

# An Efficient Color Image Segmentation Algorithm Using Hybrid Approaches

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## ABSTRACT

Color image segmentation is still a challenging problem. Literature reveals many supervised algorithms wherein the primary input is the number of segments to which the image is to be segmented. Currently researchers are focusing on unsupervised segmentation algorithms. The main advantage of the proposed method is that no a priori information is required to segment the given color image and hence considered as an unsupervised approach. The proposed method is found to be reliable and works satisfactorily on different kinds of color images. Subjective comparison and objective evaluation shows the efficacy of the proposed method over other existing methods.

## Keywords

Image Segmentation, Minimum Spanning Tree, Cycle, Region growing

## 1. INTRODUCTION

Human visual system plays a vital role in the theory of color. Color vision results from the action of three spectral sensitivities at Red (R), Green (G) and Blue (B) of the visible light spectrum. Color is a complex perceptual phenomenon and the sensation of color images arises due to the response of three neuro chemical sensors or receptors in the retina to the visible light [1]. As color images are order of the day, their high prevalence motivated the authors to propose a segmentation method on color images.

In machine vision, image processing is usually a costly operation that should nevertheless perform in real time. An efficient segmentation algorithm helps to reduce the amount of visual information that needs to be processed. Human brain is capable of simultaneously analyzing and processing many tasks and this aids in segmenting or dividing the visual image into related objects. The same task over an image by

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an algorithm is extremely difficult. Image segmentation, as a computational problem, is interesting for at least three reasons: First, there are large number of potential applications. In medical image processing, doctors measure the size of organs and tissues using images obtained from their patients. Multimedia applications using image or video encoding can benefit from robust segmentation results, leading to more efficient image transfer and storage. Second, image segmentation is interesting because it serves as a testbed for ideas from other fields like machine learning, pattern recognition, physics and engineering. For instance, in its simplest form, image segmentation can be regarded as a clustering problem. Clustering algorithms can often be used in an image segmentation framework and conversely algorithms developed for image processing can be very successful in clustering problems as well. Finally, image segmentation is domain specific. This adds to the challenge [12] because the algorithms which are highly successful for a particular theme may not work properly.

The novelty of the proposed method is that the algorithms developed by Janakiraman T.N. and Chandra Mouli P.V.S.S.R. [13] are modified substantially by combining with initial region growing segmentation algorithm to improve the performance.

The rest of the paper is organized as follows. A brief review of Graph based segmentation is presented in Section 2. The proposed method is described in Section 3. Experimental results are presented in Section 4. The performance evaluation and the analysis of the results on comparison with other methods is done in Section 5. Section 6 concludes the work.

## 2. GRAPH BASED SEGMENTATION

Recently there is resurgence for graph based image segmentation methods. Graph theory and its concepts has been dominating in image processing research. Dickinson et al [2] discussed the various types of graph algorithms used by many researchers in computer vision. C.T. Zahn [3] introduced MST for the first time for image segmentation problem. He presented a segmentation method based on MST of the graph. This method has been applied to point clustering and to image segmentation. The segmentation criterion in this method is to break MST edges with large weights. The algorithm proposed by Urquhart [4] attempts to address this shortcoming by normalizing the weight of an edge using the smallest weight incident on the vertex touching that edge. In [5], Wu and Leahy proposed a cut criterion, but it was

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biased toward finding small components. This bias was addressed with the normalized cut criterion developed by Shi and Malik [6] which takes into account self-similarity of regions. These cut-based approaches to segmentation capture non-local properties of the image, in contrast with the early graph-based methods. However, they provide only a characterization of each cut rather than of the final segmentation.

