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Performance Evaluation of Improved Color Image Segmentation Using Fuzzy Weighting and Edge Preservation

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Abstract— This paper has proposed a new EPS and FELICM approach to get better the accuracy of the color segmentation process advance. The incentive behind the proposed approach is simple and effective. If segmented area between the FELICM and Principle component analysis is same then it will be added into the final output image. If the segmented area is not identical then according to the variance based theory the minimum variance among two segmented outputs will be chosen. After this course of action color labeling will be made to color the segmented area in certain image. The relative analysis has revealed the considerable upgrading of the proposed procedure over the accessible one.

Keywords— Color Segmentation, EPS, FELICM, FUZZY.

I. INTRODUCTION

Image segmentation can be defined as the process of merging pixels having similar features into the same groups, or regions. The segmented image is then the union of distinct groups, where pixels of homogeneous regions are associated to the same groups. Numerous techniques have been proposed in the literature, where color, texture or edges features are used to describe each group [17].

Clustering partitions the unlabeled input vectors into different groups, called clusters, such that data points within a cluster are more similar to each other than they are to those belonging to different clusters, i.e., by maximizing the intra-cluster similarity while minimizing the inter-class similarity. Color image segmentation is a fundamental task in many computer vision problems. A common approach is to use fuzzy iterative clustering algorithms that provide a partition of the pixels into a given number of clusters [16] [17].

Clustering algorithms can be generally classified into two main categories: hard subspace clustering and soft subspace clustering. Hard subspace clustering methods identify the exact subspaces for different clusters, which can be divided into bottom-up and top-down subspace methods according to their subspace searching methods. Soft subspace clustering methods can measure the importance of each dimensionality to a particular cluster in the clustering process by automatically assigning different weightings to different dimensions of clusters embedded in subspaces. Clustering partitions the unlabeled input vectors into different groups, called clusters, such that data points within a cluster are more similar to each other than they are to those belonging to different clusters [8] [20].

Image segmentation is the basic requirement of any computer vision application because people are generally interested only in certain parts of the image. Image segmentation results in non overlapping objects labeled with different region numbers. It should be noticed that no general technique has been developed yet to segment an image precisely, so different techniques are taking floor to perform segmentation. The segmentation process is one of the first steps in the remote sensing image analysis: the image is partitioned into regions which best represent the relevant objects in the scene. Region attributes such as area, shape, statistical parameters and texture can be extracted and used for further analysis of the data [3] [13].

The majority of the segmentation algorithms produce two levels, or “object and background” segmentation. While such a result is appropriate for some of the ‘classical’ image processing applications such as the automatic image analysis of documents or industrial parts, it is not satisfactory for applications dealing with more complex scenes, where several objects have to be detected [2].

II. SEGMENTATION TECHNIQUES

There are different types of segmentation techniques are defined used in digital image processing. Some of them are classified are below:

2.1 Thresholding

Thresholding is the process of converting a multilevel image into a binary image i.e. it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of an image based on a comparison with some threshold value T (intensity or color value). When T is constant, the approach is called global thresholding; otherwise, it is called local thresholding. Global thresholding methods can fail when the background explanation is irregular. The advantage of obtaining first a binary image is that it reduces the complexity of the data and simplifies the process of identification and classification [14].

Multilevel thresholding has multiple thresholds and groups the pixels having gray level within a threshold. The thresholding based methods can be broadly classified as non parametric and parametric. The existing techniques can be viewed as either fixed and, or adaptive. Otsu's method is a non parametric one and yields an optimal threshold to minimize the intra class variances and maximize the inter class variances [27].
Thresholding is a simple shape extraction technique. If it can be assumed that the shape to be extracted is defined by its brightness, then thresholding an image at that brightness level should find the shape. Thresholding is clearly sensitive to change in intensity: if the image intensity changes then so will the perceived brightness/color of the target shape. Unless the threshold level can be arranged to adapt to the change in brightness level, any thresholding technique will fail. Its attraction is simplicity: thresholding does not require much computational effort. Unfortunately, the result of histogram equalization is sensitive to noise, it can affect the resulting image quite dramatically and this will help us to determine the minute changes in the original images clearly [10].

