2011 International Conference on Computer and Software Modeling
IPCSIT vol.14 (2011) © (2011) IACSIT Press, Singapore

Colour Based Image Segmentation Using Fuzzy C-Means Clustering

Tara Saikumar [1], P. Yugander [2], P. Sreenivasa Murthy [3] and B.Smitha[2]

[1] CMR Technical Education Society, Group of Institutions, Hyderabad-04, India
[2] Kakatiya Institute of Technology and science,Warangal-15,India.
[3] CMR Institute of Technology, Hyderabad-04, India

Abstract. Mostly due to the progresses in spatial resolution of satellite imagery, the methods of segment-based image analysis for generating and updating geographical information are becoming more and more important. This work presents a new image segmentation based on colour features with Fuzzy c-means clustering unsupervised algorithm. The entire work is divided into two stages. First enhancement of color separation of satellite image using decorrelation stretching is carried out and then the regions are grouped into a set of five classes using Fuzzy c-means clustering algorithm. Using this two step process, it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the colour is not frequently used for image segmentation, it gives a high discriminative power of regions present in the image.

Keywords: Spatial Resolution, Image segmentation, Fuzzy c-means, Satellite Image, Pixel.

1. Introduction

In remote sensing, the process of image segmentation is defined as: “the search for homogenous regions in an image and later the classification of these regions”. It also means the partitioning of an image into meaningful regions based on homogeneity or heterogeneity criteria. Image segmentation techniques can be differentiated into the following basic concepts: pixel oriented, Contour-oriented, region-oriented, model oriented, color oriented and hybrid. Color segmentation of image is a crucial operation in image analysis and in many computer vision, image interpretation, and pattern recognition system, with applications in scientific and industrial field(s) such as medicine, Remote Sensing, Microscopy, content based image and video retrieval, document analysis, industrial automation and quality control. The performance of color segmentation may significantly affect the quality of an image understanding system .The most common features used in image segmentation include texture, shape, grey level intensity, and color. The constitution of the right data space is a common problem in connection with segmentation/classification. In order to construct realistic classifiers, the features that are sufficiently representative of the physical process must be searched. In the literature, it is observed that different transforms are used to extract desired information from remote-sensing images or biomedical images**.** Segmentation evaluation techniques can be generally divided into two categories (supervised and unsupervised).

The first category is not applicable to remote sensing because an optimum segmentation (ground truth segmentation) is difficult to obtain. Moreover, available segmentation evaluation techniques have not been thoroughly tested for remotely sensed data. Therefore, for comparison purposes, it is possible to proceed with the classification process and then indirectly assess the segmentation process through the produced classification accuracies. For image segment based classification, the images that need to be classified are segmented into many homogeneous areas with similar spectrum information firstly, and the image segments' features are extracted based on the specific requirements of ground features classification. The color homogeneity is based on the standard deviation of the spectral colors, while the shape homogeneity is based on the compactness and smoothness of shape. There are two principles in the iteration of parameters:

1) In addition to necessary fineness, we should choose a scale value as large as possible to distinguish different regions; 2) we should use the color criterion where possible. Because the spectral information is the most important in imagery data, the quality of segmentation would be reduced in high weightiness of shape criterion. This work presents a novel image segmentation based on color features from the images. In this we did not used any training data and the work is divided into two stages. First enhancing color separation of satellite image using decorrelation stretching is carried out and then the regions are grouped into a set of five classes using Fuzzy c-means clustering algorithm. Using this two step process, it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the color is not frequently used for image segmentation, it gives a high discriminative power of regions present in the image. The present work is organized as follows: Section 2 describes the enhancing color separation of satellite image using decorrelation stretching. Section 3 describes the Fuzzy c-means clustering method. In section 4 the proposed method of segmentation of image based on color with Fuzzy c-means clustering is presented and discussed.

2. De-correlation Stretching

De-correlation stretching enhances the color separation of an image with significant band-to-band correlation. The exaggerated colors improve visual interpretation and make feature discrimination easier. We apply decorrelation stretching with the de-corrstretch function. The number of color bands, NBANDS, in the image is taken three. But we can apply de-correlation stretching regardless of the number of color bands. The original color values of the image are mapped to a new set of color values with a wider range. The color intensities of each pixel are transformed into the color eigen space of the NBANDS-by-NBANDS covariance or correlation matrix, stretched to equalize the band variances, and then transformed back to the original color bands. To define the band wise statistics, we can use the entire original image, with the subset option, or any selected subset of it.

3. Fuzzy c-Means Clustering (FCM)

The standard fuzzy c-means objective function for partitioning $\{x_k\}_{k=1}^{N}$ into c clusters is given by

$$J(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \left\| x_k - v_i \right\|^2 \tag{3.1}$$

Where $\{x_k\}_{k=1}^{N}$ the feature vectors for each pixel are, $\{v_i\}_{i=1}^{c}$ are the prototypes of the clusters and the array $[u_{ik}] = U$ represents a partition matrix, namely

$$\sum_{i=1}^{c} u_{ik} = 1 \mid 0 \le u_{ik} \le 1, \forall k = 1,2,3....N \tag{3.2}$$

and

$$0 \le \sum_{k=1}^{N} u_{ik} \le N \tag{3.3}$$

The parameter p is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. The FCM objective function is minimized when the high membership values are assigned to pixels whose intensities are close to the centroid of their particular class, and low membership values are assigned when the pixel data is far from the centroid.

