Available online at http://ijim.srbiau.ac.ir

Int. J. Industrial Mathematics Vol. 1, No. 1 (2009) 77-85

Multi Resolution Fuzzy Segmentation of Satellite Images

E. Golpar-Raboky [a] *, M. Hasanzade [a], T. Lotfi [a], F. Fattahzadeh [a]

(a) *Computer Engineering Department, Sharif University of Technology, Tehran,Iran.*

Abstract

Satellite image segmentation, as a main step of remotely-sensed image processing, is often accomplished by clustering when ground truth is not available to provide samples to train a supervised classifier. To solve this problem, here we propose a new purposes approach for fuzzy segmentation error reduction fuzzy logic-based algorithms as well as structural information is utilized in our proposed multi-resolution Fuzzy C-Mean (FCM) clustering algorithm. The results show that the multi resolution based FCM can improve the result of the standard FCM for an unsupervised classification approach.

Keywords : Satellite image, segmentation, classifier, fuzzy segmentation, fuzzy C-mean, multi resolution.

1 Introduction

Remote sensing, the science of obtaining and interpreting information from remotely-sensed devices, is widely used and has several application in many field such as agriculture, civilization, forestry, traffic control, and fire control. In this applications satellite image processing is an important step. There is an extensive literature imagery using parametric or nonparametric statistical or structural techniques [1] and it is often accomplished by clustering when ground truth is not available to provide samples to train a supervised classifier [2]. As a non-hierarchical clustering method, fuzzy clustering, has proved to be efficient in clustering a set of given vectors into a few homogenous groups. The fuzzy clustering is becoming more popular because it produces the crisp results when needed. Also, fuzzy clustering is less prone to falling into local optima than the crisp clustering algorithm. The idea of fuzzy clustering came from the Hard CMeans (HCM) method proposed by ruspini (1969).Dunn (1973) generalized the minimum-variance clustering procedure to

*Corresponding author. Email address: g_ raboky@math.sharif.edu

a Fuzzy ISODATA clustering technique. Bezdek (1981) generalized Dunn's approach the Fuzzy C-Mean (FCM) algorithm [14]. Besides the above mentioned benefits, the FCM algorithm, similar to the other clustering methods, segments the image in regions with only similar spectral properties and does not consider relationship between pixels in the spatial domain. To solve the above mentioned problem several approach proposed [17, 18, 19]. In [17] a prior geometrical information is added to improve the result. The proposed approach in [18] models the intensity inhomogeneities as a gain field that causes image intensities to smoothly and slowly vary trough the image space and in [19] the objective function in FCM algorithm to include a multiplier field which allows the centroids for each class to vary across the image. Here we propose a new approach for fuzzy segmentation of satellite images in present of noise. In this method, multi resolution approximation of images are used to consider structural information and spatial relationship between pixels in fuzzy clustering (which has applied using FCM) and the fuzzy clustering results in different levels of hierarchy are merged to results in robust segmentation in presence of noise. The subsequent sections of this paper are organized as follows. Section 2 briefly describes the remote sensing and satellite image processing concepts. Section 3 introduces the proposed multi resolution fuzzy C-Mean algorithm (MR-FCM) in detail. Section 4 describes different experiments and finally section 5 draws the conclusion.

2 WHAT IS REMOTE SENSING

Remote sensing is the science of obtaining and interpreting information from a distance, using sensors that are not a physical contact with the object being observed.

2.1 General Concepts

The science of emote sensing in its broadest sense includes aerial, satellite, and spacecraft observations of the surfaces and atmospheres of the planets in our solar system, through the Earth is obviously the most frequent target of study [7]. The term is customarily restricted to methods that detect and measure electromagnetic energy, including visible light, that has interacted with surface materials and the atmosphere. Remote sensing of the Earth has many purpose, including making and updating planimetric maps, weather forecasting, and gathering military intelligence [7]. The field of remote sensing began with aerial photography, using visible light from the sun as the energy source. But visible light makes up only a small part of the electromagnetic spectrum, a continuum that ranges from high energy, short wavelength gamma rays, to lower energy, long wavelength radio waves. Illustrated below s portion of the electromagnetic spectrum that is useful in remote sensing of the Earth's surface [8, 9],. The Earth is naturally illuminated by electromagnetic radiation from the Sun. The peak solar energy is in the wavelength range of visible light (between 0.4 and 0.7 um). Although visible light includes the entire range of colors seen in a rainbow, a cruder subdivision into blue, green and red wavelength regions is sufficient in many remote sensing studies. Other substantial fractions of incoming solar energy are in the form of invisible ultraviolet and infrared radiation. Only tiny amounts of solar radiation extend into the microwave region of the spectrum. Imaging radar systems used in remote sensing generate and broadcast microwaves, then measure the portion of the signal that has returned to the sensor from Earth's surface [9].
Remote sensors measure electromagnetic (EM) radiation that has interacted with the

