ISSN: 0975-766X
CODEN: IJPTFI
Available Online through
Research Article
www.ijptonline.com

MODIFIED FUZZY C-MEANS CLUSTERING BASED SEGMENTATION OF CIELAB COLOR IMAGES FOR INFORMATION RETRIEVAL

V.Kalist[1], Ganesan P*[2]
[1,*2] Faculty of Electrical and Electronics Engineering, Sathyabama University, Chennai 600119, India.
Email: gganeshnathan@gmail.com

Received on 20-02-2016 *Accepted on 16-03-2016*

Abstract

This work proposed unsupervised clustering or segmentation of images in CIELab color space using modified spatial information incorporated fuzzy c-means clustering. The clustering or segmentation is the common but vital step in computer vision and image based analysis. There are a lot of algorithms and techniques for the segmentation of color images for various applications. Among these techniques for color image segmentation, the soft computing based techniques (fuzzy logic, genetic algorithm, neural network) had presented nice results. In this work, traditional fuzzy c-means clustering is modified and the distance measures such as city block, squared Euclidean and cosine is evaluated to find the cluster centers. The objective of the work is to segment the CIELab color images using modified spatial information incorporated fuzzy c-means clustering. The experimental result reveals that the proposed MFCM approach using city block distance had offered the excellent outcome for the color images.

Keywords: Clustering, Color space, RGB, CIELab, FCM, Euclidean distance, city block distance, cosine distance.

1. Introduction

In color image processing, clustering is the process of dividing an image into number of meaningful segments or clusters or sub images based on color attribute. The segmentation can be considered as a clustering problem in which each pixel in a same cluster is similar with respect to color attribute. Color based image segmentation provides more meaningful information as compared to gray level and monochrome segmentation. There are only two different variations in monochrome (binary) images and 256 variations in gray scale (intensity) images. It is very difficult to discriminate more than 25 intensity levels for human eye. However, it is very easy to discriminate more number of color shades in color images. This means that color images can provide more information as compared to gray scale images. Moreover, a simple personal computer is enough for the processing of color images. So the color based image segmentation is very popular and widely used. In this paper, unsupervised clustering or segmentation of images in CIELab color space using spatial information incorporated Fuzzy C-means (FCM) clustering method had proposed. The spatial information is very essential for clustering problems for the organization of clusters but FCM doesn't give any spatial information. So in this work, spatial information is incorporated into the traditional FCM clustering. In image processing, color space is nothing but the representation of colors in a meaningful way in the three or four dimensional Cartesian or polar coordinates. There are various color spaces for different applications. For example, RGB for displays, CMYK for printing and YCbCr for television broadcasting. Even though RGB color space is not preferred for the segmentation, most of the works had performed on this color space. In this work, the image in RGB color space had transformed into CIELab color space and then segmentation using modified FCM had performed. The remaining chapters in this work are organized as follows. A brief review of CIELab color space is presented in section 2. Section 3 had explained the proposed method for the segmentation of color images. The brief discussion on experimental result had given in section 4. The summary of conclusions had pointed out in section 5.

2. Review of Color CIELab Color Space for Image Segmentation

The input image taken from image sensor is usually in RGB color space. However, this device dependent and non uniform color space is not suitable for objects identification and recognition of colors. Moreover, it is very difficult to find out an exact color in RGB color space. CIEXYZ color space was proposed based on three imaginary primary color components X, Y and Z. All the visible colors can easily be described by positive values of X, Y, and Z. The reason for imaginary primaries in CIEXYZ is that don't keep up an association well to any real light wavelengths. The component Y is defined to match closely to luminance and the components X and Z represents the chrominance (color information). The chrominance mainly depends on the dominant wavelength and saturation. The transformation of an image from gamma corrected RGB to CIELUV color space is defined as

$$X = 0.412R' + 0.357G' + 0.180B' \quad (1)$$

$$Y = 0.212R' + 0.715G' + 0.072B' \quad (2)$$

$$Z = 0.019R' + 0.119G' + 0.950B' \quad (3)$$

The main advantage of the CIE XYZ and CIELab color space is that they are completely device independent. In device independent color space, the same color information is displayed irrespective of equipment. However, CIEXYZ space is not perceptually uniform color space and the shape is very difficult to visualize due to non linear characteristics of the chromaticity diagram. CIELab color space is uniformly derived from CIEXYZ color space.