The constrained optimization could be solved using one Lagrange multiplier

$$F_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \left\| x_k - v_i \right\|^2 + \lambda(1 - \sum_{i=1}^{c} u_{ik}) \tag{3.4}$$

Where λ denotes a Lagrange multiplier. The derivative of

F_m w.r.t u_{ik} was computed and the result was set to zero, for $p > 1$

$$\frac{\partial F_m}{\partial u_{ik}} = p u_{ik}^{p-1} \left\| x_k - v_i \right\|^2 - \lambda \tag{3.5}$$

$$u_{ik} = \left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} \frac{1}{\left\| x_k - v_i \right\|^{\frac{2}{m-1}}} \tag{3.6}$$

The identity constraint $\sum_{j=1}^{c} u_{jk} = 1 \; \forall k$ was taken into account

$$\left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} \sum_{j=1}^{c} \frac{1}{\left\| x_k - v_j \right\|^{\frac{2}{m-1}}} = 1 \tag{3.7}$$

This allows us to determine the Lagrange multiplier λ

$$\left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} = \frac{1}{\sum_{j=1}^{c} \frac{1}{\left\| x_k - v_j \right\|^{\frac{2}{m-1}}}} \tag{3.8}$$

The zero-gradient condition for the membership estimator can be rewritten as

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\left\| x_k - v_i \right\|}{\left\| x_k - v_j \right\|} \right)^{\frac{2}{p-1}}} \tag{3.9}$$

As no constraints, the computations of the prototypes were straightforward, The minimum of J was computed

with respect to v_i, and yielded the following equation

$$\nabla_{v_i} J = 0 \tag{3.10}$$

The detailed solution depends on the distance function.

In the case of the Euclidean distance, this leads to the expression:

$$2 \sum_{k=1}^{N} u_{ik}^{p} (x_k - v_i) = 0 \tag{3.11}$$

So the following could be immediately obtained

$$v_i = \frac{\sum_{k=1}^{N} u_{ik}^{p} x_k}{\sum_{k=1}^{N} u_{ik}^{p}} \tag{3.12}$$

The FCM algorithm for segmenting the image into different clusters can be summarized in the following steps:

FCM Algorithm:

Step 1: Select initial class prototype $\{v_i\}_{i=1}^{c}$.

Step 2: Update all memberships u_{ik} with Eq. (3.9).

Step 3: Obtain the prototype of clusters in the forms of weighted average with Eq. (3.12).

Step 4: Repeat step 2-3 till termination. The termination criterion is $\left\| V_{new} - V_{old} \right\| \le \varepsilon$.

Where $\|.\|$ is the Euclidean norm. V is the vector of cluster centers ε is a small number that can be set by

user (here ε =0.01).
acknowledge collaborators or anyone who has helped with the paper at the end of the text.

4. Color-Based Segmentation Using Fuzzy C-Means Clustering

The basic aim is to segment colors in an automated fashion using the L*a*b* color space and Fuzzy c-means clustering. The entire process can be summarized in following steps

Step 1: Read the image

Read the image from mother source which is in .JPEG format, which is a fused image of part of Hyderabad city of Andhra Pradesh, India with DWT fusion algorithm of Cartosat-1 and LISS-IV of Indian satellite IRS-P6 and IRS-1D.

Step 2: For colour separation of an image apply the Decorrelation stretching

Step 3: Convert Image from RGB Color Space to L*a*b* Color Space. How many colors do we see in the image if we ignore variations in brightness. There are three colors: white, blue, and pink. We can easily visually distinguish these colors from one another. The L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables us to quantify these visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can measure the difference between two colors using the Euclidean distance metric. Convert the image to L*a*b* color space.

Step 4: Classify the Colors in 'a*b*' Space Using Fuzzy C- Means Clustering. Clustering is a way to separate groups of objects. Fuzzy c-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. Fuzzy c-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Since the color information exists in the 'a*b*' space, your objects are pixels with 'a*' and 'b*' values. Use Fuzzy c-means to cluster the objects into three clusters using the Euclidean distance metric.

Step 5: Label Every Pixel in the Image Using the Results from Fuzzy c-means. For every object in our input, Fuzzy c-means returns an index corresponding to a cluster .Label every pixel in the image with its cluster index.

Step 6: Create Images that Segment the Image by Color.

5. Experimental results

The various experiment carried out on the above said imagery in MATLAB v7.6. The complete process and the standard results are summarized in subsequent figure1.

