Homogenous Region based Color Image Segmentation

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***Abstract*—In this paper an unsupervised color image segmentation method is suggested. Color image segmentation is an important but still open problem in image processing. At first, FCM is applied to the image and the cluster centers are obtained. Quite similar to the famous TSK fuzzy control model, we form several rules (*IF-THEN like*) for pixel classification. The results obtained from the rules are plotted as a histogram. An effective histogram peak detection and valley extraction (*PDVE*) algorithm is applied to the histogram and thresholds are extracted from the histogram for segmentation. The method is unsupervised and no prior knowledge of number of regions to be segmented is required. The experimental results show that the proposed approach can find homogeneous areas effectively, and with high accuracy.**

***Index Terms*—Color image segmentation, PDVE, FCM, histogram thresholding.**

I. Introduction

Image segmentation is considered as an important basic operation for meaningful analysis and interpretation of image acquired. It is a critical and essential component of an image analysis and/or pattern recognition system, and is one of the most difficult tasks in image processing, which determines the quality of the final segmentation [1]. Color of an image can carry much more information than gray level [2]. There probably is no "*one true*" segmentation acceptable to all different people and under different psychophysical conditions. Researchers have extensively worked over this fundamental problem and proposed various methods for image segmentation. These methods can be broadly classified into seven groups: (1) Histogram thresholding, (2) Clustering (Fuzzy and Hard), (3) Region growing, region splitting and merging, (4) Edge-based, (5) Physical model- based, (6) Fuzzy approaches, and (7) Neural network and *GA* (Genetic algorithm) based approaches**.**

Histogram thresholding is one of the widely used techniques for monochrome image segmentation but for color images, the situation is different due to the multi features. Since the color information is represented by tristimulus and/or some linear/nonlinear transformation of RGB, representing the histogram of a color image in a three dimensional array and selecting threshold in the histogram is not a trivial job.

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II. Previous Works

Color image segmentation always has been a challenging task for researches over the years. L**.** Busin et al. proposed a method of histogram multi-thresholding. Their algorithm iteratively constructed regions by histogram thresholding [3]. Milind M. Mushrif and Ajay K. Ray described an A-IFS Histon based multi-thresholding algorithm for color segmentation. They used the concept of rough sets for thresholding [4]. B.Sowmya and B.Sheelarani segmented color image using soft computing techniques. The soft computing techniques they used were Fuzzy C means algorithm (FCM,) Possibilistic C means algorithm (PCM) and competitive neural network [5]. Clustering is one of the most common tools used for color image segmentation. Fuzzy C means algorithm, k means algorithm and FCM with some spatial constraints have been extensively used by numerous occasions [6]-[11]. In 2001 Fan et al. proposed a method of automatic image segmentation by integrating color edge extraction and seeded region growing. They used fast Entropy thresholding for edge extraction. After they obtained color edges, which provided the major geometric structures in an image, the centroids between these adjacent edge regions were taken as the initial seeds for seeded region growing. These seeds were then replaced by the centroids of the generated homogeneous image regions by incorporating the required additional pixels step by step [12]. Fuzzy set and Fussy logic techniques are also used by researchers for solving segmentation problem. In 2007 A. Borji et al. described a CLPSO-based Fuzzy Color Image Segmentation [13], and H. D. Cheng et al. segmented color image on the basis of fuzzy homogeneity approach [14], [17]. Besides this, artificial neural network (ANN) and Genetic algorithm (GA) techniques also have been used for image segmentation [15].

The proposed method determines the dominant homogenous regions in a color image with the help of Fuzzy C means clustering. For our method, number of clusters will decide number of rules. So, from the cluster information we define *IF-THEN* based rule. Each pixel then is evaluated by each rule and the final results are stored. Finally, an efficient histogram thresholding approach with *PDVE* algorithm is applied over the results and the pixels are classified into proper classes.

