Indian Streams Research Journal
ISSN 2230-7850
Volume-3, Issue-9, Oct-2013 Available online at www.aygrt.isrj.net

IMAGE QUALITY PARAMETERS FOR THE ANALYSIS OF SEGMENTATION OF SATELLITE IMAGES IN TWO DIFFERENT COLOR SPACES

GANESAN P AND V.RAJINI
Research Scholar Sathyabama University Chennai, India
Professor SSN College of Engineering Chennai, India

ABSTRACT: Image quality parameters are the figure of merit widely used in the image processing applications to analyze and compare the output image with the input image. These measures are widely used in image compression, segmentation, feature extraction, object detection and tracking, and image based measurements. In this paper, these parameters measure the similarity or dissimilarity between the two images on the basis of comparing the corresponding pixels of the two images and present a numerical value as a result. The segmentation is one of the most challenging and important process in the image analysis. The success of the image analysis is based on the result produced in the segmentation stage. This paper presents a comparative study of the segmentation of high resolution satellite images in RGB and HSV color spaces using modified k-means clustering algorithm. The segmented images are compared with the original input images by using number of bivariate image quality parameters. To test the efficiency and robustness of the proposed method, the experiments are performed on GeoEye-1 satellite images.

KEYWORDS: Image Segmentation, Satellite Image, Color Space, RGB, HSV, K-means Clustering, Image Quality Parameters

1. INTRODUCTION

Image segmentation is the process of partitioning or dividing an image into number of sub images, segments, regions or clusters with similar attributes. This is the initial but most important step in the image analysis to gather necessary information. In this process, the image pixels are grouping according to any one characteristics of the image [4][5][6]. There are number of methods for the segmentation of satellite images such as region growing, threshold based methods, edge detection based methods, fuzzy based methods, neural based methods, genetic based methods etc. every method has its own advantages and disadvantages. The segmentation algorithm developed for one application is not well suited for other applications. For example, an algorithm developed for medical image segmentation is not well suited for satellite image segmentation. Nowadays many countries are launching satellites for various applications including mapping, agriculture, disaster management, environmental assessment and monitoring, military and metrology. The images collected from satellite contains huge amount of information for analysis and processing. But human eye is insensitive to realize small changes in the characteristics such as intensity, color, or texture. So the manual human processing is not successful to retrieve the hidden treasures of information in the satellite image. The optimal solution is the processing of satellite images with digital computers. To retrieve the information from images, we need an efficient and effective segmentation method which is most important and difficult task in the image analysis. The images received from satellite are usually in RGB color space. This color space is not preferred for image segmentation because this space is not perceptually uniform and all components should be quantized with the same precision. So the image is converted for RGB space to other color space by either linear or nonlinear transformations. In this paper, an efficient segmentation of satellite images in HSV color space using modified K-means is proposed. The remainder of the paper is organized as follows. The section 2 gives the information of k-means clustering. The section 3 covers the modified k-means clustering algorithm. The section 4 covers RGB and HSV color space. The various image quality parameters for satellite image segmentation

Indian Streams Research Journal
ISSN 2230-7850
Volume-3, Issue-9, Oct-2013 Available online at www.aygrt.isrj.net

are explained in the section 5. The section 6 describes the experiments on the proposed method and finally the section 7 concludes the paper.

2. K-MEANS CLUSTERING ALGORITHM

K-means clustering algorithm, proposed by Mac Queen, is numerical, unsupervised, non-deterministic and iterative to segment or classify or cluster or to group the objects based on characteristics or features into K number of clusters [1] [2]. This is widely used because of its simpleness and fast convergence. In this algorithm, the clustering is done by minimizing the distances between data and the corresponding cluster centroid [18]. The basic K-Means clustering algorithm is simple. This algorithm starts with finding number of cluster (K) and assuming the center of these clusters (centroid). The working principle of K-means clustering algorithm can be explained as follows: If the number of data is less than the number of cluster then consider each data as the centroid of the cluster. If the number of data is larger than the number of cluster, for each data, calculate the distance to all centroid and get the minimum distance. This data is said belong to the cluster that has minimum distance from this data. Since we are not sure about the location of the centroid, we need to adjust the centroid location based on the current updated data. Then we assign all the data to this new centroid. This process is repeated until no data is moving to another cluster anymore. The most important properties of this clustering algorithm is listed as (i) There is always 'K' number of clusters (ii) No overlapping of clusters (iii) No empty clusters i.e., atleast one data in each cluster (iv) The data in cluster is very close to its 'home' cluster than any other clusters (v) Apply k-means clustering only if the number of data is many. If the number of data is very few, when the same data is applied as input in different ways may produce different clusters.

