Color Image Segmentation Technique Using "Natural Grouping" of Pixels

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Abstract

This paper focuses on the problem Image Segmentation which aims at sub dividing a given image into its constituent objects. Here an unsupervised method for color image segmentation is proposed where we first perform a Minimum Spanning Tree (MST) based "natural grouping" of the image pixels to find out the clusters of the pixels having RGB values within a certain range present in the image. Then the pixels nearest to the centers of those clusters are found out and marked as the seeds. They are then used for region growing based image segmentation purpose. After that a region merging based segmentation method having a suitable threshold is performed to eliminate the effect of over segmentation that may still persist after the region growing method. This proposed method is unsupervised as it does not require any prior information about the number of regions present in a given image. The experimental results show that the proposed method can find homogeneous regions present in a given image efficiently.

Keywords: Segmentation, Region Growing, Natural Grouping.

1. INTRODUCTION

Segmentation of an image entails the division or separation of the image into regions of similar attributes. In another way, image segmentation is nothing but pixel classification. The level to which the segmentation process is to be carried out depends on the particular problem being solved. It is considered as an important operation for meaningful analysis and interpretation of the images acquired. It is one of the most critical components of an image analysis and/or pattern recognition system and still is considered as one of the most challenging tasks in the field of image processing. It has applications in several domains like Medical Science, Analysis of Remotely Sensed Image, Fingerprint Recognition, and Traffic System Monitoring and so on.

Image segmentation algorithms are generally based on one of two basic properties of intensity values of the image pixels: discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity values. Edge detection techniques fall in this category which is similar to boundary extraction. On the other hand, in the second category, the idea is to partition the image into different regions such that pixels belonging to a given region are similar with respect to a set of predefined criteria's. Researchers have been working on these two directions for years and have proposed various methods keeping those region based properties in mind. It should be noted that there is no fixed approach for segmentation. Based on the similarity or discontinuity criteria, many image segmentation methods have been proposed which can be broadly classified into six groups: (1) Edge Detection, (2) Histogram based method, (3) Clustering (K-Means clustering, Fuzzy C-means clustering etc.), (4) Region based methods (Region growing, Region splitting & merging), (5) Physical Model based approach,(6)Neural Network based segmentation methods [20].

The edge detection method is one of the widely used approaches to the problem of image segmentation. It is based on the detection of points with abrupt changes at gray levels. The main disadvantages of the edge detection technique are that it does not work well when images have many edges because in that case the segmentation method produces an over segmented result, and it cannot easily identify a closed curve or boundary. For an edge based method to be efficient, it should detect the global edges and the edges have to be continuous.

Histogram-based methods are very efficient in terms of time complexity when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are detected. Now the pixels in between two consecutive valleys can be considered to belong to a single cluster. One of the disadvantages of this method is that it is unable to work well when the image has no apparent gray level histogram peak. The other disadvantage is that the continuity of the segmented regions cannot be ensured. For the histogram based method to be efficient, we should focus on global peaks which are likely to correspond to the dominant regions in the image.

Clustering methods are also used for image segmentation purpose [4] [5]. The segmentation method incorporating clustering techniques encounters great difficulties when determining the number of clusters actually present in the corresponding feature space or extracting the appropriate feature.

The region based methods are based on the similarity of pixels within a region. Sometimes a hybrid method incorporating the edge based and region based methods have been proved to be useful for certain applications. The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ, can be used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region. Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Region splitting & merging is a modified algorithm that doesn't require explicit seeds. It starts off with a single region first, which is the image as a whole. Then the region is splited into four different sub region based on some dissimilarity measures to construct a quad tree structure of regions. The regions are splited to the extreme level so that no more regions splitting can be done now. Then the splited regions are merged iteratively to have the final segmentation.

The model based image segmentation assumes that given an image, its individual regions follow a repetitive form of geometrical structure. This is segmentation using texture feature.
Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of different neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen self-organizing map.

