Abstract

Background/Objectives: Image segmentation is the first step for any image processing based applications. The conventional methods are unable to produce good segmentation results for color images. Methods/Statistical analysis: We present two soft computing approaches namely Fuzzy C-Means (FCM) clustering and Self Organizing Map (SOM) network are used to segment the color images. The segmentation results of FCM and SOM compared to the results of K-Means clustering.

Results/Findings: Our experimental results shown that the Fuzzy C-Means and SOM produced the better results than K-means for segmenting complex color images. The time required for the training of SOM is higher.

Conclusion/Application: The trained SOM network reduced the execution time for segmenting color images. The performance of FCM and SOM is higher than the K-means for segmenting color images. Applications of color image segmentation are video surveillance, face recognition, fingerprint recognition, object detection, medical image analysis, and Automatic target detection.

Keywords: Clustering, FCM, Image Segmentation, K-Means, SOM, Subtractive Clustering

1. Introduction

Color image segmentation is the challenging task in image processing and contains two critical issues, firstly which color model to be used and secondly, which segmentation technique should be applied. A color space is a method by which we can specify, create and visualize colors. Several color representations, such as RGB, HSI, CMY, CMYK, YIQ, CIE L’ab’, etc., are employed for color segmentation, but none of them can dominate the others for all kinds of colors images\(^1\). Each color representation has its advantages and disadvantages. RGB model is device dependent. A CIE L’ab’ color space is a color opponent space with dimension L for lightness and ‘a’ and ‘b’ for the color-opponent dimensions, based on nonlinearly compressed CIE XYZ color space coordinates\(^2\).

The advantages of CIE L’ab’ color space are: It is designed to approximate human vision; The CIE L’ab’ color space includes all perceptible colors; It is device independent; It is used in many industries apart from printing and photography; It provides exact color specifications for paint.

The segmentation of color image has been proved to be difficult because it involves a vast amount of data processing. In computer vision literature, various methods dealing with segmentation have been discussed. Although great efforts have been devoted to it, some issues are still not fully addressed. Shirakawa and Tomoharu\(^3\) proposed evolutionary image segmentation based on multiobjective clustering. Two objectives, overall deviation and edge value, are optimized simultaneously using a multiobjective evolutionary algorithm. Yang and Huang\(^4\), have modified the objective function of the standard FCM algorithm with a penalty term that takes into account the influence of the neighboring pixels on the centre pixels for image segmentation. In \(^5\) fuzzy clustering algorithms and competitive neural network was used for color image segmentation. The self estimation algorithm was suggested for automatically finding the number of clusters using Euclidean distance. The features extracted using

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Discrete Wavelet Transform (DWT) fed to fuzzy C-means algorithm and the membership function created by FCM was used as a target to be fed to the back-propagation neural network.

Deshmukh and Shinde proposed the neuro-fuzzy system ACIS-FMC. It uses a Multilayer Perceptron (MLP) like network which performs color image segmentation using multilevel thresholding. Threshold values used for finding clusters and their labels are found automatically using FMMN clustering technique. FCM algorithm was used to define the target of the supervised feed-forward neural network and a fuzzy entropy method was deployed to set a threshold value for improving the segmented image. Dong et al. proposed a hybrid system which comprises unsupervised segmentation and supervised segmentation. The unsupervised segmentation is achieved by a two-level approach, i.e., color reduction and color clustering. The supervised segmentation involves color learning and pixel classification. Simulated Annealing (SA) has been used for finding the optimal clusters form SOM prototypes.

The color image segmentation results based on soft computing techniques are proven to be better than conventional hard clustering techniques. FCM, used for color image segmentation. A. Borji et al. proposed new method for color image segmentation using fuzzy logic. Wen-Xiong Kang et al. compared the various Image Segmentation Algorithms. Some researchers modified and expanded the typical SOM. Most of the researchers modified and expanded the FCM. N. Senthilkumaran and R. Rajesh, explained the various edge detection techniques using soft computing approaches.

Dongxiang Chi suggested that SOM with K-Means. SOM-K, a new unsupervised natural image segmentation method based on SOM and k-means and also stated that clustering method like k-means and their variants are not acceptable for considering the computational cost and a priori cluster number k needed. The various clustering methods are applied on the time series databases. When compare the clustering methods, the SOM performs well in forming clusters. Rajiv Kumar and A.M. Arthanarier proposed hybrid method that combines region-based and cluster-based. The time consumption of FCM is less when compare with the K-Means clustering method. P. Ganesan et al. proposed fuzzy based segmentation method in YCbCr Color space. RGB color space is not efficient for object specification and recognition of colors. A hybrid method, which is based on split and merge approach, is proposed for detecting the fruit defects. The k-means algorithm is used to split the original image into regions and merging by minimum spanning tree procedure.