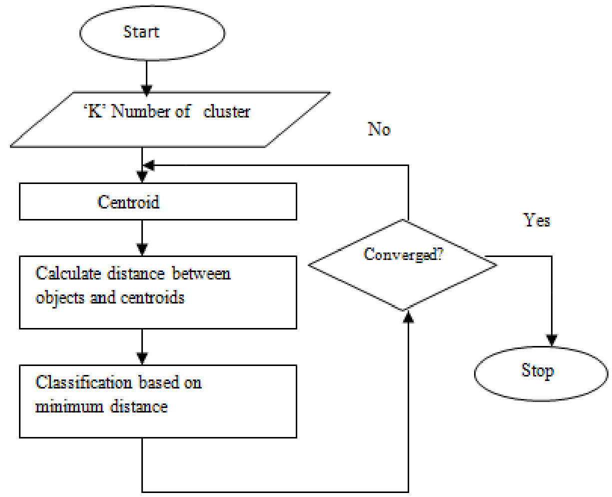

Fig 1.Flow chart for K-Means clustering algorithm

This algorithm aims at minimizing an *objective function,* in this case a squared error function which is given by

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (1)$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j , is an indicator of the distance of the n data points from their respective cluster centers.

Step 1: Determine the number of clusters, K, and assume the center of these clusters (centroid)

Step 2: Choose any random objects or the first K objects as the initial centroids

Step 3: Calculate the distance of each object to the centroids by Euclidean distance measure. The Euclidean squared distance metric uses the same equation as the Euclidean distance metric, but does not take the square root. As a result, clustering with the Euclidean squared distance metric is faster than clustering with the regular Euclidean distance. The output of K-Means clustering is not affected if Euclidean distance is replaced with Euclidean squared.

Step 4: Assign each object to the group that has the closest centroid i.e., minimum distance

Step 5: After all objects were assigned, recalculate the positions of the K centroids

The K means algorithm repeat the steps 2-4 until convergence i.e., centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated. Generally, if a problem or model has many objects and each object have several attributes and want to classify the objects based on the attributes, then we can apply this algorithm. That's why K-mean clustering can be applied for many problems such as unsupervised learning of neural network, pattern recognition, classification analysis, artificial intelligence, image processing, machine vision, etc. The main disadvantage of K-Means clustering is not generating the same result with each run, since the resulting clusters depend on the initial random assignments. So we ensure the same result on recurrent runs of the K-Means algorithm. This problem can be solved by the cluster centroids were determined using a fixed seed based randomization algorithm. As a result, every time the process starts the same centroids will be generated and the same outcome is obtained from the K-Means Clustering. The algorithm is also significantly sensitive to the initial randomly selected cluster centers. The k-means algorithm can be run multiple times to reduce this effect.

3.MODIFIED K-MEANS CLUSTERING ALGORITHM

The K-Means clustering algorithm is widely used for the segmentation problems for its simplicity and fast convergence. However, the performance of the K-means clustering is still limited due to several disadvantages as indicated in Section II. In this section, modifications on the conventional k-means clustering algorithm are introduced to overcome the aforementioned weaknesses and improve the segmentation performance. Now consider an image which has N data that have to be clustered into n centers. Let x_i be the i^{th} data and c_j be the j^{th} center with predetermined initial value where i = 1,2,...,N and j = 1,2,..., n . In this modified k-means clustering algorithm, the concept of fuzzy logic is introduced. The main idea of introducing it is to possibly allow each data member to be assigned simultaneously to more than one class by different degree of membership. This process can be achieved based upon the membership function as given by:

