# AN IMPROVED APPROACH FOR IMAGE SEGMENTATION BASED ON COLOR AND LOCAL HOMOGENEITY FEATURES

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## ABSTRACT

In this paper, we propose an improved approach for image segmentation based on color and local homogeneity features. A given image is transformed into a quantized image by a self-constructing fuzzy clustering. Then, a color-based region image and an initial seeded region image are obtained from the quantized image by color-based and homogeneity-based region growing methods, respectively. After that, we combine these two images to generate a refined seeded region image and obtain an initial segmented image by a region-based region growing. Finally, merging based on color similarities and sizes of regions is performed for avoiding the problem of over-segmentation. Compared with the other method, experimental results show that the segmented regions obtained by our approach are more reasonable and precise.

***Index Terms*—** image segmentation, fuzzy clustering, local homogeneity, color quantization, seeded region growing.

## 1. INTRODUCTION

Image segmentation plays a very important pre-processing role in many applications, such as computer vision, pattern recognition, information retrieval, etc. The main goal of image segmentation is to divide an image into regions each of which contains pixels with similar properties, e.g. color, texture, intensity, etc.

Up to now, many approaches for image segmentation have been proposed. In general, there are mainly four categories, i.e., region-growing-based [5], edge-based [4], texture-based, and hybrid techniques [1, 2, 3]. The concept of region-growing-based techniques is to group neighboring pixels with homogeneous properties into the same region according to the spatial relations. The formed regions are guaranteed to be closed. However, it usually suffers from the problem of over-segmentation, especially when the variation of colors in images is large. One of the well-known methods is seeded region growing. For the edge-based techniques, the discontinuity caused by the color or intensity variation of pixels near to the edges is considered. In general, a gradient operator is applied to each pixel for calculating a gradient value. Then, each pixel is categorized as edge or non-edge by a thresholding process. The difficulties of edge-based techniques are the selection of suitable thresholds and the generation of closed contours from edge pixels. For avoiding the over-segmentation problem, texture-based techniques are proposed by considering the texture distributions of regions. The texture analysis usually includes directionality, regularity, and coarseness properties. However, the computation complexities of many texture analysis approaches are large.

Recently, many hybrid techniques are proposed by combining two or three kinds of techniques mentioned above. Deng and Manjunath [1] proposed a JSEG method for unsupervised segmentation. A class-map of the image is obtained by a color quantization process. Then, applying a defined criterion of "good" segmentation to local windows in the class-map results in a "J-image", in which high and low values correspond to possible boundaries and interiors, respectively, of color-texture regions. Finally, a region growing method is then used to segment the image based on the multiscale J-images. Jing et al. [3] proposed another method for unsupervised image segmentation. First, a criterion for homogeneity of a certain patten is proposed. Applying the criterion to local windows in the original image results in the "H-image". The high and low values of the H-image correspond to possible region boundaries and region interiors respectively. Then, a region growing method is used to segment the image based on the H-image. Finally, visually similar regions are merged together to avoid over-segmentation.

## 2. OUR APPROACH

### 2.1. Overview

We propose an approach for image segmentation based on color and local homogeneity features. There are six phases in our approach, as shown in Figure 2. Firstly, a quantized image is obtained by a self-constructing fuzzy clustering. Secondly, according to the properties of color and spatial domains, a re-

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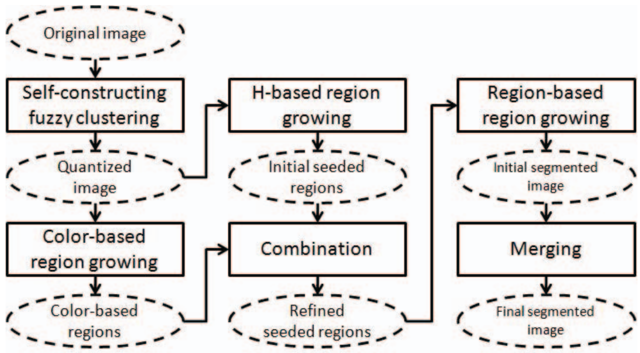


**Fig. 1**. Block diagram of our approach.

gion growing technique is employed to divide the quantized image into several connected regions and obtain a color-based region image. Thirdly, we find out those pixels with high local homogeneity by H-value calculation, group them into several seeded regions, and obtain an initial seeded region image. Fourthly, we combine the color-based region image with the initial seeded region image to generate an refined seeded region image, in which the seeded regions are more precise than those in the initial seeded region image. Fifthly, a initial segmented image is obtained by a region-based region growing. Finally, merging based on color similarities and sizes of regions is performed for avoiding the problem of over-segmentation.