The proposed technique is based on the region based method for image segmentation. In general, the region based methods suffer from the problem of selection of initial seeds. We have formalized a method to sort out this problem. The method proposed in this paper uses the concept of “natural grouping” [10] based on the three color channels to find the seed pixels. Hence each seed pixel acts as a pivot for a region of the given image. Then we start the process of region growing from each such seed pixel. After the completion of this region growing process, we obtain as many regions as the number of seed pixels. The region growing stage is followed by a region merging method which reduces the effect of over segmentation to a great extent.

The rest of the paper is organized as follows, section 2 discusses about some existing works on image segmentation, then in section 3 a problem definition is given and in section 4, our method is proposed then in section 5, some experimental results are shown and a comparison is done with some other well-known segmentation techniques to show the effectiveness of our method. Section 6 deals with the concluding discussion and future improvements that can be done.

2. A BRIEF OVERVIEW OF THE RELATED WORK

Color image segmentation has always been a challenging task for the researchers over the years. Pal & Pal [12] provided a detail review on various segmentation techniques. Among myriads of existing image segmentation techniques, many can be considered as unsupervised clustering methods. For example, region merging is the analogue of agglomerative clustering [1]. Graph cut methods such as minimal cut and normalized cut represent the clustering problem in a graph theoretic manner [2]. A major problem known as the problem of validity for this kind of methods is how to determine the number of clusters in an image. Since the problem is largely unresolved, most techniques need the user to provide a terminating criterion. B.Sowmya and B.Sheelarani segmented color image using soft computing techniques [3]. The soft computing techniques they used were Possibilistic C means algorithm (PCM) and competitive neural network. Fuzzy set and Fussy logic techniques are also used by researchers for solving segmentation problem. A. Borji et al. described a CLPSO-based Fuzzy Color Image Segmentation [6]. H. D. Cheng et al. segmented color image on the basis of fuzzy homogeneity approach [7]. Besides this, artificial neural network (ANN) and Genetic algorithm (GA) techniques also have been used for image segmentation [8]. There are numerous segmentation techniques in medical imaging depending on the region of interest. There are atlas-guided techniques and region growing segmentation methods. Some of them use a semi-automatic approach and still need some operator interaction. Others are fully automatic and the operator has only a verification role. Fan et al. proposed a method of automatic image segmentation by integrating color edge detection and seeded region growing [9]. 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. Adams and Bischof proposed another method using seeded region growing [13]. Franc Y Shis and Shouxian Cheng proposed another region based image segmentation method [14] where initial seeds are selected based on the idea of calculating standard deviation in a neighbor and to check whether the value is under a threshold and then assigning each pixel in that region as seeds. This seed selection is followed by a region growing and region merging.

"Natural grouping" of dataset is a method of identifying the hidden clusters of data points present in the dataset. For a set of data points, we can draw the scatter diagram of the set. What one perceives to be the groups present in the set is termed as the natural groups present in the set. These sorts of algorithms are better than the general clustering algorithms in the fact that, they don't need any prior information about the number of clusters present actually in the dataset. Nirmalya Chowdhury and C. A. Murthy proposed a method of obtaining natural groups present in a dataset using minimum spanning tree and bayes classifier [10]. Sugar et al. proposed an information theoretic approach for finding natural groups present in a dataset [11]. Premananda Jana and Nirmalya Chowdhury proposed another method of natural grouping of a given dataset using MST of dataset [15].

3. STAEMENT OF THE PROBLEM

Given an image *I* and homogeneity predicate *P*, the segmentation of *I* is a partition of *I* into *K* regions $\{R_1, R_2 \ldots R_K\}$ satisfying the following conditions,

Each pixel in the image should be assigned to a region.

i.e. $$\bigcup_{p=1}^{k} R_p = I \tag{1}$$

Each pixel is assigned one and only one region.

i.e. $$R_k \cap R_{kk} = \varnothing \quad \forall k, kk = 1, 2, \ldots K, k \neq kk \tag{2}$$

Each region satisfies the predicate P, which can be similarity measure in color space or similarity based on texture or any similarity criteria combining both of them etc.

i.e. $$P(R_k) = \text{True for } k=1, 2 \ldots K \tag{3}$$

Two different regions cannot satisfy P at the same time.