$$M_{ik} = \frac{1}{\sum_{j=1}^{c}\left({d_{ik}}/{d_{jk}}\right)^{\frac{2}{q-1}}} \qquad (2)$$

where d_{ik} is distance from point k to current cluster center i, d_{jk} is distance from point k to other cluster centers j and q is the fuzziness exponent where the typical value is 1. After specifying the membership for each data and applying the fitness calculation process using equation (3)

$$F(c_j) = \sum_{i \varepsilon c_j}(x_i - c_j)^2 \qquad (3)$$

The new position for each center is calculated using equation (4)

$$\boldsymbol{c_j} = {\boldsymbol{1}}/{\boldsymbol{n_j}} \sum_{i \varepsilon c_j} \boldsymbol{x_i} \qquad (4)$$

4. COLOR SPACE

Color space is a mathematical model to represent color information as three or four different color components. Color space explains how the colors are represented and specifies the components of color space accurately to learn how each color spectrum looks like [7]. Different color models are used for different applications such as computer graphics, image processing, TV broadcasting, and computer vision [3, 7, 16]. In the device dependent color space, the color produced on the display depends on the equipment used for display and the set of parameters. This category includes RGB, CMY, CMYK, YIQ, YUV, and YCbCr. In the case of device independent color space, the color produce depends only on a set of parameters irrespective of manufacturer. This category includes CIE XYZ, CIE L*U*V*, and CIE L*a*b*.

4.1 RGB Color Space

The RGB color space is represented by three dimensional Cartesian coordinate system by three values red, green and blue. RGB color space representation shown in figure 1 is additive in nature. In this additive color space, other colors are produced by adding the primary colors red, green and blue. The combination of all three primary colors produces white color and the absence of all primary color makes black. The RGB color model is represented by a unit cube and the axes are labeled as R, G and B. The origin (0, 0, 0) is considered black and the diagonally opposite corner (1,1,1) is considered as pure white. This color space is widely used in television and computer monitors. Any other color space can be obtained from a linear or non-linear transformation from RGB. This color space is device dependent. It means that the same signal or image can look different on different devices. In RGB color space, chrominance and luminance component are

Indian Streams Research Journal
ISSN 2230-7850
Volume-3, Issue-9, Oct-2013 Available online at www.aygrt.isrj.net

mixed which is why RGB color space is not chosen for color analysis and color based segmentation algorithm.

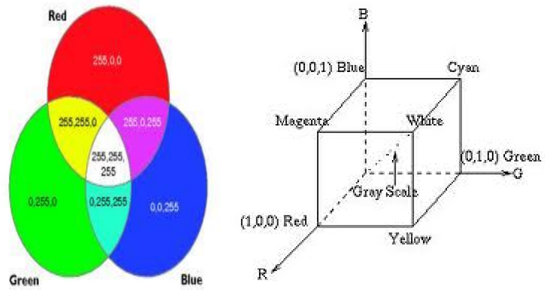

Fig 2.RGB color space representation

4.2 HSV Color Space

The HSV color space is a mathematical representation of colors in three dimensional Cartesian coordinates such as hue, saturation and value. The hue represents the color type or shade of the color by which we can easily distinguish one color from another. The hue is an angle from 0 to 2π (360 degrees), typically 0 or 360 degree represents red color, 60 degree represents yellow color, 120 degree represents green color, 180 degree represents cyan color, 240 degree represents blue color, and 300 degree represents magenta color. In this way, all the colors are represented in the HSV color space. The saturation defines the purity of the color or hue i.e., what amount of white color is mixed with hue. This can be represented as percentage that goes from 0 to 100.For example, a pure red or green or blue that has no white is 100% saturated. If some white is added, the original color is shift to newer one as the color shifts from red to pink. The third component in HSV color space is the value which represents the brightness of the color. The value component is very similar to intensity r luminance except it also varies the color saturation. The value typically ranges from 0 to 100. This range represent as the amount of light illuminating a color. Consider this example, when the hue is red and the value is low the color looks dark. When the value is low it looks bright. The value of the image is changes with the illumination but the hue and the saturation are not sensitive or less sensitive to illumination change. So for the applications like background subtraction and segmentation applications, the consideration of the value component is enough. This color space is widely used in image segmentaion,object recognition or featute detection, and image analysis.The transformation from RGB color space to HSV color space is given in the following equations