An alternative to the graph cut approach is to look for cycles in a graph embedded in the image plane. The quality of each cycle is normalized in a way that is closely related to the normalized cuts approach [9]. In [10], Felzenszwalb and Huttenlocher described an efficient graph-based segmentation by defining a predicate for measuring the evidence for a boundary between two regions. Using that predicate, an algorithm is developed which makes greedy decisions to produce segmentations that satisfy global properties. A method to build a hierarchy of partitions of an image is introduced by Haxhimusa and Kropatsch [7] in which they build a hierarchy of partitions of an image by comparing in a pairwise manner the difference along the boundary of two components relative to the differences of components internal differences. They stated the drawback of this method as the maximum and minimum criterion introduced are very sensitive to noise, although in practice it has a small impact. A MST pyramid based segmentation is carried out using dual graph contraction in [8]. A hybrid intelligent algorithm for color image segmentation is proposed in [12]. In this method, Particle Swarm Optimization is used along with MST to improve the speed of the algorithm. Janakiraman T.N. and Chandra Mouli P.V.S.S.R. [13] explored the MST and cycles to perform the image segmentation. The non-spanning edges of the MST satisfying certain criterion are added to the MST to form cycles. The cycles thus formed are refined further to obtain the final segmentation. They further introduced Euler graphs [14] to perform image segmentation in polynomial time algorithm which does the segmentation without the input of the number of segments formed.

### 3. PROPOSED METHOD

The steps involved in the proposed method are as follows:

1. Read the given RGB image.
2. Transform the RGB space into HSV space.
3. Perform initial segmentation using region growing method.
4. Perform the second phase segmentation using MST method.
5. Refinement of segments formed.

Various color spaces have been introduced to represent the colors suitable for storage and processing. Among them, HSV model is the model that separates the luminance or intensity component of pixel color from its chrominance (Hue and Saturation) components. This representation closely resembles the visual perception of colors by humans. The given RGB image is transformed into HSV model using the transformation defined in [11].

#### 3.1 Region Growing Segmentation

In region growing procedure, two or more pixels are grouped together to form regions. The basic approach is to start with a set of seed points and from these points, regions grow by

appending to each seed the neighbouring pixels (based on 8-connectivity) that have predefined properties similar to the seed point [11]. The region growing method is employed to get initial segmentation. This method produces homogeneous grouping of pixels with high similarity. Pixels having high Hue and Saturation value are considered as seed points. Two pixels  $i$  and  $j$  are considered to be similar if

$$d(i, j) \leq Th \quad (1)$$

where,

$$d(i, j) = \sqrt{(H_i - H_j)^2 + (S_i - S_j)^2 + (V_i - V_j)^2} \quad (2)$$

The region growing procedure recursively groups the similar pixels satisfying the (2) and halts when no more pixels satisfy the criteria.

#### 3.2 MST based Segmentation

The regions formed in the region growing method are considered as the input to this step. Each region formed is considered as a vertex of the graph. The edges are defined based on the adjacency relation of the vertices. The graph thus obtained is termed as a Region Adjacency Graph (RAG). The weight of an edge  $(u, v)$  is defined based on the absolute mean intensity difference of the two connecting vertices. Since each homogeneous region formed in the previous step is considered as a vertex, the mean intensity of the pixels within the region is calculated for the weight determination. The next step is applying Kruskal's [15] algorithm on RAG to generate the MST.

The idea behind using the MST is that it has the capability to detect and separate regions. The reason for choosing Kruskal's algorithm over Prim's algorithm is that the former takes the advantage of using disjoint data structures. The RAG formed in the first step is a typical dense graph and for such graphs, the ideal data structure is disjoint data structures.

Once the MST is generated, some non-spanning tree edges (edges which are not considered by the Kruskal's algorithm in the formation of MST) satisfying certain criterion are chosen for cycle formation. The pseudo code for cycle formation is given below:

Algorithm: Cycle\_Formation

Input: MST, E (the set of non-spanning tree edges)

Output: Cycles

1. Sort the set E by non-decreasing weights.
2. cycles\_formed  $\leftarrow$  {}
3. While E is not empty
4.   Extract an edge from sorted E and store its end vertices and weight in u, v and w respectively.
5.   temporary\_path=BFS(MST,u,v);  
      // Breadth First Search (BFS)
6.   flag=check\_constraint(temporary\_path);
7.   if flag is TRUE
8.     MST=union(MST,u,v,w);
9.     cycles\_formed =  
       union(cycles\_formed, temporary\_path);
10.  else
11.   remove the extracted edge from E;
12.  end; // end of if
13. end; // end of while

The end vertices of every non-spanning tree edge are extracted and calls for the BFS procedure. BFS will return the shortest path between  $u$  and  $v$ . To a tree, on adding an edge a cycle is formed. So on addition of the edge between  $u$  and  $v$  the cycle is formed. Before adding the edge, the path between  $u$  and  $v$  is extracted using BFS. The extracted path is subjected for constraint checking in line 6 of the algorithm. Those edges that satisfy the constraints are added so that a cycle is formed and it is stored in `cycles_formed` vector. The constraint imposed on the extracted path is that the difference between the maximum and minimum vertex labels should not exceed the mean pixel intensity of the region. This is imposed in order to avoid grouping pixels of varying intensities.