i.e. $$P(R_k \cap R_{kk}) = \text{False where } k \neq kk \tag{4}$$

4. THE PROPOSED METHOD IN THE FORM OF AN ALGORITHM

Fig 1 presents an overview of our algorithm. Here after finding the unique RGB tuples of pixels of a given image, we perform a MST based natural grouping of the pixels. The pixels closest to the centers of the groups thus obtained are found out. These pixels serve as the pivot for region growing image segmentation purpose. This step is immediately followed by a region merging process. We can divide the algorithm into three parts, namely, seed selection, region growing and region merging. These steps are discussed in detail in the next section,

4.1 Selection of seed pixels

Seed pixel selection is the initial step for image segmentation based on region growing. The pixels selected as seeds should satisfy the following properties,

- Every seed should be similar to its neighbors with respect to some criteria *P*.
- Any pair of seeds should be distinct with respect to the criteria *P*.

For seed pixel selection purpose, we first perform the natural grouping on the image pixels in the *RGB* feature space as *RGB* space is suitable for color display. In image processing and analysis, we often transform the *<R G B>* components into other color spaces. Every color space has its own advantages and disadvantages. Cheng et. al. compared several color spaces including *RGB, YIQ, YUV, CIE* etc. for color image segmentation purpose [16]. For performing natural grouping, we uses the natural grouping method using minimum spanning tree (MST) proposed by Premananda Jana and Nirmalya Chowdhury. Using pixels as the vertices of the MST, it has been used for obtaining the natural groups of pixels based on their RGB values. Euclidean distance (Equation 5) between the data points has been taken to be the edge weight of the said MST.

$$D_E = \sqrt{(R_i - R_j)^2 + (G_i - G_j)^2 + (B_i - B_j)^2} \quad (5)$$

Then we calculate the sum of the edge weight *(l_n)* of the MST. The threshold for cluster separation is taken to be,

$$Th_{NG} = \frac{\beta \times l_n}{n-1} \quad (6)$$

where *n* is the no of nodes in the MST [17]. It has been experimentally found that β=2 has provided consistently good results [15].

Now the edges of the MST are removed for which edge weights exceeds the threshold (6) for cluster separation. Nodes (data points or pixels here) in each path constitute different clusters of data points (pixels). The centers of those clusters are found out. Now the image pixels having intensity values nearest to those cluster centers values are selected as seeds.

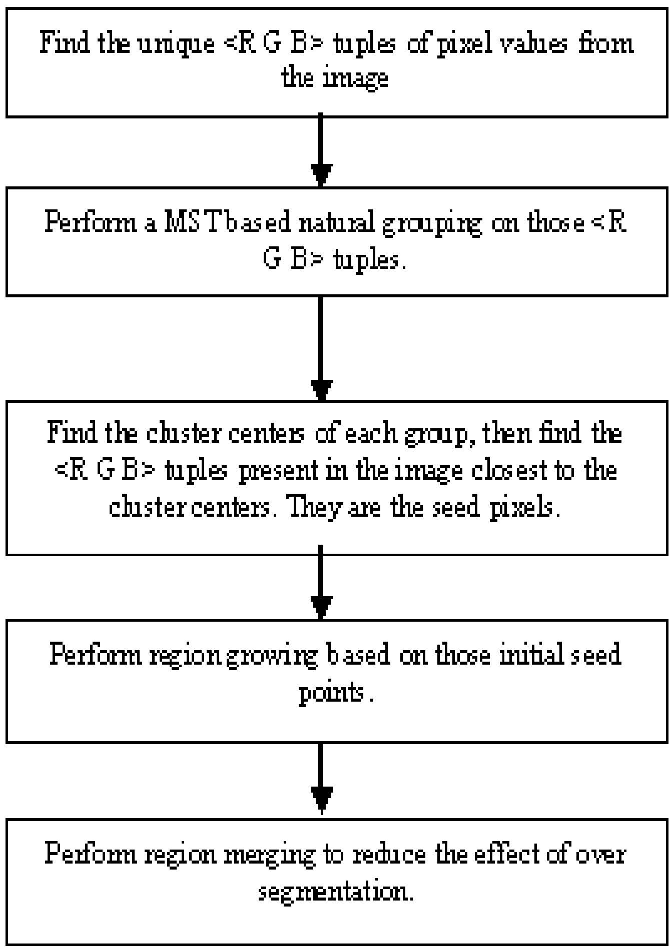


FIGURE 1: Outline of the Proposed Method.