$$H = arccos \frac{\frac{1}{2}(2R-G-B)}{\sqrt{(R-G)^2-(R-B)(G-B)}} \quad (5)$$

$$S = \frac{max(R,G,B)-min(R,G,B)}{max(R,G,B)} \quad (6)$$

$$V = max(R,G,B) \quad (7)$$

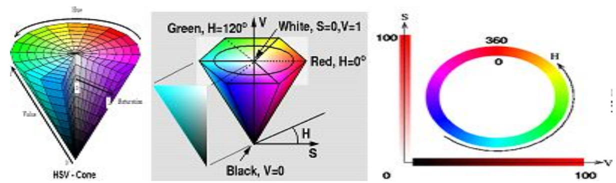

Fig 3(a).HSV Color space representation

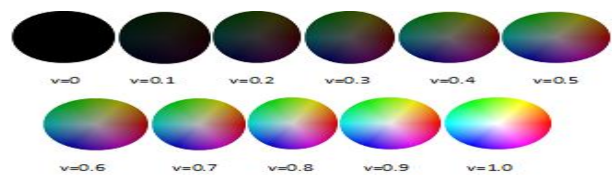

Fig 3(b).The variation of value from 0 to 1 in HSV color space

The reasons for using HSV color space in image segmentation is listed as follows:
1. The HSV color space approximate the human vision i.e., describe the colors in a way similar to how the human eye tends to perceive color
2. In RGB color space, the color is represented as a combination of three primary colors Red, Green and Blue. HSV describes color using three different components as hue(color),saturation(vibrancy) and value(brightness) .
3. In HSV color space, the intensity information can easily be separated from the color information. This is very useful in many applications such as robustness to lighting changes, or removing shadows.
4. More information can be retrieve f*rom HSV color space*
5. The RGB color space is device dependent whereas HSV color space may be device dependent or independent depending on applications.

Indian Streams Research Journal
ISSN 2230-7850
Volume-3, Issue-9, Oct-2013 Available online at www.aygrt.isrj.net

5. IMAGE QUALITY PARAMETERS FOR IMAGE SEGMENTATION

In image processing, the Image quality parameters are applied for the evaluation of the imaging system. Image quality parameters are mainly classified as univariate measures and bivariate measures. In the univariate measures the quality of the output image can easily be assessed without the explicit use of the test image. The examples for this type of measures include defocus blur, motion blur, pixel count. In the bivariate measures the quality of the output image can be tested by exploiting the differences between the corresponding pixels between the test and the output images[12][13]. Average Difference (AD), Maximum Difference (MD), Normalized Absolute Error (NAE), Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Mean Absolute Error (MAE), Peak Mean Square Error (PSNR), Structural Content (SC), Normalized Cross Correlation (NCC) is examples for bivariate measures. The bivariate measures are widely used in image based measurements, object detection and tracking, feature extraction and segmentation. These measures measure the dissimilarity between the two images on the basis of comparing the corresponding pixels of the two images. Mean Squared Error (MSE) is the average squared difference between input and segmented output image. The smaller the value of Mean Square Error, the lower the error i.e., there is a small difference between the two images. The PSNR represents a measure of the peak value of the error. If MSE is zero, then PSNR is infinity. This means that a high value of the PSNR provides a higher image quality. Similarly, the smaller value of the PSNR implies that the difference between the images is larger[14][15]. In this paper, f(j,k) and g(j,k) denote the original input and segmented output image respectively. Similarly, M and N represents the number of rows and columns respectively. The image quality parameters used in this paper for comparing the segmentation result with the original image is given as follows