Each cycle thus formed is considered as one region. At this stage, the segmentation output is over-segmentation. To get the optimum segmentation, merging of these cycles is performed. Two cases exist while merging adjacent cycles. First is that two cycles having common vertex and second is that two cycles having common edge. In the former case, merging is not possible. Such graphs are cactus graphs for which the structure remains same. In the latter case, the common edge is removed so that two cycles merge and one bigger cycle is formed. The pseudo code for cycle merging is given below:

```

Algorithm: Cycle_Merge
Input: Cycles_formed
Output: Final_regions
1. for c1 = 1 : length(cycles_formed)-1
2.   search for the common edge in the remaining cycles.
3.   if common edge is found
4.     Merge the two cycles into a new cycle and add to
       cycles_formed at the end of its list.
5.   Remove the two cycles from cycles_formed.
6.   end //end of if
7.   end // end of for

```

## 4. EXPERIMENTAL RESULTS

The algorithm is implemented using Matlab 6.5 and the CPU used is Intel Core 2 Duo T7250 @ 2.00 GHz with 1 GB RAM. The experiment is carried out on some sample images available for public usage and also on standard Berkeley Image Segmentation Database (Bsds) [17]. The results of public domain peppers image is shown in Figure 1.

Figure 2 represents the results obtained for general Lena, Baboon and other images. The first and the third column represent the original image whereas the second and fourth columns represent the corresponding segmentation results.

### 4.1 Results on Berkeley Segmentation Dataset

The Bsds contains several color images along with the ground truth. This is the benchmark dataset and is used for comparison of the results with other methods. Figure 3 represents some sample images from Bsds.

Figure 4 represents some sample images and their human segmentation or ground truth results obtained from Bsds. The results of these images are shown in Figure 5.

It is observed from the Figure 5 that the proposed algorithm segments the finest regions properly. The images are converted to HSV space without any pre-processing operations. This results in intricate findings of the proposed algorithm in determining the minute variations in the intensity

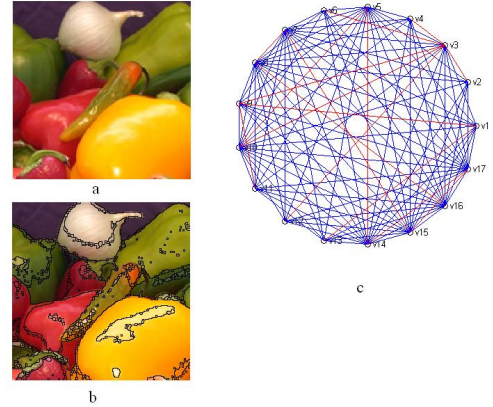


Figure 1: (a) Original Peppers image (b) Segmentation result (c) RAG and MST of (a)