2.2 Region based segmentation
Region-based segmentation is use to image characteristics to map individual pixels in an input image to sets of pixels called regions that may correspond to an object or a meaningful part of one. The objective of region-based method is a group of pixels with similar properties to form a region. The various techniques are: Local techniques, Global techniques and Splitting and merging techniques. If the image is sufficiently simple, then simple local techniques can be useful. Region splitting and merging techniques starts with splitting an image into small regions and continued till regions with required degree of homogeneity becomes produced [14].
Region splitting and merging techniques starts with splitting an image into small regions and continued till regions with required degree of homogeneity are formed. Splitting phase impacts the overall segmentation of the image. This phase results in over segmented image which is followed by the merging phase. Thus these techniques of region splitting and merging are complex and time consuming. The main objective of region growing is to map individual pixels called seeds in input image to a set of pixels called region. Region growing method starts with initial seeds and grows with neighboring homogenous elements. Seed may be pixel or region. The region growing technique is an iterative process by which regions are merged starting from individual pixels, or another initial segmentation, and growing iteratively until every pixel is processed [3] [9].
The problem of partitioning an image into a set of homogenous regions or semantic entities is a fundamental enabling technology for understanding scene structure and identifying relevant objects. Unfortunately, segmentation remains to a large extent an unsolved problem, despite being the subject of study for several decades. Although, it is well recognized that in certain scenarios utilizing segmentation can be very successful, many researchers consider reliable unsupervised general-purpose image segmentation as a hopeless goal. It is an essential first step for scene understanding and that a combined architecture for segmentation and recognition is needed [28].

2.3 Watershed segmentation
Watershed segmentation combines both the discontinuity and similarity properties successfully. It performs well when it can distinguish the background location and the foreground object. It is based on grayscale mathematical morphology. It has many advantages such as it is simple, sensitive, parallel processing, sensitive to weak edges, and can get perfectly connected and closed outlines, and has draw great attention for its fast computing and high accuracy in locating the weak edges of neighboring regions. Watershed algorithm is a method drawing on the side of mathematical morphology for image segmentation, due to its fast calculation speed and accurate closed positioning of the contour and so is attracting attention from the topography of its basic idea, image as natural landscape is covered by water, pixel gray value indicates altitude, a local minimum value and the area affected are known as the catchment basins, and the border is known as a watershed [1] [15].
Watershed transformation which is a powerful image segmentation technique is used in several applications like object-based motion estimation, medical imaging, multi-spectral satellite imagery, computer vision, etc. However, the major problem of this technique is over-segmentation. Several approaches have been proposed for improving watershed algorithm by extracting markers or by filtering. In mathematical morphology, watershed algorithm is based on immersion principle, aiming at separating an image into homogeneous areas. An image can, indeed, be observed as a relief in which we associate an altitude to the grey level of each pixel. The Watershed is defined as the peak forming the limit between two basins. It operates on the gradient image where contours are enhanced appearing as local maxima in the image. After re sorting the peaks identified as contours, watershed based segmentation algorithm finds out the homogenous regions as the inner basins regions [23]
The major drawback of watershed segmentation is that it generates excessive over segmentation for most natural images due to false gradients caused by kinds of noises and textures. To cope with this problem, many works has been done. Appropriate smoothing strategy is able to suppress noise; spurious local minima are reduced accordingly. Furthermore, median filter and morphological gradient reconstruction are also used in the watershed-based segmentation algorithms. There are many hybrid segmentation algorithms combining watershed transform with other models which achieved promising results for certain applications, but they may fail in other images [10].

2.4 Fuzzy based segmentation
The Fuzzy C- means is the most widely used algorithm in image segmentation because it has robust characteristics for ambiguity and it can maintain much more information than hard segmentation methods. FCM has been successfully

applied to feature analysis, clustering, and classified designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. An image can be represented in various feature spaces and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. The standard Fuzzy C-Means clustering is one of the most widely used fuzzy clustering algorithms. The FCM algorithm attempts to partition a finite collection of elements into a collection of fuzzy clusters with respect to some given criterion [12].