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k) - g(j,k)]^{2} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k) - g(j,k)]^{2}} \quad (9)$$

$$PSNR = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N} f(j,k) - g(j,k)]^{2} / \sum_{j=1}^{M}\sum_{k=1}^{N} Max\,[f(j,k)]^{2} \quad (10)$$

$$NCC = \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k)g(j,k)] / \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k)]^{2} \quad (11)$$

$$AD = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k) - g(j,k)] \quad (12)$$

$$MD = Max\,\{[f(j,k) - g(j,k)] \quad (13)$$

$$NAE = \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k) - g(j,k)] / \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k)] \quad (14)$$

$$SC = \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k)]^{2} / \sum_{j=1}^{M}\sum_{k=1}^{N}[g(j,k)]^{2} \quad (15)$$

$$SNR = \sum_{j=1}^{M}\sum_{k=1}^{N}[f(j,k)]^{2} / \sum_{j=1}^{M}\sum_{k=1}^{N}[g(j,k)]^{2} \quad (16)$$

6. EXPERIMENTAL SETUP AND RESULT

A data base was created which consists of 25 GeoEye-1 multispectral satellite images. Generally Geoeye-1 collected a multispectral image at 1.65 meter resolution and then sharpened in the panchromatic mode so that the final image is full color with 0.50 mete resolution. Geoeye-1 satellite was launched successfully from Vandenberg Air Force Base in California on September 6th, 2008. GeoEye-1 has the highest resolution of any commercial imaging system and be able to collect images with a ground resolution of 0.41-meters in the panchromatic or black and white mode [19][20]. Figure 4 shows the original satellite images in RGB color space and these images are transformed into HSV image by linear transformation given in equation (5) - (7). These HSV images are shown in figure 5.

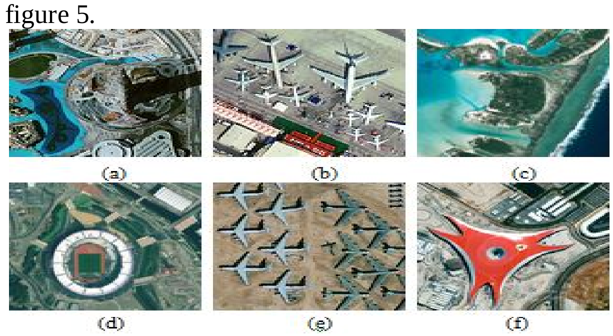

Fig 4.Input images in RGB color space (Satellite images courtesy of GeoEye)

The satellite images in RGB and HSV color space are segmented using the modified k-means clustering algorithm. This experiment is performed for four and five clusters and the result is shown in fig (6) – fig (9).

Indian Streams Research Journal
ISSN 2230-7850
Volume-3, Issue-9, Oct-2013

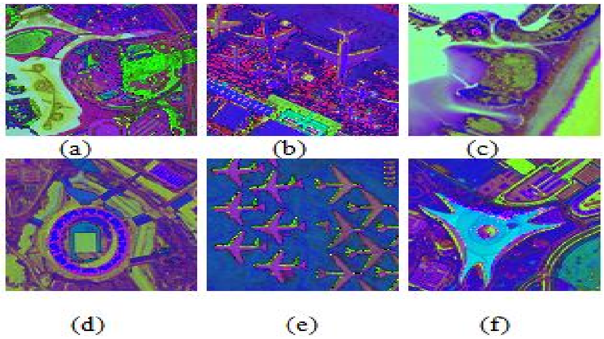

Fig 5.Input images in HSV color space (Satellite images courtesy of GeoEye)

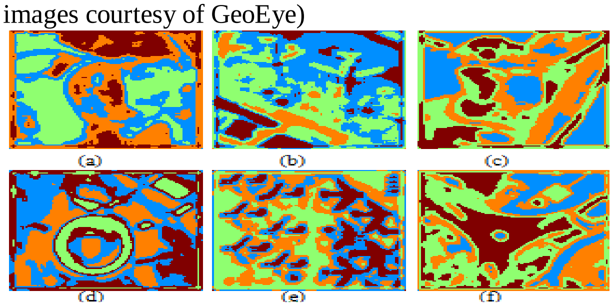

Fig 6.The segmentation result of 4(a) – 4(f) using modified k-means clustering algorithm. The number of cluster is fixed as four.