### 2.2. Self-Constructing Fuzzy Clustering

Given an image with $N_1 \times N_2$ pixels and each pixel is associated with a color signal $(x_1, x_2, x_3)$ where $x_1$, $x_2$, and $x_3$ denote the $R$, $G$, and $B$ values, respectively. The first phase of our approach is to group all colors of pixels into clusters with a self-constructing fuzzy clustering algorithm, such that the colors in the same cluster have a sufficiently high degree of similarity. We assume that a cluster $C_j$ is represented by $(G_{1j}, G_{2j}, G_{3j})$ where $G_{1j}$, $G_{2j}$, and $G_{3j}$ are Gaussian membership functions of $R$, $G$, and $B$, respectively. Each $G_{ij}$, $1 \leq i \leq 3$, has the center $m_{ij}$ and standard deviation $\sigma_{ij}$. Let $n_j$ be the number of colors contained in cluster $C_j$ and $J$ be the number of clusters we have obtained so far. Obviously, $J$ is set to 0 initially.

We use color signals as the basis for clustering. For a pixel color signal $(x_1, x_2, x_3)$, we calculate the following similarity measure:

$$d(x_1, x_2, x_3; C_j) = \prod_{i=1}^{3} \exp\left[-\left(\frac{x_i - m_{ij}}{\sigma_{ij}}\right)^2\right] \tag{1}$$

for all $1 \leq j \leq J$. We say that $(x_1, x_2, x_3)$ passes the similarity test on cluster $C_j$ if

$$d(x_1, x_2, x_3; C_j) \geq \rho_1 \tag{2}$$

where $0 \leq \rho_1 \leq 1$ is a predefined threshold. If $J = 0$ or $(x_1, x_2, x_3)$ fails to pass the similarity test on any existing cluster, we create a new cluster $C_k$, $k = J + 1$, with

$$m_{ik} = x_i, \;\; \sigma_{ik} = \sigma_0 \tag{3}$$

for $1 \leq i \leq 3$, where $\sigma_0$ is a predefined initial value. Apparently, we must have

$$J = J + 1, \;\; n_k = 1 \tag{4}$$

for this case.

Otherwise, let cluster $C_t$ be the cluster with the largest value of similarity $d$. We say that $(x_1, x_2, x_3)$ is most similar to cluster $C_t$, and cluster $C_t$ is modified to include $(x_1, x_2, x_3)$ as its member, as follows:

$$\begin{aligned} \sigma_{it} &= \{\frac{(n_t - 1)(\sigma_{it} - \sigma_0)^2 + n_t {m_{it}}^2 + {x_i}^2}{n_t} \\ &\quad - \frac{n_t + 1}{n_t}(\frac{n_t m_{it} + x_i}{n_t + 1})^2\}^{\frac{1}{2}} + \sigma_0, \qquad (5) \\ m_{it} &= \frac{n_t m_{it} + x_i}{n_t + 1}, \qquad (6) \end{aligned}$$

for all $1 \leq i \leq 3$ and $n_t = n_t + 1$. Note that $J$ is not changed in this case. The above process is iterated until all the blocks have been processed. At the end, we have $J$ fuzzy clusters, $C_1$, $C_2$, ..., and $C_J$. After that, the color of each pixel is replaced with the mean of the corresponding cluster to generate a quantized image.

### 2.3. Color-Based and H-based Region Growing

After the quantized image is obtained, we use a color-based region growing technique to divide it into several connected regions. A color-based region is formed by connecting a set of pixels with the same color according to the spatial relationship of eight-connectivity.

Besides, in the third phase, we find out those pixels with high local homogeneity by H-value calculation, group them into several seeded regions, and obtain a seeded region image. The calculation of H values is proposed by Jing et al. in [3]. For each pixel $(x, y)$ in the quantized image, we consider its $R$, $G$, and $B$ values separately. Let the considered attribute be $I(x, y)$. The H value of $(x, y)$ about $I(x, y)$ is calculated as follows. For each neighboring pixel $(x_i, y_i)$ in the square neighborhood of $(x, y)$ with width $2N+1$, we firstly calculate the corresponding vector $\vec{cp}_i = (x_i - x, y_i - y)$ and then obtain a vector $\vec{f_i}$ by the following equation:

$$\vec{f_i} = (I(x_i, y_i) - I(x, y)) \cdot \frac{\vec{cp}_i}{\|\vec{cp}_i\|}. \tag{7}$$

After that, we calculate the sum of all the vectors $\{\vec{f_i} | 1 \leq i \leq (2N + 1)^2\}$ by the following equation:

$$\vec{f} = \sum_{i=1}^{(2N+1)^2} \vec{f_i}. \tag{8}$$

Finally, the H value of $(x, y)$ about $I(x, y)$ is calculated by the equation: $H = \|\vec{f}\|$. Since we consider the $R$, $G$, and $B$ values of a pixel $(x, y)$ separately, we have three $H$ values for $(x, y)$, i.e., $H_R$, $H_G$, and $H_B$. To combine there three $H$ values, we use the following equation:

$$H = \sqrt{{H_R}^2 + {H_G}^2 + {H_B}^2}. \tag{9}$$

To decide the initial seeded regions, we employ the method proposed in [3] which utilizes both global and local information.