Fuzzy clustering is often suitable for classification of data in decision oriented applications like tissue classification, tumor detection etc. One of the most difficult tasks in image analysis and computer vision applications is to classify correctly the pixel values as there are no crisp boundaries between objects in an image. In order to deal with this difficult task, fuzzy clustering techniques are proving to be a successful research area. The method of image segmentation using fuzzy clustering technique provides a mean of classifying pixel values with a great amount of correctness. The advantage of Fuzzy systems is that they are easy to understand, because the membership functions partition the data space properly [9].

A new fuzzy connectivity based anisotropic region growing algorithm has been developed that uses tensor scale to facilitate region growing along local structure while arresting cross-structure leaking. In our approach, anisotropy of local structures through tensor scale is incorporated into the theoretical fuzzy connectivity model through a new local parameter control strategy. The notion of a tensor scale is a unified representation of local structure size, orientation and anisotropy. Effectiveness of fuzzy connectivity is highly dependent on the choice of the affinity relation. On the other hand, softening the rules to capture the broken continuity may cause leaking through other regions. However, a human expert may capture the broken continuity implicitly using the contextual knowledge of local structures. Here, we develop an anisotropic region growing algorithm where the growing rules adapt to local structure geometry. To solve this problem, we use tensor scale that gives an ellipsoidal representation of the local structure at every image point and construct a local structure-adaptive formulation of the fuzzy affinity function [11].

Image segmentation can be defined as the process of merging pixels having similar features into the same groups, or regions. The segmented image is then the union of distinct groups, where pixels of homogeneous regions are associated to the same groups. Numerous techniques have been proposed in the literature, where color, texture or edges features are used to describe each group. Only gray level images were considered by early segmentation methods. As color images become the norm in a wider range of and thanks to advancements in color technology and computation power, the interest of color image segmentation techniques has grown. Among them, we focus on the clustering approach, especially the fuzzy c-means algorithm, which is used by many segmentation methods. However, this algorithm requires initializing the centers of each cluster, and is known to be intractable for very large data sets such as color images. Image clustering is an effective method for image original segmentation, but it usually regards the pixels as isolated samples and ignores the spatial relationships among pixels, so it is very sensitive to noise [5] [17].

III. PROPOSED ALGORITHM

3.1 Problem definition

The survey has shown that the most of the existing techniques have focused on the complex regions. Therefore not much work has been done for the images with mixed regions. The effect of the regions on the segmentation has been neglected by many researchers. The effect of the color on the segmentation results has also been neglected by many researchers.

3.2 Proposed algorithm

The proposed method of image segmentation process is described following steps provided below.

Step 1: We have used an RGB image as input color image. The original image is extracted into individual red (R), green (G), and blue (B) color channels.

Step 2: The EPS is applied on the RGB image to smoothes missing information as holding the sharp edges and successfully remove noise without blurring inter-region edges in the image.

Step 3: Now apply Rgb2hsv transforms colors from RGB space (red/green/blue) into HSV space (hue/saturation/value).Value (brightness) gives the amount of light in the color; hue describes the dominant wavelength and Saturation is the amount of Hue mixed into the color.

Step 4: PCA is applied on all the blocks of the HSV image and the data set is reduced. It is useful for the compression and classification of data.

Step 5: Apply variance based integration on segmented outputs by PCA and FEILCM.

$If\ seg_{img\,1}.object(i*i) == seg_{img\,2}.object(i*i)$

$\quad add\ to\ the\ output\ O(x,y)$

$else$

$\quad If\ VAR(seg_{img\,1}.object(i*i)) >= VAR(seg_{img\,2}.object(i*i))$

$\quad\quad add\ seg_{img\,2}\ the\ output\ O(x,y)$

$\quad else$

$\quad\quad add\ seg_{img\,1}\ the\ output\ O(x,y)$

$\quad End$

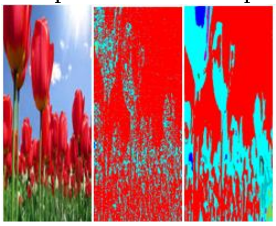
End

Step 6: In edge pixel processing, calculate the average value of the HSV image is formed by the PCA and FEILCM.