III. Steps of Proposed Method

The color image is at first divided into three channels (Red, Green and Blue). Here we have considered that each pixel as a

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three featured data point (each color channel as a feature). Over this image data FCM is performed.

A. Fuzzy C Means Algorithm and Its Application to the Proposed Method

The classic FCM algorithm is given by the following mathematics programming:

$$J_m(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^m d^2(x_k, v_i) \quad (1)$$

With

$$\sum_{i=1}^{c} u_{ij} = 1, \qquad 1 \le j \le n \quad (2)$$

$$u_{ij} \ge 0, \quad 1 \le i \le c, 1 \le j \le n \quad (3)$$

$$\sum_{j=1}^{n} u_{ij} > 0, \quad 1 \le i \le c \quad (4)$$

Where $X = \{x_1, x_2, ...x_n\} \subset R^s$, s is the dimension of the space (in this case s=3), n is the number of unclassified pixels, c is the number of clusters, m is the fuzzy factor (m is taken as 2), $d_{ij} = \| x_j - v_i \|$ is the distance between samples x_j and cluster center v_i with $1 \le i \le c$. u_{ij} is the membership of the j^{th} sample to the i^{th} clustering center. The mathematics programming is solved through the following steps:

Initialization: Initialize centers $V^{(0)}$, let k=0; Choose ε >0.

Step 1: Calculate $U^{(k)}$ using (5)

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} (d_{ik} / d_{jk})^{2/(m-1)}} \quad (5)$$

Step 2: Calculate $V^{(k+1)}$ using (6)

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \quad (6)$$

Step 3: If $\| V^k - V^{(k+1)} \| < \varepsilon$, then stop; otherwise let k=k+1 and return to step 1.

The algorithm above can also start from membership matrix $U^{(0)}$.

In the proposed method we have assumed that the color image is a data set with each point having three features. We perform FCM over the image data set to extract the cluster centers. One of the disadvantages of FCM algorithm is that we need to supply the number of clusters we wish to create. In our method, we fixed the number of clusters 9. Note that, we take this number of cluster same for all the experimental images as our purpose is to convert each cluster information into a rule. To reduce the time of convergence of FCM we also fixed the number of iterations to 25. We got this iteration limit after experimenting over 100 images and carefully observing the number of iterations for each case. After 25 iterations we obtain 9 cluster centers and a fuzzy membership matrix U .

B. Rule Identification Scheme

For identification of systems and controlling it, *TSK model* is a very powerful tool and extensively used now a days. The main purpose of the tool is to build a mathematical fuzzy model of the system [16]. They suggested that a fuzzy implication R can be like:

R: If $f(x_1 is A_1 .... x_k is A_k)$ then $y = g(x_1, ..., x_k)$;

Where y is the variable whose value is inferred and $x_1, ...x_k$ are the input variables. The general idea of a rule is like:

IF Antecedent THEN Consequent

Let v_i , $i = 1,2,....,c$ be the centroids of the clusters obtained by FCM on input color image data set. The rule formation process, as can be guessed, derives its inspiration from the famous TSK fuzzy rule based system. We translate the i[th] cluster into a rule of the form:

R_i^{TSK} : If x_k is "*CLOSE TO*" v_i then

$$y_k = \frac{u_{ik}\sqrt{(x_k - v_{ik})^2}}{\sum_{i=1}^{c} u_{ik}} \quad (7)$$

Note that, "x_k is CLOSE TO v_i " is an antecedent clause with p components (here p=3). Thus R_i^{TSK} : If x_1 is CLOSE to v_{i1} and .... and x_p is CLOSE to v_{ip} . Here y_k is the computed output for k[th] input point and u_{ik} is the fuzzy membership of k[th] point to i[th] cluster. The value of u_{ik} is taken from the membership matrix of FCM. So for every input point (i.e. for every tristimulus pixel) we calculate the value of y.