This perceptually uniform color space has many advantages such as device independent, linear visual perception as compared to other color spaces. In perceptual uniform color spaces, any two colors those are equally far- away in the color space are equally distant perceptually. In CIELab color space, the component L indicates the actual visual difference and the color information (red/blue and yellow/blue) are stored in u and v components. CIELab color space is defined as

$$L = 116\, f(Y/Yn) - 16 \qquad (4)$$

$$a = 500[f(X/Xn) - f(Y/Yn)] \qquad (5)$$

$$b = 200[f(Y/Yn) - f(Z/Zn)] \qquad (6)$$

3. Proposed Method for Unsupervised Clustering of Satellite Images

In this work, unsupervised clustering or segmentation of images in CIELab color space using spatial information incorporated FCM clustering method had proposed and explained. Figure 1 illustrates the proposed approach for the segmentation of satellite images.

The input image in RGB color space is sharpened in spatial domain using sharpening algorithm and then smoothened using Gaussian filter. After the enhancement process is over, the image is transformed to device independent CIELab color space.

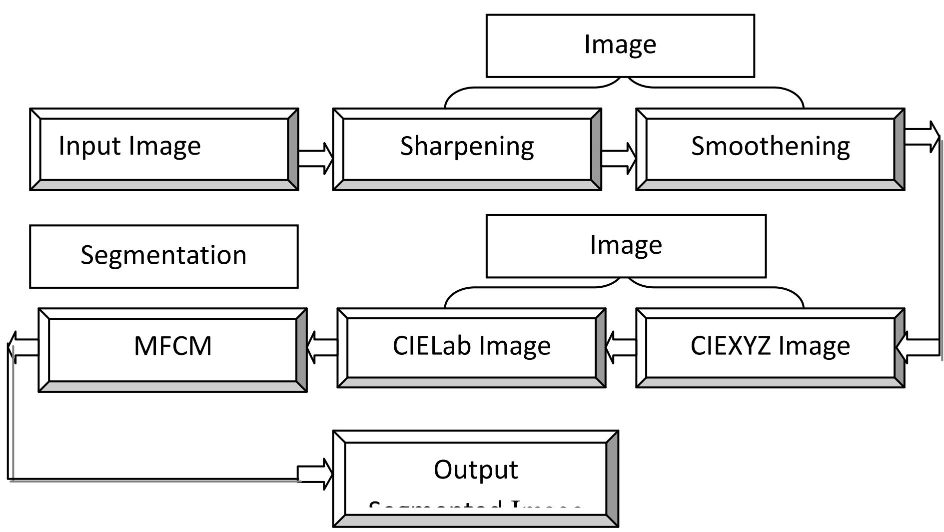

Figure 1: Proposed method for unsupervised clustering

The next step is the segmentation of color images using a suitable segmentation method. In this work, unsupervised clustering is performed using modified spatial information incorporated FCM clustering method. This modified FCM (MFCM) is explained as follows.

Step 1: The input satellite image is transformed to data matrix X

Step 2: Presume the number of clusters, c ($2 \leq c \leq n$), n is the length of the image data and fix the fuzziness parameter m > 1

Step 3: Work out the fuzzy partition matrix U_{ij} and the i^{th} cluster center V_i using (7) and (8)

$$U_{ij} = \sum_{k=1}^{c}\left\{\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right\}^{-2/m-1} \qquad (7)$$

$$V_i = \frac{\sum_{j=1}^{n}(U_{ij})^m x_j}{\sum_{j=1}^{n}(U_{ij})^m} \qquad (8)$$

Step 4: Calculate the spatial function S_{ij} and the weight function W_{ji} by using (9) and (10)

$$S_{ij} = \sum_{k\in W(x_j)} U_{ik}\alpha_{k1} + \frac{\sum_{k\in(x_j)} U_{ik}\alpha_{k2}}{\sum_{t=1}^{c}\sum_{k\in W(x_j)} U_{tk}} \qquad (9)$$

$$W_{ji} = \frac{1}{1+e^{-\left\{\frac{\|x_j-v_i\|^2}{\sum_{j=1}^{n}\|x_j-v_i\|^2\left(\frac{c}{n}\right)}\right\}}} \qquad (10)$$