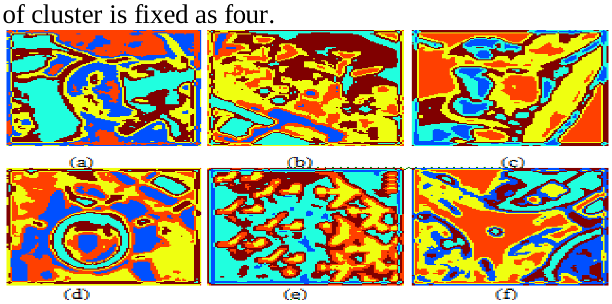

Fig 7.The segmentation result of 4(a) – 4(f) using modified k-means clustering algorithm. The number of cluster is fixed as five.

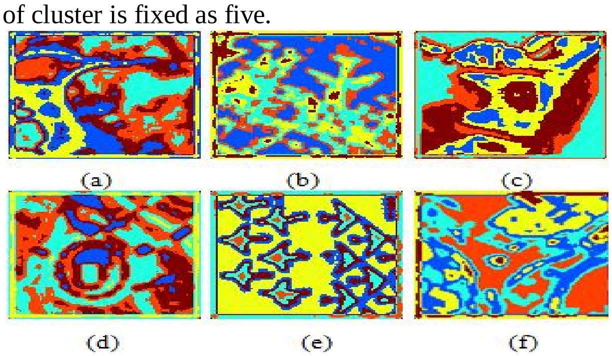

Fig 8.The segmentation result of 5(a) – 5(f) using modified k-means clustering algorithm. The number of cluster is fixed as four.

Available online at www.aygrt.isrj.net

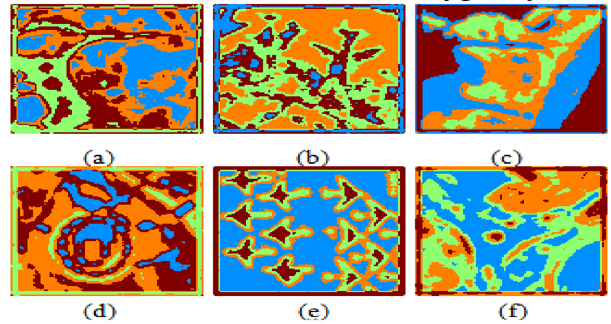

Fig 9.The segmentation result of 5(a) – 5(f) using modified k-means clustering algorithm. The number of cluster is fixed as five.

Figure 10 shows the GeoEye Satellite.

Fig 10.GeoEye Satellite

The tables show the comparative study of our experimental results based on image quality parameters.

Table 1.Comparison of input images in RGB color space (fig 4) and its segmentation results (fig 6). In this case the number of cluster is four.

Parameter	Image 4a and 6a	Image 4b and 6b	Image 4c and 6c	Image 4d and 6d	Image 4e and 6e	Image 4f and 6f
MSE	7.3190e+ 003	5.0005e+ 003	6.9516e+ 003	5.4263e+ 003	8.8644e+ 003	8.1620e+ 003
RMSE	85.5513	70.7140	77.1467	73.6632	94.1509	90.3437
RMSE2	9.1680	8.0903	9.8610	10.9653	10.7619	10.4187
PSNR	9.4863	11.1407	10.3845	10.7858	8.6543	9.0128
NCC	0.9794	1.0141	0.9260	0.9034	0.9285	0.8539
AD	-18.6731	-16.854	0.9878	4.7570	-20.5373	10.4992
MD	235	238	177	195	166	214
NAE	0.5571	0.4228	0.4474	.4176	0.6918	0.4862
MAE	25.1849	17.9406	1.5940	32.6075	28.9961	2.4341
SNR	-0.0064	0.0014	-0.0089	-0.0069	-0.0596	-0.0014
SC	0.7430	0.7760	0.8852	0.7876	0.7243	0.9819

Table 2.Comparison of input images in RGB color space (fig 4) and its segmentation results (fig 7). In this case the number of cluster is five.