2. Fuzzy C-Means Clustering

FCM Clustering algorithm is frequently used in pattern recognition. FCM assigns membership to each data point on the basis of distance between the cluster and the data point. The algorithm is based on minimization of the objective function (1).

\[ \sum_{i=1}^{N} \sum_{j=1}^{C} U_{ij}^{m} \| x_i - c_j \|^2 \]  

Where \( N \) is the number of data, \( c \) is the number of clusters, \( u_{ij} \) is the degree of membership of \( x_i \) in the cluster \( j \).

There are four main steps in this approach for segmenting the color images:

Step1: Image acquisition
Step2: Preprocessing: To convert an image in RGB into CIE L’a’b’
Step3: Clustering by using Fuzzy clustering method.
Step4: Segmentation process: Assign label to highest membership value in each column of the partition matrix \( U \) that indicates a data point belongs to which cluster center. Find the segmented images from the labeled matrix.

The FCM clustering process has been carried out with variety of images. The segmentation results are shown in Figure 3 and Table 1.

3. Self-organizing Map (SOM)

A Self-organizing Map (SOM) network is a type of artificial neural network that is trained using unsupervised learning. The SOM map consists of a competitive layer which can classify a dataset of vectors with any number of dimensions into as many classes as the layer has neurons. The neurons are arranged in a 2D topology, which allows the layer to form a representation of the distribution and a two-dimensional approximation of the topology of the dataset. The SOM learn to cluster data based on similarity, topology. The goal of learning in the self-organizing map is to cause different parts of the network to respond similarly to certain input pattern.
Table 1. Experimental results of FCM on L’a’b’ color space

| Image Size | No. of cluster | Running Time in seconds | No. of iterations | Objective function minimization status |
|------------|----------------|-------------------------|-------------------|----------------------------------------|
| 225x225    | 4              | 2.23272                 | 49                |                                        |
| 148x111    | 4              | 0.68907                 | 40                |                                        |
| 150x120    | 4              | 0.79848                 | 48                |                                        |
| 225x225    | 3              | 1.542816                | 42                |                                        |
| 259x194    | 3              | 0.64425                 | 18                |                                        |
| 225x225    | 4              | 2.41344                 | 43                |                                        |

4. Determining the Number of Clusters and Cluster Validity

If the number of clusters is manually specified, the segmentation may not be effective. Two main issues in clustering are determining the number of clusters and measure to evaluate the quality of the clusters.

4.1 Finding Number of Cluster

In this paper we have used an algorithm based on co-occurrence matrix for finding the number of clusters.

Algorithm: Co-occurrence matrix based method

Step 1: Read an image I
Step 2: Transform image I to HSV color space.
Step 3: Calculate the co-occurrence matrix $T$ for $H$ values.
Step 4: Pick the diagonal values of co-occurrence matrix and store them in $d$.
Step 5: Find the local maximum from the diagonal values by i) finding the mean of the diagonal values of co-occurrence matrix, ii) defining $K$ as the number of values that are greater than or equal to the mean value.
Step 6: $K$ is the final number of clusters.

Subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. When Compared to K-means and FCM, this result is a little bit behind the accuracy achieved in those other techniques. But we can use this method for initializing the cluster center.

4.2 Method of Cluster Validation

The hardest problem in comparing different clustering algorithms is to find an independent measure to evaluate the quality of the clusters. In our paper we have used the silhouette index value for evaluating the cluster compactness. The silhouette value for each pixel is a measure of how similar that pixel is to pixels in its own cluster vs. pixels in other clusters, and it ranges from -1 to +1. For pixel $i$, it is defined as

$$s(i) = \frac{b_i - a_i}{\max(a_i, b_i)}$$

Where ‘$a_i$’ is the average distance from the $i$th pixel to the other pixels in the same cluster, and ‘$b_i$’ is the minimum average distance from the $i$th pixel to the pixels in a different cluster, minimized over all different clusters. It is clear...
from the above definition \(-1 \leq s(i) \leq 1\). The silhouette value is calculated using (1) for each pixel of the clustered image. For fixing the correct number of clusters the following method is used in our paper.