Step 5: The updated membership function is computed using

4. Experimental Result and Discussion

Fig 2(a) illustrates the input satellite image of Grampians National Park forest fires (Victoria, Australia) which had acquired from Landsat 8 satellite sensor on 28-01-2014. The input image in RGB color space is sharpened in spatial domain using sharpening algorithm and then smoothened using Gaussian filter. Fig 2(d) and 2(e) depicted the CIEXYZ and CIELab version of the input image.

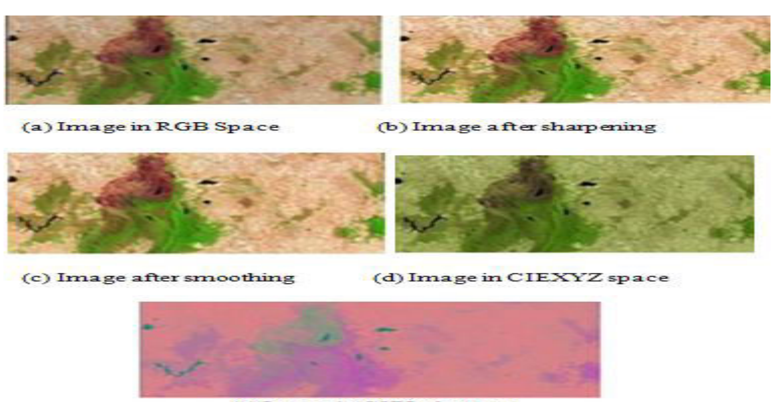

Figure 2: Representation of test image in three different color spaces.

Figure 3 illustrates the three different components or layers of CIELab image. The image is divided into one luminance (L) and two chrominance (a and b) layers.

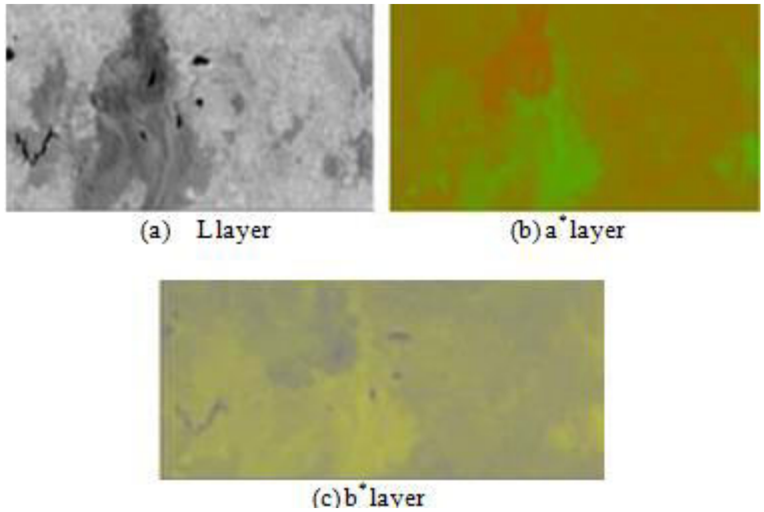

Figure 3: Representation of CIELab image as three components or layers

The segmentation result for various clusters using the different distance measures is depicted from fig 4 to fig 8.