Earth's surface. Interactions with matter can change the direction, intensity wavelength content, an polarization of EM radiation. The nature of these changes is dependent on the chemical make-up and physical structure of the material exposed to the EM radiation. Changes in EM radiation resulting from its interactions with the Earth's surface therefore provide major clues to the characteristics of the surface materials [9].

2.2 Types of Resolution

The spatial, spectral, and temporal components of an image or set of images all provide information that can be used to form interpretations about surface materials and conditions. For each of these properties we can define the resolution of the mages produced by the sensor system. These image resolution factors place limits on what information we can derive from remotely sensed images. Spatial resolution is a measure of the spatial detail in an image, which is a function of the design of the sensor and its operation altitude above the surface. Each of the detectors in a emote sensor measures the energy received from a finite patch of the Ground surface. The smaller these individual patchesare, the more detailed will be the spatial information that we can interpret from the image. For digital images, spatial esolution is most commonly expressed as the ground dimensions of an image cell [9].

The spectral resolution of a remote sensing system can be described as its ability to distinguish different parts of the range of measured wavelengths. In essence, this amounts to the number of wavelength intervals ("bands") that are measured, and how narrow each interval is. An "image" produced by a sensor system can consist of one very broad wavelength band, a few broad bands, or many narrow wavelength bands. The names usually used for these three image categories are panchromatic, multispectral, and respectively. Taken aerial photographs using black and white visible wavelength range (blue, green, and red).

Because this film is sensitive to all visible colors, it is called panchromatic c film. A panchromatic image reveals spatial variations in the gross visual properties of surface materials, but does not allow spectral discrimination. Some satellite remote sensing systems record a single very broad band to provide a synoptic overview of the scene, commonly at higher spatial resolution than other sensors on board. Despite wavelength ranges, such bands are also commonly referred to as panchromatic bands [9].

In order to digitally record the energy received by an Individual detector in a sensor, the continuous range of Incoming energy must be quantized, or subdivided into a umber of discrete levels that are recorded as integer values. Many current satellite systems quantize data into 256 levels (8 bits of data in a binary encoding system). The thermal infrared bands of the ASTER sensor are quantized into4096 levels (12 bits). The more levels can be recorded, the greater is the radiometric resolution of the sensor system [9].

The surface environment of the Earth is dynamic, with change occurring on time scales ranging from seconds to decades or longer. The seasonal cycle of plant growth that affects both natural ecosystems and crops is an important example. Repeat imagery of the same area through the growing season adds to our ability to recognize and distinguish plant or crop types. A timeseries of images can also be used to monitor r changes in surface features due to other natural processes or human activity. The time-interval separating successive images in such series can be considered to define the temporal resolution of the image sequence [9].

In order to provide increased spectral discrimination, remote sensing systems which are designed to monitor the surface environment employ a multispectral design : parallel sensor arrays detecting radiation in a small number of broad wavelength bands . Most satellite systems use three to six spectral bands in the visible to middle infrared wavelength region. Some systems also employ one or more thermal infrared bands. Bands in the infrared range are limited in width to avoid atmospheric water vapor absorption effects that significantly degrade the signal in certain wavelength intervals (see the previous page Atmospheric Effects).
These broad-band multispectral systems allow discrimination of different types of vegetation, rocks and soils, clear and turbid water, and some man-made materials. A three-band sensor with green, red, and near infrared Bands is effective at discriminating vegetated and non vegetated areas. Color-infrared film used in some aerial photography provides similar spectral coverage, with the red emulsion recording near infrared, the green emulsion recording red light, and the blue emulsion recording green light.

2.3 Satellite image processng

In satellite images we need to do some preprocessing steps to make the images more appropriate for subsequent process. These steps are as follows: Enhancement, registration, fusion and segmentation.