Step 7: Finally applied the color labeling on the HSV image plane to color the segment image.

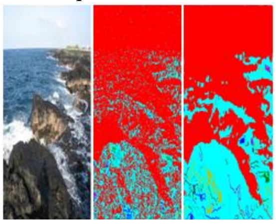
IV. EXPERIMENTAL RESULTS

These are some following images which helps to compare the results of proposed algorithm with existing approch. A new EPS and FELICM approach to get better the accuracy of the color segmentation process further. The comparative analysis has shown the significant improvement of the proposed technique over the available one.



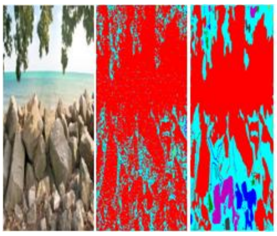
(a) (b) (c)

Fig-1 (a) Original image (b) Result of existing approach (c) Result of Proposed method



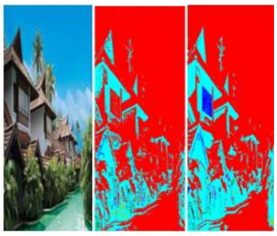
(a) (b) (c)

Fig-2 (a) Original image (b) Result of existing approach (c) Result of Proposed method



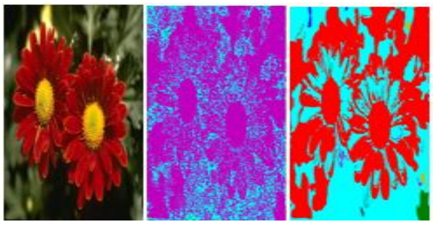
(a) (b) (c)

Fig-3 (a) Original image (b) Result of existing approach (c) Result of Proposed method



(a) (b) (c)

Fig-4 (a) Original image (b) Result of existing approach (c) Result of Proposed method



(a) (b) (c)

Fig-5 (a) Original image (b) Result of existing approach (c) Result of Proposed method

These Figures shows better human visibility of original image by using proposed algorithm as compared to previous technique. This method can efficiently enhance the overall quality and visibility of local details. The experiments show that EPS and FELICM method is insensitive to the isolated regions and obtains more accurate edges and clustering than previous technique.

V. PERFORMANCE EVALUATION

This section contains the cross confirmation between base paper and Proposed techniques. Some well-known image performance metrics for digital images have been selected to prove that the performance of the proposed method is quite better than the other methods.

5.1. MSE Analysis

The mean square error is the cumulative squared error between the compressed and the original image.A lower value for MSE means less error. mean square error is one way to evaluate the difference between an estimator and the true value of the quantity being estimated. It can be calculated as:

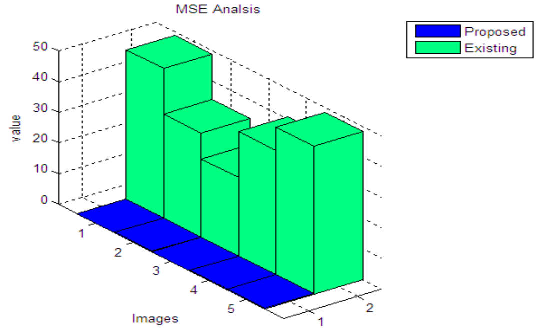
$$MSE= \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N}$$

Where M and N are the number of rows and columns in the input image I_1 and output image I_2 respectively.