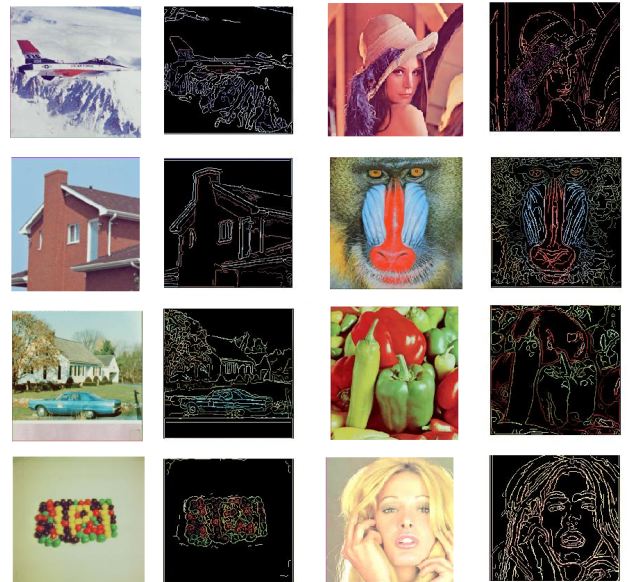


Figure 2: Some general purpose images and their segmentation results

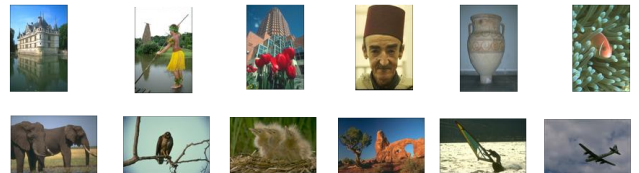


Figure 3: Some sample images from Bsds

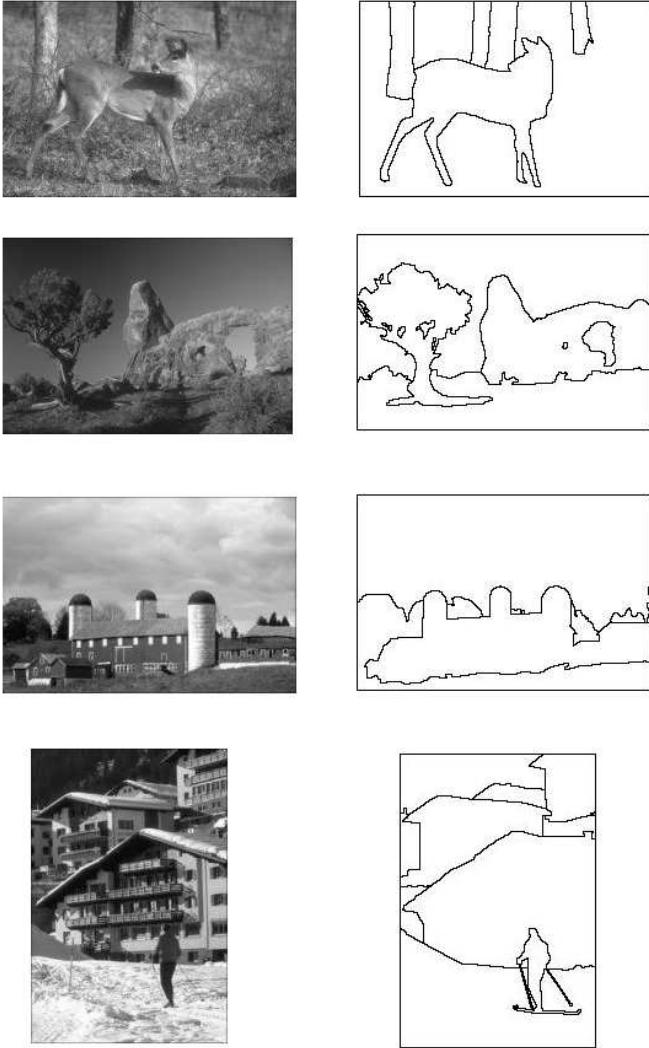


Figure 4: Sample images and their ground truths taken from Bsds

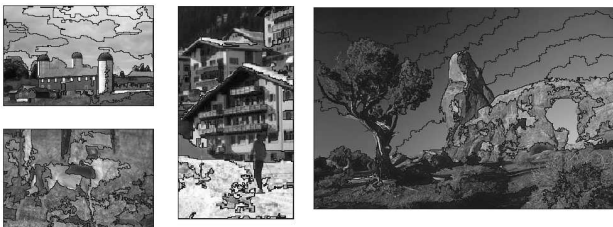


Figure 5: Results of the images in Figure 4

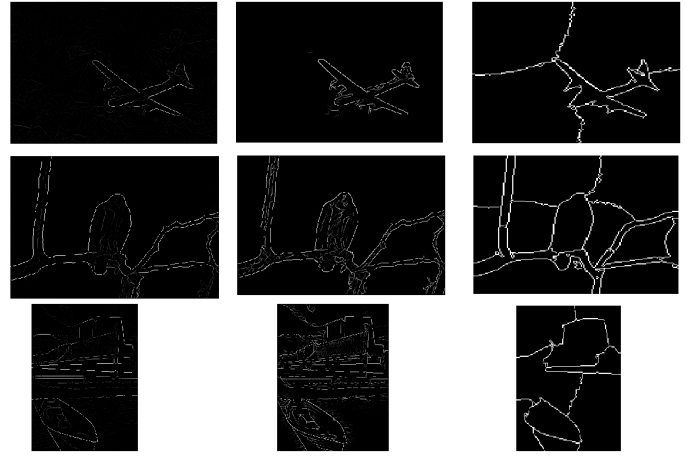


Figure 6: Comparison of results of some sample images with other existing methods

levels to different segments.

In Figure 6, we have compared the results of the proposed method with other existing methods [19], [20]. The first column represents the results of global probability of boundary method, second column represents the results of multi-scale method and the last column represents the results of the proposed method.

## 5. PERFORMANCE EVALUATION

In this section, the segmentation results obtained are compared and performance evaluation measures are presented. For comparison, the results of the recent works [18, 19, 20] posted in Bsds are considered. In addition, the results obtained for [13] are also used for comparison since the proposed method is an improved version. Martin [16] in his thesis, proposed the use of precision and recall values to characterize the agreement between the boundary elements of the regions of two segmentations. Given two segmentations,  $S_1$  and  $S_2$ , where  $S_1$  is the result of the any segmentation algorithm and  $S_2$  is the ground truth, precision is proportional to the fraction of boundary pixels from  $S_1$  that matches with the ground truth  $S_2$  and recall is proportional to the fraction of boundary pixels from  $S_2$  for which a suitable match was found in  $S_1$ . They are calculated as