4.2 Region growing step

Seed pixels selected by the above method acts as the pivot for each possible region. For efficiency purpose, every region in the image should contain a seed pixel. But in our proposed method of seed selection, it may so happen that no seed falls in any of the Region of Interest. We eliminate this problem effectively in this region growing stage. In the beginning, we are performing region growing from those initially selected seed pixels. Steps for region growing process are stated below,

- For each natural group we compute the Euclidian distance of all data points from the remaining data points of that cluster using the formula (5). The maximum distance so obtained is recorded. Then we sort those recorded distances in the increasing order and chooses the minimum value to be the threshold (Th_{RG}) for region growing purpose.
- For each seed pixel, we compute the Euclidian distance between the seed pixel and four of its neighboring pixels.
- If the distances thus found are less than the threshold (Th_{RG}), then they are included in the region marked by that particular seed.
- If one or more of the neighboring pixels do not satisfy the condition for region growing as stated above, then they remain unassigned.
- The above methods are repeated for all the seeds.
- For a given seed, the pixels included by region growing method narrated above are labeled by the color (RGB) of the seed pixel.
- Label all the unassigned pixels by the color of the seed pixel to which they are nearest.

4.3 Region merging step

It is possible that the above mentioned method for region growing may result in generation of more number of segments than that is actually present in a given image. Thus at this stage, one needs to use a suitable region merging criteria to merge those regions which should not be given the identity of separate regions. So to get rid of this over segmentation problem a method of region merging is employed which is described below,

FIGURE 2: Some Sample Images from the Database Used for Experimentation.

Two regions (R and R') are merged if,

- They are adjacent.
- If the Euclidian difference between their mean color intensity values is within the threshold value (Th_{RM}):

$$Th_{RM} = \sqrt{b^2(R) + b^2(R')} \tag{7}$$

where *b(R)* is defined as: -

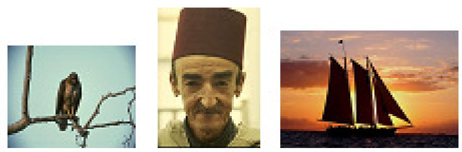
$$b(R) = g \times \sqrt{\frac{1}{2 \times Q}\left(\frac{1}{|R|}\right) \ln \frac{R_{|R|}}{\partial}} \tag{8}$$

where g is the maximum of particular color channel (R or G or B) of the mean color value of region R. Q is total no of elements in the set of random variable that is used to represent each color channel. Basically q denotes the level of merging. For our purpose we make use q from 1 to 32 and observe the changes in result. |R| represent the cardinality (no of pixels) of region R. ∂ is a parameter which is defined as $1/|I|^2 * 6$ where $|I|$ is the cardinality of the image *I.*

The merging threshold is based on the work done by Nock and Nielsen [18] where they segment images using statistical region merging technique. The above mentioned threshold *(Th_{RM})* is based on the statistical measure having the idea that pixels within a region have the same expectation value and pixels in different regions have different expectation value.

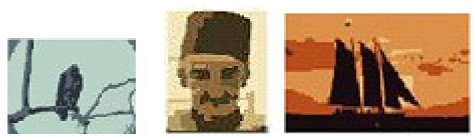
5. EXPERIMENTAL RESULTS AND DISCUSSIONS

We implemented the algorithm in matlab and tested it on a Pentium Core-2 Duo system with 3 GB RAM. We have performed our experiment on about 100 images collected from the web. Fig. 2 shows some ample images from the database created. fig 3 shows some of the samples from the collected image database for showing experimental results. The images are color images of different resolutions. We resized the images into 100 x 100 after starting the segmentation process. The images are basically scenery images. We have also performed comparison with some well-known segmentation techniques.