**Algorithm for Finding Cluster Validity**

**Step 1** Read an image I.

**Step 2** Preprocessing.

**Step 3** Initialize the number of clusters \(K = 2\) and set the previous silhouette value = 0.

**Step 4** While \(k \geq 2\) do the following

**Step 5** Cluster the image using any algorithm.

**Step 6** Find the silhouette index value for the image by \(s(i) = \text{mean}\) (silhouette values of all pixels in image I).

**Step 7** If \(s(i) > \text{previous silhouette value}\)

\(k = k + 1 / \text{increase the number of clusters}\)

\(\text{Previous silhouette value} = s(i)\)

\(\text{goto step 4.}\)

Else return \(k - 1 / \text{K-number of clusters.}\)

**Step 8** Stop.

5. Result and Discussion

**Table 2.** Cluster count found by co-occurrence matrix based method and Subtractive clustering

| SNo. | Image          | No. of clusters found by Co-occurrence matrix based method | No. of clusters found by Subtractive clustering |
|------|----------------|----------------------------------------------------------|-------------------------------------------------|
| 1    | Test Image 1   | 4                                                        | 3                                               |
| 2    | Test Image 2   | 4                                                        | 3                                               |
| 3    | Test Image 3   | 5                                                        | 2                                               |
| 4    | Test Image 4   | 2                                                        | 2                                               |

Test Image 5

Test Image 6

Test Image 7

Test Image 8

Test Image 9

Test Image 10

Test Image 11

Test Image 12

Test Image 13

Test Image 14

(Continued)
All the algorithms are executed and tested using MatlabR2013a with a variety of images. For a sample, the results of few images are discussed. FCM is applied to the L*a*b* color space transformed image for improving the segmentation results which are shown in Figure 3. The advantage of FCM is that unlike K-means clustering a pixel may belong to more than one cluster. The main drawbacks of FCM are computational time and more sensitive to initialization conditions of cluster number and cluster center. Different number of clusters is also chosen for segmenting the various test images. In many clustering algorithms such as K-means and FCM need number of clusters as input. Two Methods co-occurrence based and subtractive clustering for finding number of clusters of test images and the results are shown in Table 2 and the comparison between the methods have been shown in Figure 1. Both methods are produced same results for 10 test images out of 23 images. From the silhouette index for the clustering images after applying K-means, FCM and SOM with various number of cluster counts, the results shown that co-occurrence based method is better than subtractive clustering method to determine the number of clusters needed for images. Most of the images have higher silhouette index for k = 2. But k = 2 is not sufficient for many complex color images. In such cases start from k = 3. So these methods act as prior step for clustering algorithms. The execution time of subtractive clustering is higher than the co-occurrence based method. The execution time is lowest for K-means and highest for FCM and SOM. The execution time is very less for the trained SOM used for segmentation.

### Table 2. Continued

| SNo. | Image | No. of clusters found by Co-occurrence matrix based method | No. of clusters found by Subtractive clustering |
|------|-------|----------------------------------------------------------|-----------------------------------------------|
| 15   | Test Image 15 | 3                                                         | 4                                             |
| 16   | Test Image 16 | 4                                                         | 3                                             |
| 17   | Test Image 17 | 3                                                         | 3                                             |
| 18   | Test Image 18 | 3                                                         | 3                                             |
| 19   | Test Image 19 | 3                                                         | 3                                             |
| 20   | Test Image 20 | 3                                                         | 3                                             |
| 21   | Test Image 21 | 3                                                         | 3                                             |
| 22   | Test Image 22 | 4                                                         | 4                                             |
| 23   | Test Image 23 | 3                                                         | 4                                             |

**Figure 1.** Comparison of cluster count found by co-occurrence matrix based method and Subtractive clustering.
As compared to K-means algorithm FCM is better for complex color images. The Table 4 providing the parameter silhouette values for the evaluation of cluster compactness of K-Means, FCM and SOM. As it is clearly evident from the Table 4 the performance of K-Means method are less effective compare to FCM and SOM for the complex color images. Advantage of FCM is each pixel is assigned membership to each cluster unlike K-means clustering a pixel may belong to more than one cluster. The main drawback of FCM is Computational time, more Sensitive to initialization condition of cluster number and cluster center.

We have chosen random initialization for SOM because with random initialization our cluster (segment) centers have good chance of searching the maximum color segmentation space available. SOM produces result close to FCM but results of SOM can be more optimized by combining another method. The experimental results of SOM are shown in Figure 4. In Table 4 it can be seen that silhouette values of 13 test images segmented by FCM and SOM are higher than K-Means. Table 3 consists of this details and comparison chart shown in Figure 2. When the k value is small then K-Means performance is good.