C. Threshold Process for Final Classification

$y_i, i = 1,2,....,n$ is the rule output for every pixel. In 2000 Heng-Da Cheng and Ying Sun proposed an effective method of histogram analysis for homogeneity detection [17]. We adopt a similar histogram peak detection and valley extraction *(PDVE)* algorithm to threshold the values of y. At first, we create a histogram of y. A classical histogram is a statistical graph counting the frequency of occurrence of each gray level in an image or in part of an image [18]. Here the values of y of a pixel are the measure of homogeneity for that very pixel within the region it fits. As the rule base is formed, we calculate the closeness of a pixel from a cluster center by equation (7). Thus the value y_i for i[th] pixel signifies its measure of homogeneity to a particular class.

D. Steps of Peak Detection and Valley Extraction (PDVE) Algorithm for Histogram Analysis

The histogram obtained from the values of y is of complex nature with significant variations. So we develop peak detection and valley extraction algorithm *(PDVE)* which analyses the histogram step by step and finally extracts the valleys required as threshold value for segmentation. A histogram of the analyzing features of an image can produce a global description of the image's information and is utilized as an important basis of statistical approaches in image processing. The basis of histogram analysis approach is that the regions of interest tend to form modes (a dominating peak that can represent a region) in the corresponding histogram. Then, a typical histogram analysis generally carries out three steps [17]:

- *Recognize the dominant modes of the histogram.*
- *Find the valleys between different modes.*
- *Apply the extracted thresholds to the image for segmentation.*

We apply *PDVE* algorithm to perform the above mentioned three tasks.

PDVE algorithm:

1) Find the set of points corresponding to the local maximums of the histogram according to the equation:

$$P_0 = \{i, h(i) \mid h(i) > h(i-1) \,\&\, h(i) > h(i+1)\} \quad (8)$$

We consider local neighborhood of consecutive three bins of histogram and find maximum frequency value of occurrence among them and discard others. The points in set P_0 form a new curve. On this new curve, repeat the above operation. The result forms set P_1.

$$P_1 = \{(p_{i,} h(p_i)) \mid h(p_i) > h(p_{i-1}) \\ \& h(p_i) > h(p_{i+1}), p_i \in P_{0\}} \quad (9)$$

All the points in set P_1 are much more significant than the points in set P_0 in determination of the peaks of the histogram. ***2)*** The first step of thresholding is to remove small peaks. If a peak is too small compared to the biggest peak, then it is removed. Thus, the steps are, Find $y_{\max}$; if y_i / $y_{\max}$ < 0.02 then remove y_i.

The second step is to choose one peak if two peaks are too close. For two peaks $h(p_1)$ and $h(p_2)$, $p_2 > p_1$ if $p_2 - p_1 < 10$ then $h = \max\{h(p_1), h(p_2)\}$. In this way the peak with bigger value is chosen.

The third step is to ignore a peak if the valley between two peaks is not obvious. We examine the obviousness of the valley by calculating the average value for the horizontal axis value between the two peaks. We consider the valley between the two peaks is not obvious if the average value is too big compared to the peaks. Suppose h_{avg} is the average value among the points between peak p_2 and p_1 then

$$h_{avg} = \frac{\sum_{p_i=p_1}^{p_i=p_2} h(p_i)}{p_2 - p_1 + 1} \quad (10)$$

If $h_{avg} / \{(h(p_1) + h(p_2))/2\} > 0.5$ we decide that the valley is not obvious enough to separate two peaks. So we ignore the peaks with smaller value. The threshold value 0.5 is based on the experiments on more than 50 different color images.

This algorithm *PDVE* locates the globally significant peaks of the histogram. After the peaks are selected, the minimum values between any adjacent peaks are the valleys. The valleys are the boundaries for the segmentation [17].