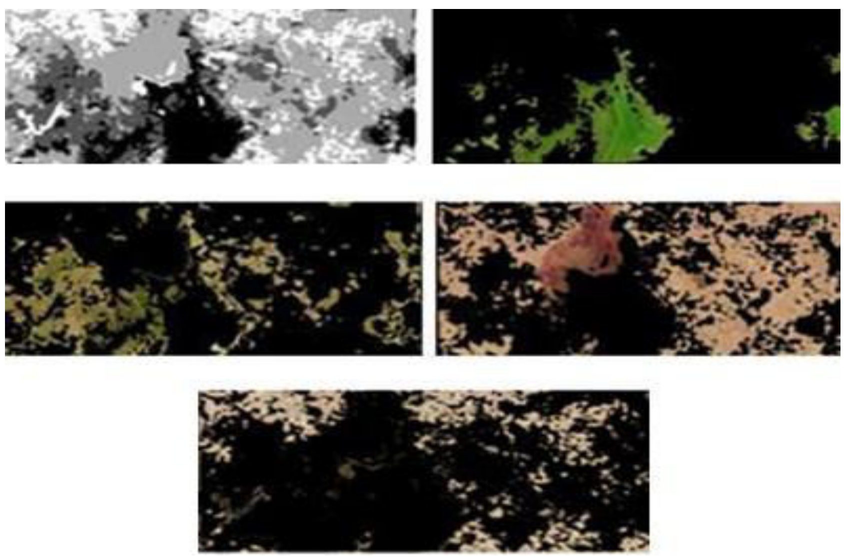

Figure 4: The unsupervised clustering outcome for four clusters using city block distance

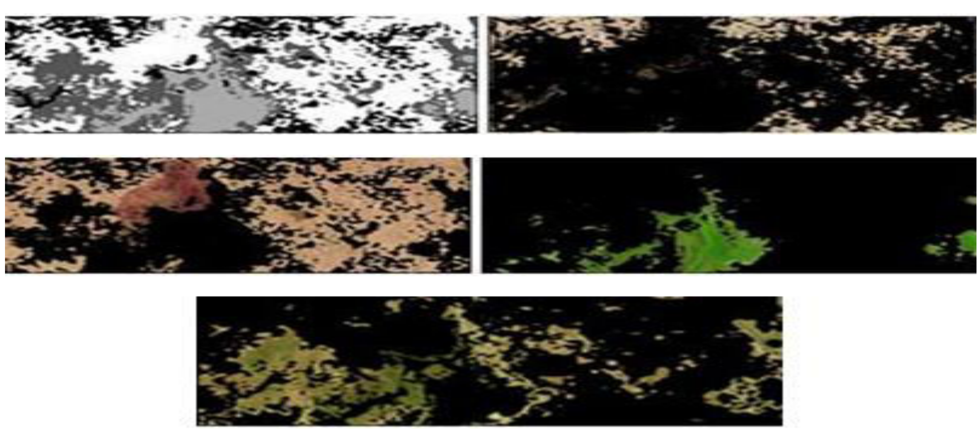

Figure 5: The unsupervised clustering outcome for four clusters using squared Euclidean distance

Table-I: Clustering Result for Four Clusters using City Block Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	6	623144	126,162
2	6	554855	105,169
3	10	555560	133,149
4	6	583440	140,153

Table-II: Clustering Result for Four Clusters using Euclidean Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	21	3.796e+006	132.7,146.2
2	22	3.814e+006	125.6,161.4
3	18	4.018e+006	103.5,169.5
4	23	3.771e+006	140.7,152.3

Table-III: Clustering Result for Four Clusters using Cosine Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	25	21.2084	0.6690,0.7430
2	22	21.2084	0.5156,08558
3	20	21.2084	0.7120,0.7017
4	18	21.27	0.6075,0.7938

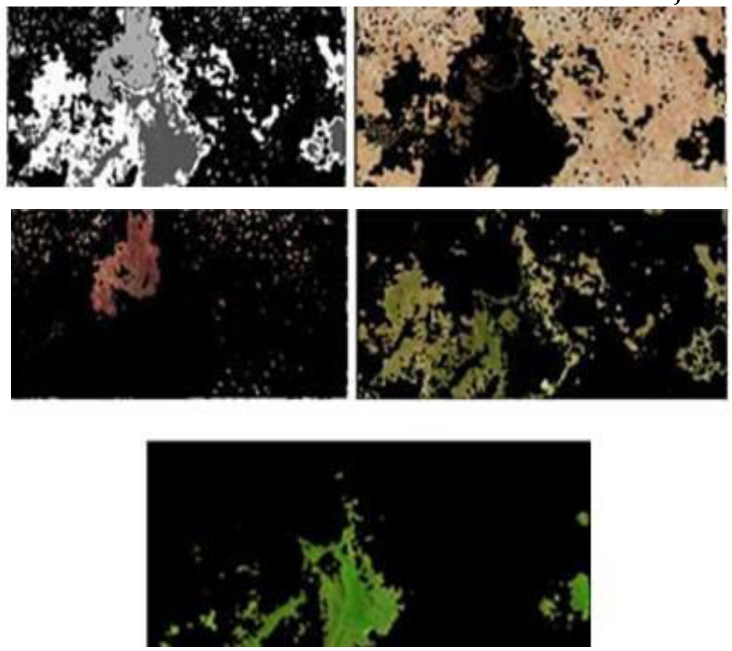

Figure-6: The unsupervised clustering outcome for four clusters using cosine distance.