Table-5.1.1: Mean Square Error Evaluation

Images	**Existing**	**Proposed**
1	**48.7893**	**0.1256**
2	**33.9046**	**0.1568**
3	**25.5740**	**0.0572**
4	**40.6789**	**0.1408**
5	**48.2234**	**0.1256**

Table-5.1 illustrates the evaluatation of existing and proposed methods. By using proposed algorithm, the results of MSE becomes lower than previous results. So the main goal as mean square error is less in every case.
The following graph represents the information of mean square error and evaluates it within two statements. Green bar reveal the existing method and Blue bar define the proposed method which are improved as compared to earlier ones. This decrease represents improvement in the objective quality of the image.



Graph-5.1.2: MSE of previous results and proposed results for different images

5.2 PSNR Analysis

Peak signal to noise ratio is defined as a term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation, due to its dynamically property. It is an approximation to human perception of reconstruction quality.

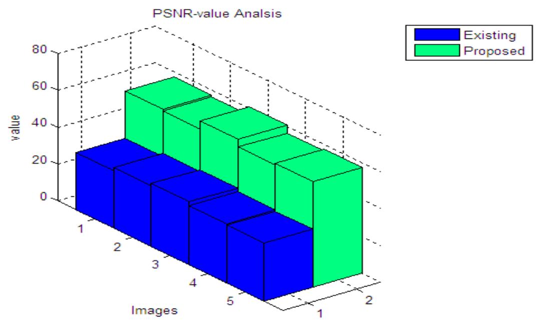
Table-5.2.1: Peak Signal to Noise Ratio Evaluation

Images	Existing	Proposed
1	**31.2816**	**57.1744**
2	**32.8622**	**56.2101**
3	**34.0868**	**60.5929**
4	**32.0711**	**56.3168**
5	**31.3322**	**57.1764**

Table-5.2.1shows the comparison of Peak signal to noise ratio between existing and proposed method. By using proposed algorithm the value of PSNR becomes higher as compared to previous results.
To compute the peak signal to noise ratio, firstly calculate the mean square error. It can be calculated as by following given formulas such as:

$$PSNR \ = 10log_{10}\left(\frac{R^2}{MSE}\right)$$

Where R is the maximum fluctuations occurred in the input image data type.
The following graph shows the representation of PSNR value analysis difference between previous and proposed techniques. Blue bar reveal the existing method and Green bar define the proposed method which are better as compared to previous ones.



Graph-5.2.2: PSNR of previous results and proposed results for different images

5.3 RMSE Analysis

The root mean square value of a set of values is the square root of the arithmetic mean of the square of the values. Whereas root mean square error measures how much error there is between two datasets. It usually compares a predicted value and observed value. Basically it can be calculated as by following mathematical expression such as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}_i)^2}$$

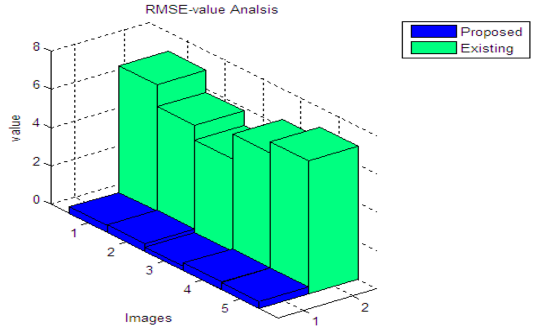
Where $x_i$the forecast value of the parameter, $\bar{x}_i$ is the corresponding verifying value and N is the number of verifying points. RMSE is a measure of the "average" error, weighted according to the square of the error. Its range is from 0 to infinity.

Table-5.3.1: Root Mean Square Error Evaluation

Images	Existing	Proposed
1	6.9849	0.3544
2	5.8228	0.3960
3	5.0571	0.2391
4	6.3780	0.3753
5	6.9443	0.3543

Table-5.3.1 shows the comparison of Root mean square error between existing and proposed method. By using proposed algorithm the value of PSNR becomes higher as compared to previous results.

The following graph demonstrates the representation of RMSE value analysis between previous and proposed techniques. Green bar reveal the existing method and Blue bar define the proposed method which are superior as compared to previous ones.