Parameter	Image 4a and 7a	Image 4b and 7b	Image 4c and 7c	Image 4d and 7d	Image 4e and 7e	Image 4f and 7f
MSE	6.7774e+003	4.8120e+003	2.2580e+003	6.1457e+003	9.7212e+003	7.8893e+003
RMSE	82.3251	69.3688	47.5181	78.3946	98.5961	88.8217
RMSE2	7.0048	10.6171	8.7278	8.7257	8.2306	10.8319
PSNR	9.8202	11.3075	14.5936	10.2451	8.2536	9.1604
NCC	1.0004	0.8480	1.0247	0.8948	0.9367	0.8454
AD	-24.7041	6.0258	-5.5713	1.0653	-30.7475	4.3670
MD	226	235	172	188	196	220
NAE	0.5289	0.4489	0.2676	0.4236	0.6765	0.4825
MAE	20.4209	31.0079	15.8151	31.1984	23.0226	39.0821
SNR	-0.0168	0.0075	-0.0089	-0.0046	-0.0596	-0.0014
SC	0.7358	1.0563	0.8660	0.9580	0.6908	1.0090

Table 3.Comparison of input images in HSV color space (fig 5) and its segmentation results (fig 8). In this case the number of cluster is four.

Parameter	Image 5a and 8a	Image 5b and 8b	Image 5c and 8c	Image 5d and 8d	Image 5e and 8e	Image 5f and 8f
MSE	6.5626e+003	3.6585e+003	1.2024e+004	8.2453e+003	4.2332e+003	7.7993e+003
RMSE	81.0101	60.4857	109.6558	90.8035	65.0632	88.3134
RMSE2	11.5309	7.6070	6.8404	6.6680	9.4810	4.9527
PSNR	9.9600	12.4977	7.3302	8.9688	11.8641	9.2103
NCC	0.9672	1.2441	1.5223	1.2793	1.0467	1.4178
AD	-4.1271	-32.6583	-73.9295	-55.8383	-15.6719	-61.8802
MD	175	120	161	159	169	160
NAE	0.5333	0.4740	1.0676	0.7704	0.4600	0.8491
MAE	32.6409	7.5386	7.9821	8.4702	17.3543	4.7112
SNR	0	0	0	0	0	0
SC	0.7780	0.5620	0.2996	0.4445	0.7282	0.3797

Table 4.Comparison of input images in HSV color space (fig 5) and its segmentation results (fig 9). In this case the number of cluster is five.

Parameter	Image 5a and 9a	Image 5b and 9b	Image 5c and 9c	Image 5d and 9d	Image 5e and 9e	Image 5f and 9f
MSE	6.9357e+003	3.2863e+003	5.2667e+003	7.6334e+003	4.1642e+003	8.7104e+003
RMSE	83.2807	57.3265	72.5723	87.3693	64.5308	93.3295
RMSE2	10.7679	8.9167	6.5305	6.2274	9.0909	7.7935
PSNR	9.7199	12.9637	10.9154	9.3036	11.9355	8.7304
NCC	0.8715	1.1537	1.3576	1.2749	1.0524	1.3211
AD	0.0561	-22.0516	-48.4121	-57.6184	-18.7104	-57.6708
MD	194	123	161	161	170	167
NAE	0.4966	0.4630	0.7448	0.7689	0.4831	0.9533
MAE	32.3427	12.2922	7.1498	7.5069	17.1010	11.1887
SNR	0	0	0	0	0	0
SC	0.8977	0.6374	0.4383	0.4567	0.7246	0.3948

7. CONCLUSION

In the satellite image processing, segmentation is the most important but difficult process to gather enormous amount of information. There is no unique system or method for processing the satellite images. Usually all the multispectral images are in RGB color space. But the RGB color space is not efficient for object specification and recognition of colors. Moreover the chrominance and the luminance component are mixed and it is difficult to determine specific color in RGB space and. So there is a need for transformation of image in RGB color space into other color space. The HSV color space approximates the human vision. In this space, the illumination variations in the image can easily be solved because the value component is independent of the color. So we have opted this color space for satellite image segmentation. The satellite images are segmented using the modified k means clustering algorithm because this is very simple and faster as compared to other segmentation methods. The numbers of satellite images are segmented using the proposed method and the experimental result shows the efficiency of the proposed approach. Finally the segmentation result is evaluated by using various image quality parameters to compare the result of the RGB and HSV images. The result clearly shows that the HSV color space is more efficient and effective for satellite image segmentation.