**Table 3.** Silhouette values of test images with FCM and SOM performance higher than the K-Means

| Image          | K-Means | FCM  | SOM  |
|----------------|---------|------|------|
| Test Image 6   | 0.7213  | 0.7939 | 0.7426 |
| Test Image 7   | 0.769   | 0.7939 | 0.7387 |
| Test Image 8   | 0.696   | 0.7517 | 0.7389 |
| Test Image 9   | 0.6417  | 0.7479 | 0.7395 |
| Test Image 11  | 0.7195  | 0.7495 | 0.7383 |
| Test Image 12  | 0.7433  | 0.7931 | 0.7401 |
| Test Image 13  | 0.9564  | 0.9679 | 0.9041 |
| Test Image 15  | 0.7345  | 0.7513 | 0.7367 |
| Test Image 16  | 0.7348  | 0.7494 | 0.7362 |
| Test Image 18  | 0.525   | 0.7492 | 0.7338 |
| Test Image 19  | 0.6965  | 0.7469 | 0.7288 |
| Test Image 20  | 0.6556  | 0.7926 | 0.7334 |
| Test Image 22  | 0.7281  | 0.7942 | 0.7392 |
| Test Image 23  | 0.6768  | 0.7497 | 0.7396 |

![Figure 2. Comparison chart for silhouette values of the the images clustered by FCM and SOM with high Silhouette values than K-Means clustering.](image)

![Figure 3. The experimental results of FCM on L*a*b color space test images. a) Original image. b) Segmented image. c) Marker image.](image)
Comparison of Clustering Methods for Segmenting Color Images

**Table 4.** Silhouette index value for K-Means, FCM and SOM for the test images

| SNo. | Image         | K-Means | FCM          | SOM |
|------|---------------|---------|--------------|-----|
|      |               | No. of clusters | Silhouette index value | No. of clusters | Silhouette index value |       |
| 1    | Test Image 1  | 3       | 0.7534       | 3       | 0.7480       | 0.7377 |
|      | Test Image 2  | 3       | 0.7519       | 3       | 0.7492       | 0.7372 |
|      | Test Image 3  | 3       | 0.7328       | 3       | 0.7344       | 0.7240 |
|      | Test Image 4  | 6       | 0.6795       | 6       | 0.7236       |       |
|      | Test Image 5  | 2       | 0.8268       | 2       | 0.7937       | 0.7358 |
|      | Test Image 6  | 2       | 0.7221       | 2       | 0.7939       |       |
|      | Test Image 7  | 3       | 0.7276       | 3       | 0.7475       | 0.7426 |
|      | Test Image 8  | 4       | 0.6988       | 4       | 0.7375       |       |
|      | Test Image 9  | 3       | 0.6174       | 3       | 0.7479       | 0.7387 |
|      | Test Image 10 | 3       | 0.6541       | 4       | 0.7356       |       |
|      | Test Image 11 | 3       | 0.6593       | 4       | 0.7338       |       |
|      | Test Image 12 | 2       | 0.7433       | 2       | 0.7931       |       |
|      | Test Image 13 | 3       | 0.6887       | 3       | 0.7476       | 0.7401 |
|      | Test Image 14 | 3       | 0.6497       | 4       | 0.7377       |       |
|      | Test Image 15 | 3       | 0.9564       | 2       | 0.9679       | 0.9041 |
|      | Test Image 16 | 3       | 0.9097       | 3       | 0.9038       |       |
|      | Test Image 17 | 2       | 0.8621       | 2       | 0.7945       |       |
|      | Test Image 18 | 3       | 0.8099       | 3       | 0.7485       | 0.7375 |
|      | Test Image 19 | 4       | 0.7316       | 4       | 0.7330       |       |
|      | Test Image 20 | 2       | 0.8343       | 2       | 0.7934       |       |
|      | Test Image 21 | 3       | 0.7463       | 3       | 0.7488       | 0.7352 |
|      | Test Image 22 | 3       | 0.7245       | 4       | 0.7341       |       |
|      | Test Image 23 | 3       | 0.5250       | 3       | 0.7492       | 0.7338 |

**Figure 4.** The experimental results of SOM arranged in 4 columns namely a,b,c and d. a) Original image. b) Segmented RGB image. c) Edge image. d) Silhouette index.
6. Conclusion

In this paper we have segmented the color images using K-means, FCM and SOM. FCM clustering algorithm applied on the CIE L*a*b* color reduced image. The trained SOM network reduced the execution time for segmenting color images. The performance of FCM and SOM is higher than the K-means for segmenting color images.

7. References

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