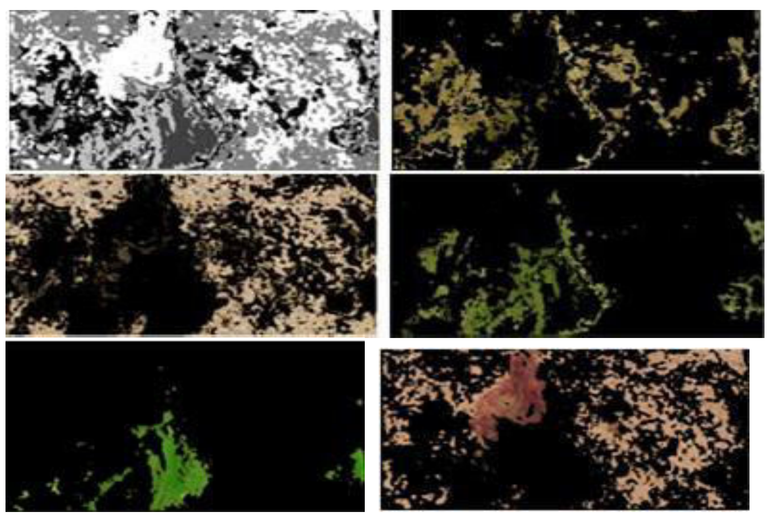

Figure 7: The unsupervised clustering result for five clusters using city block distance

Table-IV: Clustering Result for Five Clusters using City Block Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	10	507084	127,162
2	10	503416	107,168
3	5	500587	142,152
4	15	507097	133,147
5	11	503190	137,153

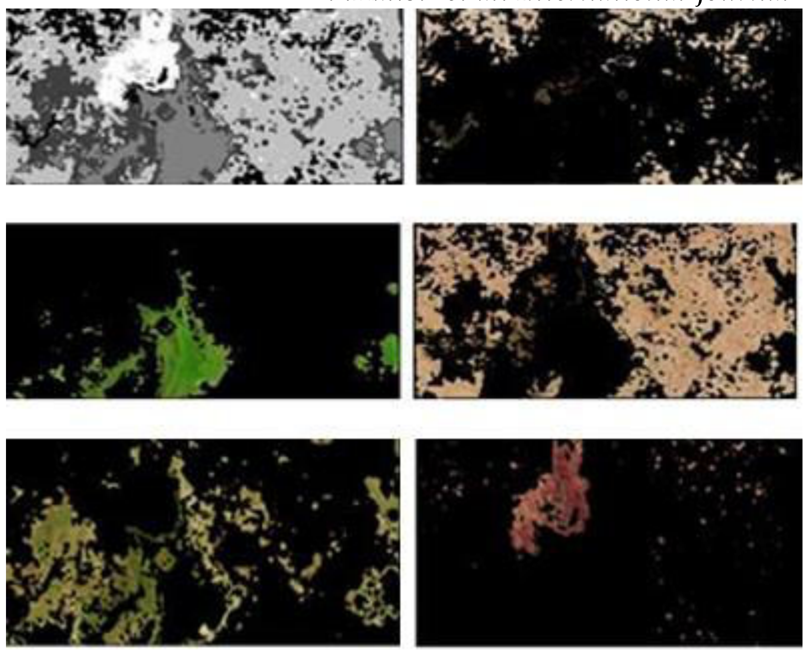

Figure-8: The unsupervised clustering result for five clusters using squared Euclidean distance.