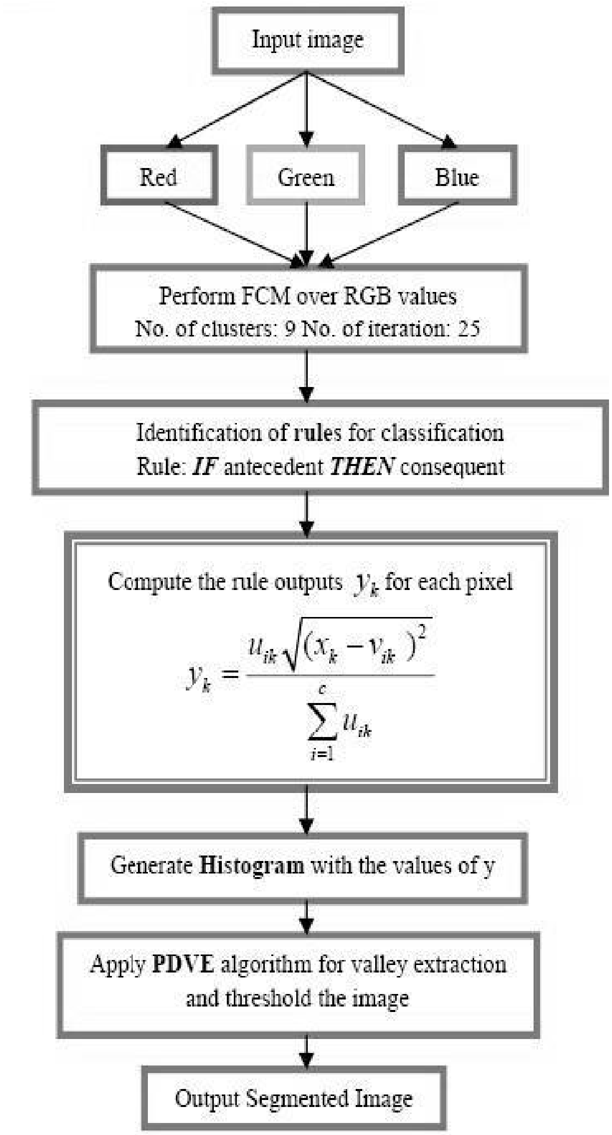

Fig. 1. Flow chart of the Segmentation algorithm

IV. Segmentation Results and Analysis

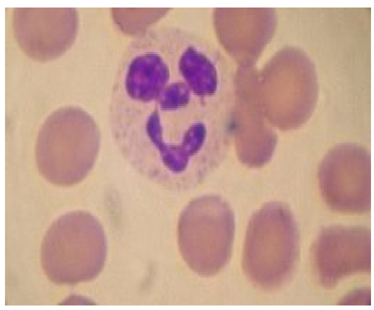

Fig. 2.(a) Cell image

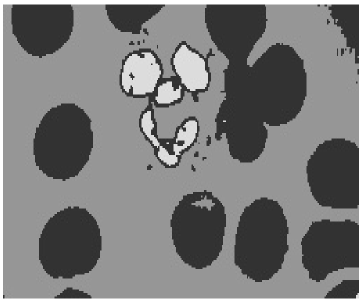

Fig. 2.(b) Segmented image

Fig. 2.(a) is the original cell image and 2.(b) is the segmented image. The image is segmented into three dominant regions.

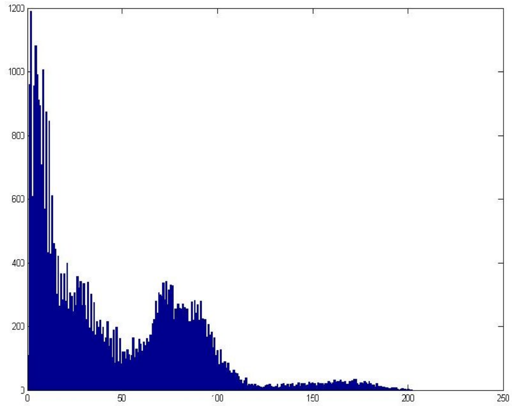

Fig. 3.(a)