Registration Images

One can make qualitative interpretation from an image sequence (or mages obtained from different sensors) by a simple visual comparison . If you wish to combine information from different dates in a color composite display, (or to perform a quantitative analysis such as spectral classification,)first you need to ensure that the images are spatially registered and spectrally normalized. Spatial registration means that corresponding cells in defferent images that denote the same areas on the grand, are correctly identified, and matched in size. Registration a set of images requires several steps. The first step is usually georefrencing the images: In each image an identifying set of control points with known map coordinates. The control points coordinates can be obtained from another georefrenced image or map, or from a set of positions collected in the field using a Global Positioning System (GPS) receiver. Control points are assigned in TNTmips in the Georefrence process (Edit / Georfrence). One can find step-by-step instructions on using the Georefrence process in [16]; the booklet getting started : Georefrencing.
When all the images have been georefrenced, one can use the Automatic Resampling process(Process / Raster / Resampling/ Automatic) to reproject each image to a common map coordinate system and cell size [10, 11, 12].

Fusing Data from Different Sensors

Materials commonly found at the Earth's surface(such as soil, rocks, water, vegetation, and man-made features)posse many distinct physical properties that control their interactions with electromagnetic radiation. In the preceding pages we have discussed remote sensing systems that use three separate parts of the radiation spectrum: reflected solar radiation (visible and infrared), emitted thermal infrared, and imaging radar. Because the interaction of EM radiation with surface features in these spectral regions are different, each of the corresponding sensor systems measures a different set of physical properties.

Although each type of system by itself can reveal a wealth of information about the identity and condition of surface materials, one can learn even more by combining image data from different sensors. Interpretation of the merged data set can employe rigorous quantitative analysis, or more qualitative visual analysis [13].

Segmentation A wide range of segmentation techniques are available in the literature, some of them are described in the next section. The goal of image segmentation is find regions that represent objects of meaningful parts of objects. We assume three categories of image segmentation methods; 1)region growing and shrinking, 2)clustering, 3)boundary detection [3].
The region growing and shrinking method segments the image into regions by operating principally in the row and column, (r, c)-based image space. Some of the used techniques are local, in which small areas of image are processed at a time; others are global, in which the entire image is considered during processing and some of them combine local and global techniques; such as split and merge and watershed segmentation [5].
Clustering techniques are image segmentation methods by which individual elements are placed into groups ; these groups are based on some measure of similarity within the group. The major different between these techniques and region growing techniques is that domain other than the row and column (r, c)-based image space (the spatial domain) may be considered as the primary domain for clustering. Some of these domains include color space, histogram spaces, or complex feature spaces.
Spherical coordinate transform (SCT), Principal components transform (PCT), histogram thresholding and fuzzy C-Mean method are examples of clustering methods [4].
Boundary detection is also used for image segmentation and is performed by finding boundaries between objects, thus indirectly defining the objects. Thresholding, edge linking, extended Hough transform, and generalized Hough transform are examples of boundary detection methods.
Image segmentation methods can also be a combination of region growing, clustering, and boundary detection. Opteimal image segmentation is also likely to be achieved by focusing on the application [6].

3 PROPOSED MULTI-RESOLUTION FUZZY SEGMENTATION ALGORITHM

Fuzzy C-Mean clustering is one of the well-known unsupervised clustering techniques, which can be used for unsupervised image segmentation. In Fuzzy clustering approach a pixel is not an indecomposable unit in the image. In fact, in fuzzification and inference units of a fuzzy clustering system a pixel can belongs to several classes with different membership degrees. Then, in Defuzzification process, the last unit of the system, crisp clusters are made.
The feature vector for image clustering in gray scale images is the pixel intensity, but in multi-spectral remote sensing image it is the resulted vector from fusion step.
Besides the advantages of fuzzy clustering, the FCM segments the image in regions with similar properties and dos not consider relationship between pixels in spatial domain. Moreover, in the presence of nose it can not perform properly.
To describe this undesired effect we have proposed a multi resolution fuzzy C-Mean

method. In this method we use spatial information extracted from multi-resolution approximation that is obtained by wavelet transform.

The wavelet transform provides a hierarchical framework for interpreting the image. At each level of the hierarchy, the image is passed through a low-pass filter that provides a smooth approximation, and a bans-pass filter that captures the details . After the filtering, the corresponding images are sub sampled by two and the resolution is reduced by half. The two-pass filtered versions can be used as the representations that best approximation the original image at multiple resolution [6].