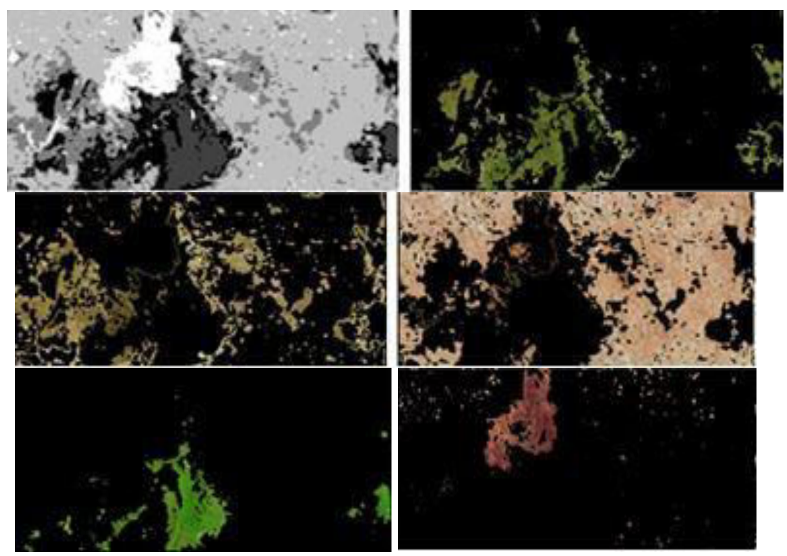

Figure-9: The unsupervised clustering result for five clusters using cosine distance.

Table-V: Clustering Result for Four Clusters using Squared Euclidean Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	23	2.968e+006	132.3,144.1
2	23	2.875e+006	124.5,161.7
3	13	2.873e+006	103.2,169.6
4	40	2.968e+006	138.1,153.2
5	16	2.873e+006	151.2,146.5

Table-VI: Clustering Result for Four Clusters using City Block Distance Measure.

Cluster Number	No. of iteration	Sum of distance	Cluster centers
1	36	13.5176	0.5763,0.8168
2	26	13.5176	0.4976,0.8667
3	43	13.5176	0.6325,0.7742
4	19	13.5264	0.6732,0.7392
5	38	13.5176	0.7178,0.6958

Table-VII: Comparison of Clustering Result using Peak Signal to Noise Ratio (PSNR).

Distance Measure	Three clusters	Four clusters	Five clusters	Six clusters
City block	14.88	17.82	21.88	24.12
Squared Euclidean	16.62	16.53	17.34	20.60
Cosine	15.09	17.98	22.79	23.56

Table-VIII: Comparison Clustering Result using Execution Time (In Seconds).

Distance Measure	Three clusters	Four clusters	Five clusters	Six clusters
City block	1.2636	1.3104	1.8720	2.5272
Squared Euclidean	1.6068	1.6380	2.3868	3.1512
Cosine	1.435	1.5912	3.0420	3.9780

The graphical representation of clustering result for different distance measures using peak signal to ratio and number of iterations is illustrated in fig 9 and 10 respectively.

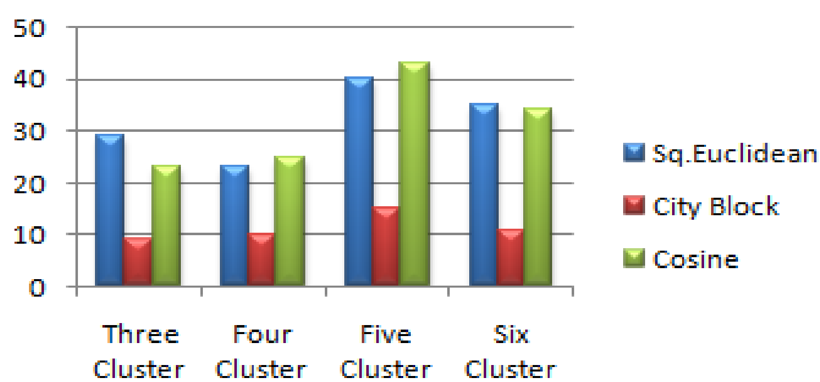

Figure-9: The number of iteration for unsupervised clustering for various clusters.

Figure-10: The execution time for various clusters.