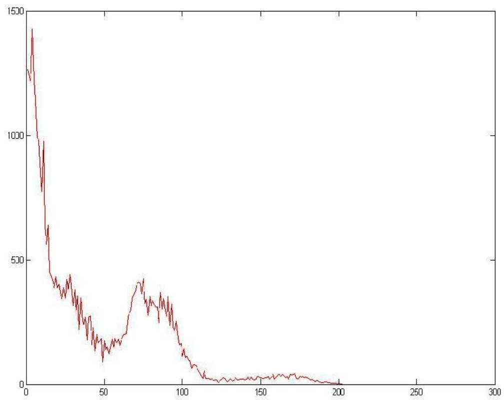

Fig. 3.(b)

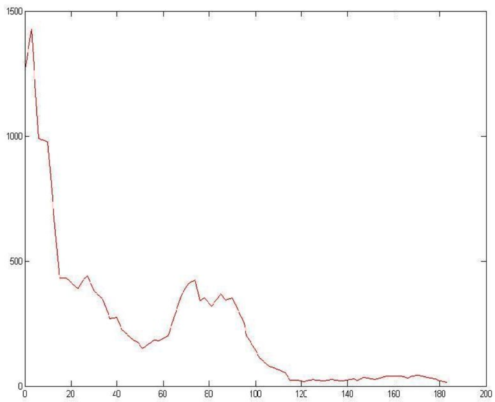

Fig. 3.(c)

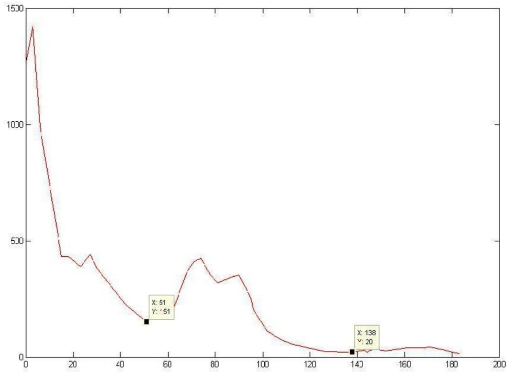

Fig. 3.(d)

Fig. 3.(a) is the histogram obtained for the Fig. 2.(a) cell image. It is clear that the image contains three dominant regions. Examining the histogram one can easily see three regions that define three segments. Fig. 3.(b) is the plot of peaks of histogram. We apply *PDVE* algorithm to Fig. 3.(b) and Fig. 3.(c) is generated as a intermediate stage. Fig. 3.(c) consists of the significant peaks of the histogram. Thresholding is performed over Fig. 3.(c) and finally simplified result is obtained and shown in Fig. 3.(d). The valley points for segmentation of the cell image are obtained and they are 51 and 138 as shown in Fig. 3.(d). So the three pairs of threshold values are (0-51), (51-138), (138-256). With these threshold values we get the segmentation result as Fig. 2. (b).

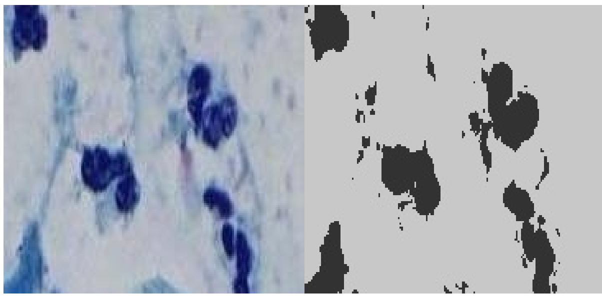

Fig. 4.(a) Blood cell image, (b) segmented blood cell image

Fig. 5.(a) Original flower image, (b) segmented image

V. Conclusion and Future Works

The proposed method is tested on different images. It produced stable and fairly good results. Consistent acceptable outputs over different kinds of real life images have proved robustness of the presented scheme. Thus, the proposed method may be handy for any computer vision task where extraction of region and segments is required for a large set of images for feature extraction or for any other work. Our next venture will be comparing proposed algorithm with other similar methods and analyze the performance on the basis of parameters like computing time, execution complexity and accuracy of the system output in presence of noise.

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