Graph-5.3.2: RMSE of previous results and proposed results for different images

5.4 Entropy Analysis

Entropy is a measure of the efficiency of a particular data items. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. It is consider the spread of states which a system can adopt. A low entropy system occupies a small number of such states, while a high entropy system occupies a large number of states.

Table-5.4.1: Entropy Analysis Evaluation

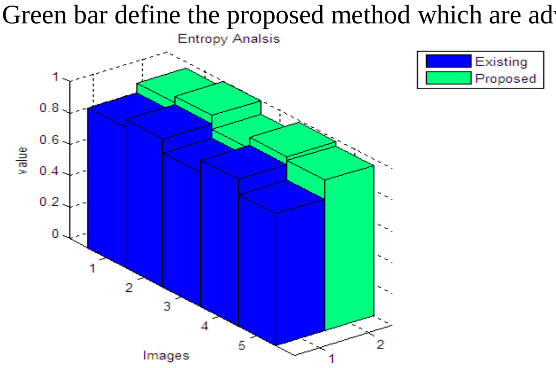
Images	Existing	Proposed
1	0.8938	0.9572
2	0.9420	0.9975
3	0.8535	0.9111
4	0.9326	0.9829
5	0.8359	0.9564

Table-5.4.1 shows the comparison of Entropy analysis between existing and proposed method. By using proposed algorithm the value of Entropy becomes higher as compared to previous results. Generally entropy may be defined by following mathematical expression such as:

$$H= -sum(P.\star\ \log_2 P)$$

Where P contains the histogram counts returns from imhist mat lab function. By default, entropy uses two bins for logical arrays and 256 bins for uint8, uint16 or double arrays.

The following graph shows the representation of entropy value analysis between previous and proposed techniques. Blue bar reveal the existing method and Green bar define the proposed method which are advanced as compared to prior ones.



Graph-5.4.2: Entropy of previous results and proposed results for different images

The entropy concept, which is used to represent the certainty of dimensions in the identification of a cluster, is introduced into clustering. Because the weights in extend subspace clustering algorithms are controllable by entropy parameter [11].

5.5 Accuracy
Accuracy is generally defined as the degree of correctness. It is how close a measured value is to the actual value and it is also used as a statistical measure of how well a binary classification test correctly identifies a condition. It is the proportion of true results among the total number of cases examined.

$$A=\frac{No.of\ TP+No.of\ TN}{No.of\ TP+FP+FN+TN}$$

Whereas TP is correctly the true positive, TN is the true negative, FP is the false positive, and FN is the false negative.
Accuracy is defined in terms of sensitivity and specificity, whereas sensitivity measures the proportion of actual positives which are correctly identified and is complementary to the false negative relation. On the other hand, specificity measures the proportion of negatives which are correctly identified and it's complimentary to the false positive rate.

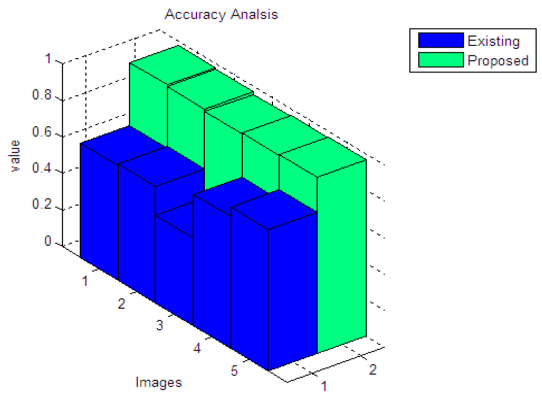
$$\text{Sensitivity}=\frac{No.of\ TP}{No.of\ TP+No.of\ FN}$$

$$\text{Specificity}=\frac{No.of\ TN}{No.of\ TN+No.of\ FP}$$

Table-5.5.1: Accuracy Analysis Evaluation

Images	Existing	Proposed
1	0.6269	0.9754
2	0.6398	0.9665
3	0.4799	0.9527
4	0.7186	0.9619
5	0.7708	0.9656

Table-5.5.1 shows the comparison of Accuracy analysis between existing and proposed method. By using proposed algorithm the value of Accuracy becomes higher as compared to previous results.
The following graph shows the representation of Accuracy value analysis between previous and proposed techniques. Blue bar reveal the existing method and Green bar define the proposed method which are advanced as compared to prior ones.