In multi resolution approximation, a single pixel at resolution j covers a block of 2j pixels in the original image (where $j = 0$ is the resolution of the original image and j increases as the resolution gets coarser). As such, the spatial interaction between pixels is considered. By utilizing the above mentioned multi resolution approximation of images with wavelet transform we obtain an enhanced for clustering in our algorithm.

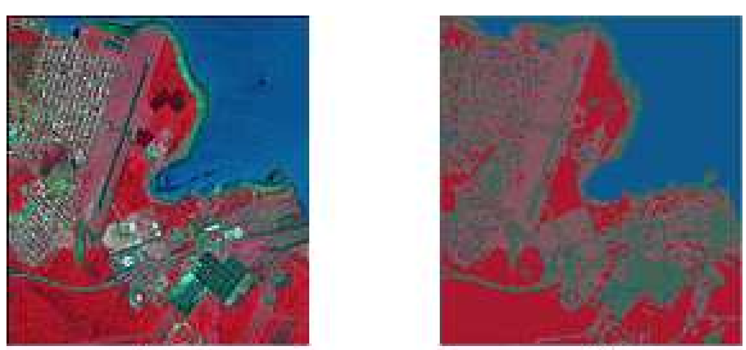
In the proposed algorithm, first, we apply the FCM clustering algorithm on the original image. The output of the FCM clustering process on original image is n matrices of membership degrees to n clusters such that the size of matrices is the same as the size of the image. Then, in order to obtain the multi-resolution approximation we apply the wavelet transform (with Daubichies filters) independently to each spectral band. So the obtained images with lower resolution will have the same number of bands as the original image. Then, the FCM clustering is applied on the low-pass filtered version of previous level image. The resulted matrices of clustering at level j are up-sampled and zero order hold interpolated to obtain a corresponding membership degree for each pixel of the original image. Finally, the results of clustering at different levels of the hierarchy are merged by weighted average and defuzzification by max operator result in crisp final cluster.

4 EXPERIMENTAL RESULTS

The proposed algorithm, multi resolution fuzzy C-Mean (MR-FCM) , is evaluated using several images from SPOT satellite [20] with Matlab software.

In order to reduce the computational cost and the effect of irrelevant neighbors with respect to the pixel size of satellite images, we have used 1-level Daubechies wavelet transform in our experiments.

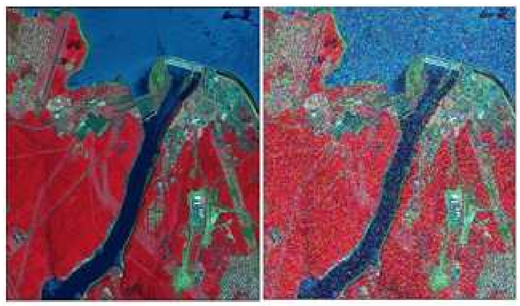
Figure 1 shows the wavelet subimages and corresponding FCM cluster of a sample image and Figure 2 shows the MR-FCM output of a typical noisy image.



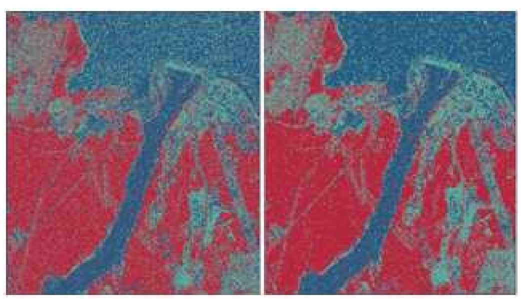
(a) (b)

(c) (d)

Fig. 1. Wavelet 1-level subimages of a part of the input image(a and the(a a c) and theire corresponding FCM clusters(b and d)



(a) (b)



(c) (d)

Figure 2: Segmentation Results. a) Original image, b) noisy image, segmentation result of noisy image using c) FCM and d) MR-FCM

The subjective results of the typical noisy image in Fig. 2 show more homogenous regions in proposed algorithm result than the FCM algorithm.
In order to evaluate the robustness of an algorithm objectively in the presence of noise, we compare the segmentation result of a noisy image with that of original image. If one calculates the overlap ratio of two segmentation for each algorithm, the larger ratio corresponds to more robust one.
Table 1 shows the comparison of FCM and MR-FCM for defined robustness parameter.