5. Conclusion

In this work, unsupervised clustering or segmentation of images in CIELab color space using spatial information incorporated FCM clustering method had proposed and elucidated. The test image had segmented into number of clusters using proposed method. Even though the results of only one images had shown and analyzed, the proposed method can be applied and worked equally well for all types of images. The success of the proposed method for color image clustering is based on various factors such as the complexity of the image, color space, image sensor and other environmental issues. In this work, the proposed method had analyzed using squared Euclidean, city block and cosine distance measures. Based on the experimental results, the execution time is less for city block based clustering method as it requires only less number of iterations. PSNR value is directly proportional to the number of clusters. In most cases, PSNR had provided its best value to city block based clustering method.

6. References

1. Zhengjian Ding, Jin Sun, Yang Zang. FCM Image Segmentation algorithm based on color space and spatial information.International journal on computer and communication. Vol 2, No 1, 2013.

2. Saha Sahaphong S. Unsupervised Image segmentation using automated Fuzzy C-Means", 7^{th} IEEE Conference on computer and IT, Bangkok; 2007.p.690-694.

3. Corbalán M.CM, Millán, M. S. and Yzuel, M. J. Color pattern recognition with CIELab coordinates. Opt. Eng. vol. 41, no. 1, 2002. p. 130–138.

4. Ganesan, P. and Rajini, V., "Segmentation and Comparison of Water Resources in Satellite Images using Fuzzy based Approach", Advances in Intelligent Systems and Computing (ISSN 2194-5357), Advances in Soft Computing, Springer Verlag, Vol. 308, No. 1.pp 685-692, 2015.

5. Yang. Image segmentation by Fuzzy C Means Clustering Algorithm with a novel penalty term. Computing and Informatics, Vol. 26; 2007.p.17-31.

6. Ganesan, P. and Rajini, V., "Unsupervised Segmentation of Satellite Images based on Neural Network and Genetic Algorithm", Advances in Intelligent Systems and Computing (ISSN 2194-5357), Advances in Soft Computing, Springer Verlag, Vol. 309, No. 2, pp 319-326, 2015

7. Poggi G, Scarpa G, Zerubia J B. Supervised segmentation of remote sensing images based on a tree-structured MRF model. *IEEE Trans*. Geosci. Remote Sens. vol. 43, no. 8, 2005. p. 1901–1911.

8. Hanbury A and Serra J. Mathematical morphology in the CIELAB space. Image Anal. Stereol. 21- 3, 2002.p. 201–206.

9. Thoonen G, Mahmood Z, Peeters S, Scheunders P. Multisource classification of color and hyper spectral images using color attribute profiles and composite decision fusion. Selected topics in applied earth observations and remote sensing, IEEE journal of, 5-2, 2012. p.510-521.

10. Han Y. A Simple and Efficient Color Recovering System for Content Sharing Website. IEEE Transactions on Consumer Electronics. Vol. 56, No. 2, May 2010. p.863-869.

11. James M. Kasson and Wil Plouffe, "An Analysis of Selected Computer Interchange Color, Spaces," ACM Transactions on Graphics, Vol. 11, No. 4, pp.373-405, 1992.

12. http://eros.usgs.gov/image gallery/image-week-2

13. Awad M, Chehdi K, Nasri A. Multi-component image segmentation using a hybrid dynamic genetic algorithm and fuzzy C-means. IET Image Process. Vol. 3, Iss. 2, 2009. p. 52–62.

14. Ganesan, P. and Rajini, V., "Satellite image segmentation based on YCbCr Color space", Indian Journal of Science and Technology, India, Vol.8, No.1, Jan 2015.

15. Nikhil R. Pal, Kuhu Pal and James C. Bezdek (2005), "A Possibilistic Fuzzy C Means clustering algorithm", IEEE transactions of fuzzy systems, Vol. 13, No. 4, pp. 517-530.

16. Ganesan, P.; Rajini, V., "Assessment of satellite image segmentation in RGB and HSV color space using image quality measures," Advances in Electrical Engineering (ICAEE), 2014 International Conference on , vol., no., pp.1,5, 9-11 Jan. 2014 doi: 10.1109/ICAEE.2014.6838441.

17. http://www.poynton.com/Poynton-color.html

Corresponding Author:

Ganesan P*,

Email: *gganeshnathan@gmail.com*