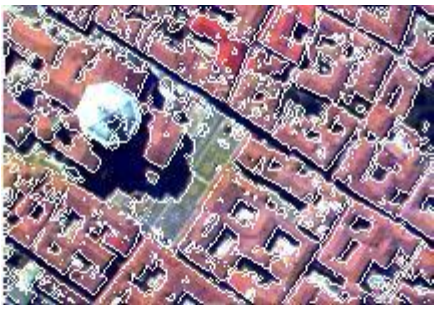
Now, for better comparison between noted algorithms, segmentation results for other part of image represented in Fig. 4.



(a)



(b)



(c)

Fig. 4. The results of segmentation depend on selection of (a) First; (b) second; and (c) tertiary dimension reduction algorithm

The segmentation depending on tertiary algorithm is more precise, as seen in Fig. 4.

V. Conclusion

Three different methods have been introduced and the results are presented. As we said before, we should reduce the spectral bands due to the lack of useful information in some sort of bands. Therefore, the simulation results have been shown according to all existing spectral bands. The simulation results provide this fact that the images with higher SNR (signal to noise ratio) are more precise in comparison with the two mentioned methods. Choosing the number of parameters in an optimized form has an inevitable effect on increasing the accuracy and speed of processing.

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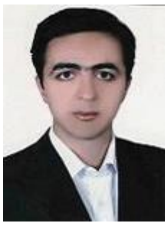
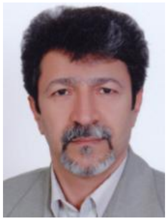


Ali Bakhshi received his Bachelor's degree in Power Engineering in 2004 from Aliabad Branch, Islamic Azad University. He completed his Masters Degree in Electronics Engineering from Science and Research Branch, Islamic Azad University, Tehran, in 2008. He has been working as Faculty Member, Dept. of Electrical Engineering, Shahrood Branch, Islamic Azad University, Shahrood. His research interests are Signal and Image Processing. He has published over 16 papers in national/international Conferences. He is Senior Member of IACSIT.



Prof Mohammad Hassan Ghassemian was born in Iran in 1956. He received the B.S.E.E. degree from Tehran College of Telecommunication in 1980 and the M.S.E.E. and Ph.D. degree from Purdue University, West Lafayette, USA in 1984 and 1988 respectively. Since 1988, he has been with Tarbiat Modares University in Tehran, Iran, where he is a Professor of Computer and Electrical Engineering. His research interests focus on Multi-Source Signal/Image Processing and Information Analysis and Remote Sensing. He has trained more than 80 MS and PhD students who have assumed key positions in software and computer systems design applications related to signal and image processing, in the past 20 years. He is an IEEE Senior member.

Dr Alireza Ahmadyfard received his Bsc degree in Electronic Engineering in 1989 from Esfahan university of technology and Msc degree in Communication Engineering in 1994 from Amirkabir university of technology . He earned his Ph.D. in Image processing and Computer vision from CVSSP (Center for Vision Speech and Signal Processing) at University of Surrey in 2002. He is director of Electrical Engineering Department in Shahrood University of Technology. His research interest is Digital signal processing, object recognition, image based inspection and human identification using biometrics. He has published several papers in national/international Journals/Conferences. He has guided several post Graduate students.