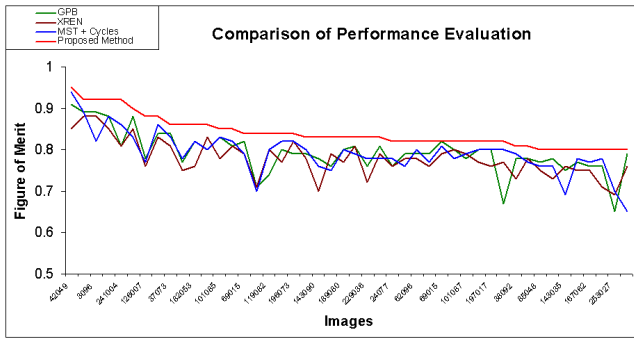
$$Precision(P) = \frac{Matched(S_1, S_2)}{|S_1|} \quad (3)$$

$$Recall(R) = \frac{Matched(S_2, S_1)}{|S_2|} \quad (4)$$

where  $|S_1|$  and  $S_2$  are the total boundary pixels in the corresponding segmentations. Precision is also termed as the probability that the result is valid and similarly recall is the probability that the ground truth data was detected.

A low precision value indicates over-segmentation. Similarly a low recall value indicates under-segmentation. Martin has derived a single figure of merit  $F$  using precision and recall values. It is defined as

$$F = \frac{PR}{\alpha R + (1 - \alpha)P} \quad (5)$$



**Figure 7: Comparison of results of some sample images with other existing methods**

where P and R represent precision and recall respectively and  $\alpha$  is a scaling constant with a value 0.5.

For evaluating the segmentation results of the proposed methods with other existing methods, Precision, Recall and F-measure have been implemented since Bsds have been evaluated using these three measures.

The proposed algorithm is executed over the 100 images in the database and the F-measure shows that the proposed method exhibits higher value compared to the other three methods. A graph is plotted for some images in [17] and their corresponding F-measure value and is shown in Figure 7.

## 6. CONCLUSIONS

In this paper, a novel algorithm is proposed using hybrid approaches. The novelty of the approach lies in improving the efficiency of an existing algorithm and combined with region growing method. The proposed method is treated as an unsupervised approach because it does not require any input from the user. The experimental results shows the efficacy of the method over any image domain.

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