Graph-5.5.2: Accuracy of previous results and proposed results for different images

VI. CONCLUSION
Clustering based methods are a procedure in which an image or say pixels are transformed into clusters may belong together because of the same color, texture etc. The analysis has revealed that the prior methods have concentrated on the composite regions. Therefore not much work has been done for the pictures with blended locales. The impacts of the districts on the separation have been unseen by frequent analysts. The collision of the color on the division results has additionally been dismissed. This paper has proposed a new EPS and FELICM approach to improve the accuracy of the color segmentation procedure further. The motivation behind the proposed approach is simple and effective. If segmented area between the FELICM and Principle component analysis is same then it will be added into the final output image. If the segmented area is not same then according to the variance based theory the minimum variance among two segmented outputs will be selected. After this procedure color labeling will be done to color the segmented area in given image. The proposed technique has been designed and implements using MATLAB toolbox. The comparative analysis has shown the major improvement of the proposed technique over the available one.
This work has not measured the use of adaptive thresholding to segment the given image. Therefore in near future we will try to discover adaptive thresholding using evolutionary optimization.

REFERENCES

[1] Rahman, Md, and Md Islam. "Segmentation of color image using adaptive thresholding and masking with watershed algorithm" IEEE International Conference on Informatics, Electronics & Vision (ICIEV), pp. 1-6., May 2013.

[2] Qiu, Tianshuang, Aiqi Wang, Nannan Yu, and Aimin Song. "LLSURE: local linear SURE-based edge-preserving image filtering" IEEE International Conference on Image Processing, no. 1, pp. 80-90. 2013.

[3] Wang, Haoxing, Longquan Dai, and Xiaopeng Zhang. "Edge Guided High Order Image Smoothing" IEEE International Conference on Pattern Recognition, pp. 682-686. November 2013.

[4] Rahman, Md, and Md Islam. "Segmentation of color image using adaptive thresholding and masking with watershed algorithm" IEEE International Conference on Informatics, Electronics & Vision (ICIEV), pp. 1-6., May 2013.

[5] Li, Nan, Hong Huo, Yu-ming Zhao, Xi Chen, and Tao Fang. "A Spatial Clustering Method with Edge Weighting for Image Segmentation" IEEE International Conference on Geoscience and Remote Sensing Letters, vol. 10,pp. 1-5, Sept 2013.

[6] Xu, Ziyue, Zhiyun Gao, Eric A. Hoffman, and Punam K. Saha. "Tensor scale-based anisotropic region growing for segmentation of elongated biological structures" IEEE International Symposium on Biomedical Imaging, pp. 1032-1035. May 2012.

[7] Gong, Maoguo, Zhiqiang Zhou, and Jingjing Ma. "Change detection in synthetic aperture radar image based on fusion and fuzzy clustering." IEEE International Conference on Image Processing, pp. 2141-2151., April 2012.

[8] Han, Xianwei, Yili Fu, and Haifeng Zhang. "A fast two-step marker-controlled watershed image segmentation method" International Conference on Mechatronics and Automation, pp. 1375-1380. August 2012.

[9] Bao, Linchao, Yibing Song, Qingxiong Yang, and Narendra Ahuja. "An edge-preserving filtering framework for visibility restoration" IEEE International Conference on Pattern Recognition (ICPR),pp. 384-387, November 2012.

[10] Han, Xianwei, Yili Fu, and Haifeng Zhang. "A fast two-step marker-controlled watershed image segmentation method" International Conference on Mechatronics and Automation, pp. 1375-1380. August 2012.

[11] Xu, Ziyue, Zhiyun Gao, Eric A. Hoffman, and Punam K. Saha. "Tensor scale-based anisotropic region growing for segmentation of elongated biological structures" IEEE International Symposium on Biomedical Imaging, pp. 1032-1035. May 2012.