REFERENCES

I. J. Pérez, R. Pazos , L. Cruz, G. Reyes, R. Basave, and H. Fraire "Improving the Efficiency and Efficacy of the K-means Clustering Algorithm Through a New Convergence Condition", Gervasi and M. Gavrilova (Eds.):

ICCSA 2007, LNCS 4707, Part III, pp. 674–682. Springer-Verlag Berlin Heidelberg 2007.

II. S. J. Redmond, C. Heneghan, "A method for initialising the K-means clustering algorithm using kd-trees. Science direct", Pattern Recognition Letters 28 (2007) 965–973.

III. Ganesan, P., and V. Rajini. "Segmentation and edge detection of color images using CIELAB color space and edge detectors." Emerging Trends in Robotics and Communication Technologies (INTERACT), 2010 International Conference on. IEEE, 2010.

IV. Ganesan, P., and V. Rajini. "A method to segment color images based on modified fuzzy-possibilistic-c-means clustering algorithm." Recent Advances in Space Technology Services and Climate Change (RSTSCC), 2010. IEEE, 2010.

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

VI. X.Li, X.Lu, J.Tian," Application of fuzzy c-means clustering in data analysis of metabolomics", Analytical chemistry, Vol 80, no.11, pp. 4468-4475, 2009.

VII. http://learn.colorotate.org/color-models.html

VIII. www.equqsys.de

IX. http://www.mathworks.com/

X. R. C. Gonzalez, 2006. Digital Image Processing, Prentice Hall of India, Second Edition.

XI. Sahaphong,S, "Unsupervised Image segmentation using automated Fuzzy c-Means", 7th IEEE Conference on computer and IT, Bangkok, 690-694,2007

XII. A.M. Eskicioglu and P.S. Fisher, "A survey of quality measures for gray scale image compression", Proceedings of Space and Earth Science Data Compression Workshop (Nasa Conference Publication 3191), Utah, Apr 02, 1993, pp.49-61.

XIII. A.M. Eskicioglu and P.S. Fisher, "Image Quality Measures and Their Performance", IEEE Transactions on Communications, Volume 43, No. 12, Dec 1995 pp. 2959-2965.

XIV. Ismail Avcıbas¸ Bulent Sankur and Khalid Sayood (2002) 'Statistical evaluation of image quality measures', Journal of Electronic Imaging Vol. 11, No. 2, pp. 206-223.

XV. Hamid Rahim Sheikh, Muhammad Farooq Sabir and Alan C. Bovik (2006) 'A statistical evaluation of recent full reference image quality assessment algorithms', IEEE Trans Image Processing, Vol. 15, No. 11, pp. 3440-3451

XVI. NoorA.Ibraheem and MokhtarM.Hasan, "Understanding Color Models: A Review", ARPN Journal of Science and technology,Vol.2,No.3,Apr 2012,pp.265-275.

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

XVIII. T. Kanungo, D. Mount, N. Netanyahu, C. Piatko, R. Silverman, and A. Y. Wu "An efficient k-means clustering algorithm: analysis and implementation," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, No. 7, 2002.

XIX. www.satelliteimagingcorporation.com

XX. www.geoeye.com

Ganesan P is working as Assistant Professor in the department of Electronics and Control Engineering in Sathyabama University, Chennai, Tamilnadu, India. He has received his B.E degree from Madurai Kamaraj University, M.E., Degree from Sathyabama University. He is pursuing the Ph.D. degree in the area of image processing. His areas of interest include image and video processing, and computer vision.

V. Rajini is a professor in SSN College of Engineering, Chennai, Tamilnadu, India. She Obtained the B.E. and M.E. degrees from Annamalai University and the Ph.D. degree from Anna University. She has 18 years of teaching and academic experience. Her area of research includes image processing, power systems and high voltage engineering.