Table 1. COMPARISON BETWEEN FCM AND MR-FCM WITH DEFINED ROBUSTNESS PARAMETER

	FCM	MRFCM
Segmentation Overlap Ratio	0.4967	0.4840

The results of table which are obtained by average over more than 20 pictures of SPOT satellite [20] show that the proposed approach performed significantly better than the traditional FCM clustering algorithm in the presence of noise. Our proposed method fastens the segmentation in comparison with FCM method in about 10%.

5 CONCLUSION

In this paper, we have presented an approach for segmentation of remotely-sensed imagery using multi-resolution and spatial techniques. Wavelet transform was used to model image content in different levels. The proposed MR-FCM algorithm was evaluate and it was shown that it improves the result of the standard FCM in an unsupervised classification process. The obtained segmented images show more homogeneous regions when we compared with standard FCM which don't use the spatial information in noisy conditions and they show better robustness of algorithm in the presence of noise. A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

References

[1] D. A. Landgrebe, "Signal Theory Methods in Multispectral Remote Sensing," John Wiley & Sons, Inc., 2003.

[2] J. A. Richards, "Remote sensing digital Image Analysis," Springer-Verlag, Berlin, 1993.

[3] G. A. Baxes, "Digital Image Processing : Principals and Applications," NY: Wiley, 1994.

[4] M. Carlotto, "Histogram Analysis Using a Scale- State Approach," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 9, No. 1, pp. 121-129, 1987.

[5] E. Dougherty, Lotufo, "Hand-on Morphological Image Processing," Bellingham, WA: SPIE Press, 2003.

[6] S. E. Umbaugh, "Computer Imaging: Digital Image Analysis and Processing," CRC Press, 2005

[7] S. A. Drury, "Image Interpretation in Geology (2nd ed.)," London: Chapman and Hall, 283 p., 1993.

[8] T. M. Lillesand, and R. W. Kiefer, "Remote Sensing and Image Interpretation (3rd ed.)," New York: John Wiley and Sons. , 750 p., 1993.

[9] F. F. Sabins, "Remote Sensing: Principles and Interpretation (3rd ed.)," New York: W. H. Freeman and Company. 494 p. 1997.

[10] J. R. Jensen, "Introductory Digital Image Processing: a Remote Sensing Perspective (2nd ed.)," Upper Saddle River, NJ: Prentice-Hall. 316 p. 1996.

[11] A. N. Rencz, "Remote Sensing for the Earth Sciences Manual of Remote Sensing, (3rd ed.)," Volume 3. New York: John Wiley and Sons.707 p.,1999.

[12] R. A. Schowengerdt, "Remote Sensing: Models and Methods for Image Processing (2nd ed.)," New York: Academic Press. 522 p. 1997.

[13] A. H. Pellemans, R. W. Jordans, R. Allewijn, "Merging multispectral and panchromatic SPOT images with respect to the radiometric properties of the sensor," Photogrammetric Engineering and Remote Sensing, Vol. 59, No. 1, pp. 81-87, 1993.

[14] A. Abadpour, S. Kasaei, "A new fpca-based fast segmentation method for color images," in The 4th IEEE International Symposium on Signal Processing and Information Technology (ISSPIT 2004), Rome, Italy, 2004.

[15] F. F. Sabins, "Remote Sensing: Principles and Interpretation (3rd ed.)," New York: W. H. Freeman and Company. 494 p, 1997.

[16] Installation guide, sample data, and the latest version of TNTlite. Online Available: http://www.microimages.com

[17] P. Dulyakarn, Y. Rangsanseri, "fuzzy c-means clustering using spatial information with application to remote sensing," 22nd Asian Conference on Remote sensing, 5-9 Nov. 2001.

[18] L. Dzung, J. L. P. Pham, "Adaptive Fuzzy Segmentation of Magnetic Resonance Images," IEEE Transactions on Medical Imaging, Vol. 18, No. 9, September 1999.

[19] L. P. Dzung, L. P. Jerry, "An adaptive fuzzy C-Mean Algorithm for image segmentation in the presence of intensity inhomogeneities," Pattern Recognition Letter, vol. 20, pp. 57-68, 1998.

[20] http://www.spotimage.fr/html/_ 62