[12] Mondal, Koushik, Paramartha Dutta, and Siddhartha Bhattacharyya. "Efficient fuzzy rule base design using image features for image extraction and segmentation" International Conference on Computational Intelligence and Communication Networks, pp. 793-799. November 2012.

[13] Yu, Jing, and Qingmin Liao. "Fast single image fog removal using edge-preserving smoothing" IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1245-1248, May 2011.

[14] Singha, Manimala, and K. Hemachandran. "Color Image Segmentation for Satellite Images" International Journal on Computer Science & Engineering (IJCSE), vol. 3, pp. 3756-3762., Dec 2011.

[15] Wang, Lei, and Lin Zhang. "Watershed segmentation based on gradient reconstruction and region merging" International Conference on, Computer Science and Network Technology, vol. 3, pp. 1585-1589. December 2011.

[16] Zhu, Lin, Longbing Cao, and Jie Yang. "Soft subspace clustering with competitive agglomeration" IEEE International Conference in Fuzzy systems, pp. 691-698, June 2011.

[17] Le Capitaine, Hoel and Carl Frelicot. "A fast fuzzy c-means algorithm for color image segmentation." International Journal on Computer Science & Engineering, pp. 1074-1081, 2011.

[18] Havens, Timothy C., Radha Chitta, Anil K . Jain, and Rong Jin. " Speedup of fuzzy and possibilistic kernel c-means for large –scale clustering ." IEEE International Conference on Fuzzy systems (FUZZ), pp. 463-470., June 2011.

[19] Wang, Lei, and Lin Zhang. "Watershed segmentation based on gradient reconstruction and region merging" International Conference on, Computer Science and Network Technology, vol. 3, pp. 1585-1589. December 2011.

[20] Zanaty, E.A., and Sultan Aljahdali. "Improving Fuzzy algorithms for automatic image segmentation." IEEE International Conference on Multimedia computing and systems, (ICMCS), pp. 1-6., April 2011.

[21] Ji, Qinghua, and Ronggang shi. "A noval method of image segmentation using watershed transformation." IEEE International Conference on Computer Science and Network Technology (ICCSNT), pp. 1590-1594, December 2011.

[22] Du, Wenliang, Xiaolin Tian, and Yankui Sun. "A dynamic threshold edge-preserving smoothing segmentation algorithm for anterior chamber oct images based on modified histogram" IEEE International Conference on Image and Signal Processing, vol. 2, pp. 1123-1126. October 2011.

[23] Verma, Om Prakash, Madasu Hanmandlu, Seba Susan, Muralidhar Kulkarni, and Puneet Kumar Jain. "A simple single seeded region growing algorithm for color image segmentation using adaptive thresholding" IEEE International Conference on Communication Systems and Network Technologies (CSNT), pp. 500-503., June, 2011.

[24] Niu, Sijie, Yuan Jia, and Pengcheng Liu. "Gradient vector flow and watershed transformation combined segmentation algorithm" International Conference on Artificial Intelligence, Management Science and Electronic Commerce, pp. 4003-4006. August 2011.

[25] Du, Wenliang, Xiaolin Tian, and Yankui Sun. "A dynamic threshold edge-preserving smoothing segmentation algorithm for anterior chamber oct images based on modified histogram" IEEE International Conference on Image and Signal Processing, vol. 2, pp. 1123-1126. October 2011.

[26] Zghal, N. S., and Dorra Sellami Masmoudi. "An improved OTSU based watershed segmentation and its implementation on Virtex II pro platform" 7th International Journal Multi-Conference on Systems Signals and Devices, pp. 1-5. June 2010.

[27] Swaroop Pradhan, S., Dipti Patra, and P. Kumar Nanda. "Adaptive Thresholding Based Image Segmentation with Uneven Lighting Condition" IEEE International Conference on Industrial and Information Systems, pp. 1-6. December 2008.

[28] Adamek, Tomasz, Noel E. O'Connor, and Noel Murphy. "Region-based segmentation of images using syntactic visual features" International Journal, 2005