6. Conclusions

Using color based image segmentation; it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the color is not frequently used for image segmentation, it gives a high discriminative power of regions present in the image. This kind of image segmentation may be used for mapping the changes in land use land cover taken over temporal period in general but not in particular.

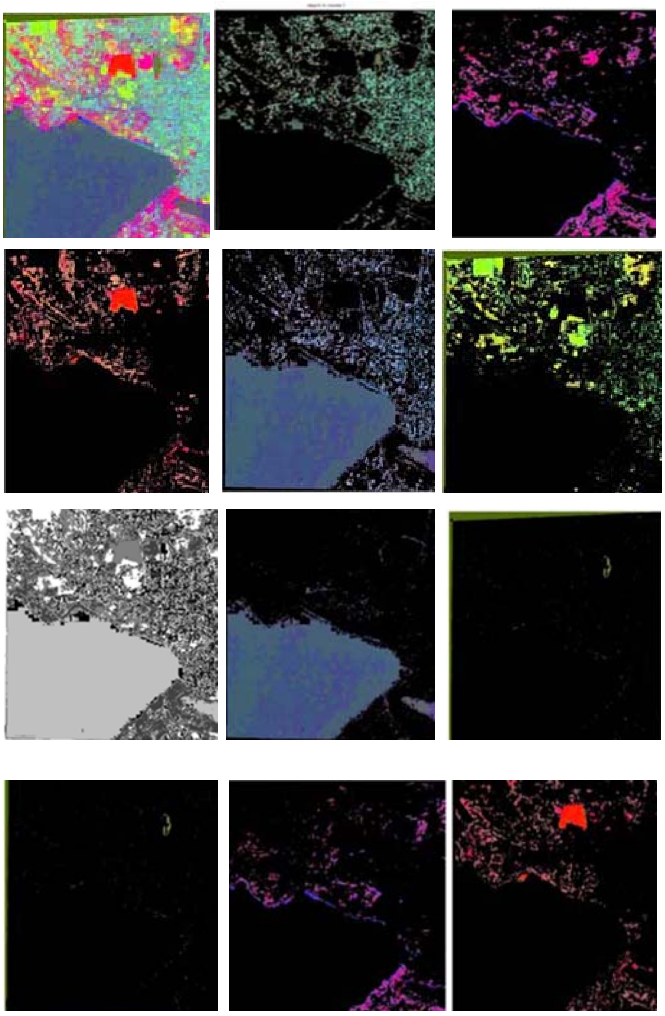

Figure :1

a. De-correlation Stretch image,
b. Object in Cluster one,
c. Object in Cluster two,
d. Object in Cluster three,
e. Object in Cluster four,
f. Object in Cluster five,
g. Clustered index image,
h. Nucle of cluster one,
i. Nucle of cluster two,
j. Nucle of cluster three,
k. Nucle of cluster four,
l. Nucle of cluster five

7. References

[1] X. Bresson and J. Thiran Image. Segmentation Model Using Active contour and Image Decomposition. IEEE, International Conference on Image Processing, pp 1657-1660 Atlanta, USA, 2006.

[2] X. Dresson, S. Esedoglu, P. Vandergheynst, J. P. Thrian and S. Osher. Fast Global minimization of the active contour/ snake model. *Journal of Mathematical image and Vision*, 2007.

[3] V. Caselles, R. Kimmel, G. Sapiro. Geodesic active contours. *Int. J. Computer Vision.* 22(1), 61–79 (1997).

[4] S. Kichenassamy, A. Kumar, P. Oliver, A. Tannenbaum and Yezzi, A. Conformal curvature flows: from phase transitions to active vision. Arch. Ration. Mech. Anal. 134, 275–301 (1996) .

[5] V. Caselles. F. Catté, T. Coll and F. Dibos. A geometric model for active contour in image processing. Nummer.Math, Vol 66, pp 1-31, 1993.

[6] T. F. Chan and L. Vese. Active contours without edges. *IEEE Transaction on Image Processing.* vol 10(2), 266-277, 2001.
[7] J. Canny. A Computational Approach to Edge Detection, IEEE Trans. *Pattern Analysis and Machine Intelligence*. 8(6):679–698, 1986.
[8] R. Deriche. Using Canny's criteria to derive a recursively implemented optimal edge detector, *Int. J. Computer Vision*. Vol. 1, no.2, pp. 167–187, April 1987.
[9] D. Maar, E. Hildreth. Theory of edge detection. *Proceedings of Royal Society of London*. vol. 207, 187-217, 1980.
[10] J.-F. Aujol, G. Gilboa, T. Chan, S. Osher. Structure-texture image decomposition—modeling, algorithms, and parameter Selection. *Int. J. Computer Vision*. 67(1), 111–136, (2006).
[11] J. C. Bezdek. *Pattern Recognition with Fuzzy Objective Function Algorthims*. Plenum Press, New York, 1981.
[12] K. L. Wu, M. S. Yang. Alternative c-means clustering algorthims. *Pattern Recognition.* vol.35, pp.2267-2278, 2002.