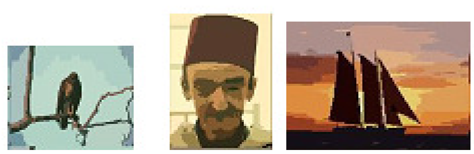
(a) (b) (c)

FIGURE 3: Some Sample Images Collected for Experiment.



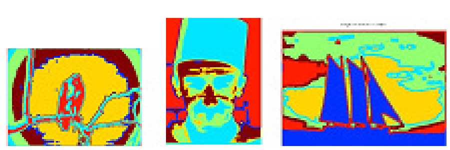
(a) (b) (c)

FIGURE 4: Results of the Proposed Method.



(a) (b) (c)

FIGURE 5: Results of the Statistical Region Merging Based Method.



(a) (b) (c)

FIGURE 6: Results of the K-Means Based Method.

Fig 4, Fig 5 and Fig 6 show the comparison of the results obtained by our method with the results obtained by [18] and [19]. We obtain both the implementation versions of those algorithms from the web. In fig 4, the results of the segmentation process obtained by the proposed method on some sample images collected are depicted. Then the results of [18] are shown in fig 5. The results show that our method is relatively free from over segmentation problem. This problem is there in most of the results obtained by the method proposed in [18]. For example, in the result shown in Fig 5(a), the sky is segmented in three different segments while our method shows in Fig 4(a) that the sky is segmented into two parts. Besides, the algorithm proposed in [18] sometimes over merged some regions which make the result difficult to analyze. For example, in the picture Fig 5(b), the right eye of the man is merged with the eye brow and the region covering them. But in our method in Fig 4(b), the eye and eye brow can be identified separately. The sky in Fig 4(c) is easy to understand in comparison with the result in Fig .5(c).

We have made another comparative study with the segmentation algorithm using k-means clustering proposed by Tse-Wei Chen Yi-Ling Chen Shao-Yi Chien [19]. Fig 6 shows the results. This algorithm label a segmented region by a randomly selected color value. The results in 6(a) and 6(c) show that, the sky is over segmented in more number of segments. Whereas the result in 6(b) shows that, most of the parts are over merged.

Our algorithm lacks in two aspects. It requires an additional scanning of the source image after the region growing stage. The preprocessing step needed for the natural grouping step, i.e. drawing the MST requires some addition storage as it requires building the adjacency matrix of the pixel points. Except these two shortcomings, the algorithm works fine for most of the images.

The time complexity for our algorithm spans three different phases: natural grouping for seed selection, region growing and region merging. The natural grouping is MST based and we use Prim's algorithm for finding the MST. Time complexity of prim's algorithm is O (E+V) logV where E is the no of edges and V is the no of vertices present in the MST. It requires O (E) to find the groups. The time complexity of seed selection is O(c x m x n) where c is the number of clusters obtained and m x n is the image resolution which is 100 x 100. In region growing, each unclassified pixel is inserted into the sorted list exactly once. Checking neighboring regions and calculating distances can be done in constant time. Putting a pixel into the sorted list requires log (m x n). Therefore, it takes O((m x n) log(m x n)) for region growing. After the completion of the region growing, we again scan the whole image to label the unassigned pixels. It takes O (m x n) time.

In region-merging, calculating the differences between regions takes O (r^2), where r is the number of regions. To calculate sizes for all the regions, it takes O (m x n). Usually, r is much less than m x n. To merge two regions, we need to label the pixels in the two regions, calculate the mean for the new merged region, and calculate the distances between this and other regions. Therefore, it takes O(m x n) to merge two regions.

6. CONCLUSION

We have presented an efficient algorithm for color image segmentation with automated seed selection. We performed natural grouping on the image pixels to find out different color bands present in the image. Experimental results show that our method can produce good results. This work can be carried on in future by incorporating texture feature along with color feature for region growing purpose as texture is an important region descriptor.

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