### 2.4. Combination

The main goal of this phase is to refine the initial seeded regions by combining the information of color-based regions and initial seeded regions. For each color-based region, we combine it into one seeded region or label it as non-seeded region by considering as follows. If the color-based region overlaps only one seeded region, then we combine it into the seeded region. Otherwise, we calculate the overlap ratio between the color-based region and each seeded region. If none of the ratios is higher than a predefined threshold, then we combine the color-based region into the seeded region with the highest overlap ratio. Otherwise, the color-based region and the seeded regions with overlap ratios higher than the threshold are combined together to form a new seeded region. Finally, we have a set of refined seeded regions formed by color-based regions and the other set of non-seeded regions.

### 2.5. Region-Based Region Growing

Unlike the region growing method in [3], we grow the regions based on the color-based regions which are labeled as non-seeded. We calculate the Eucliden distance of colors between each non-seeded color-based region and each seeded region. Then, we combine the non-seeded region with the lowest distance into the corresponding seeded region and update the color and size of the seeded region. This process is repeated until all non-seeded regions are processed. Finally, we have an initial segmented image.

### 2.6. Merging

There are two steps included in the merging phase. The first step is to merge regions by color similarities. We calculate the dissimilarity between each pair of neighboring regions. The dissimilarity is defined as that in [3]. Then, the pair of neighboring regions with the smallest dissimilarity are merged together to form a new region if the dissimilarity is smaller than a threshold. The process is repeated until all dissimilarities are larger than the threshold. In the second step, we combine the smallest region into the neighboring region with the smallest dissimilarity until all sizes of regions are bigger than a threshold. After above two steps are done, we have a final segmented image.

## 3. EXPERIMENTAL RESULTS

To demonstrate the performance of our approach, we compare the segmentation results generated by Jing's approach and our approach. Figures 2-5 show the segmentation results on four different images, i.e., chimpanzee, sea and mountain, butterfly, and elephant. We can see that the segmentation results produced by our approach are better than those produced by Jing's method. Jing's method generates some unreasonable small regions and imperfect regions. However, the segmented regions generated by our method are nearly perfect.

## 4. CONCLUSIONS

We propose an improved approach for image segmentation. The key contributions are described as follows. A color-based region image is obtained by a robust self-constructing fuzzy clustering. With the information of color-based regions, we can improve the initial seeded regions generated by local homogeneity features and obtain more precise and reasonable seeded regions. Besides, the region growing in our approach is region-based instead of the pixel-based employed generally. Therefore, our approach considers the information of quantized colors and local homogeneity features and presents a more precise and reasonable segmentation capability.

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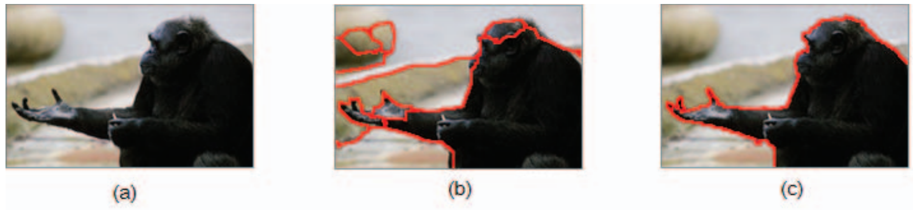


**Fig. 2**. Chimpanzee. (a) Original image. (b) Result by Jing's approach. (c) Result by our approach.

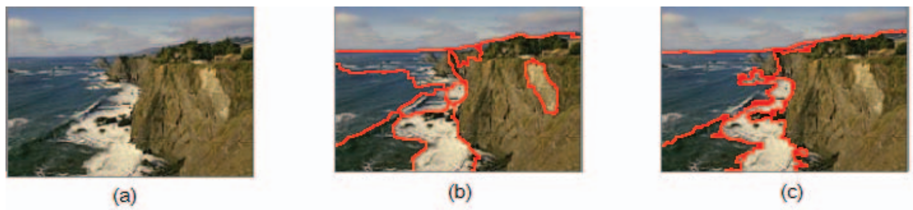


**Fig. 3**. Sea and mountain. (a) Original image. (b) Result by Jing's approach. (c) Result by our approach.


**Fig. 4**. Butterfly. (a) Original image. (b) Result by Jing's approach. (c) Result by our approach.

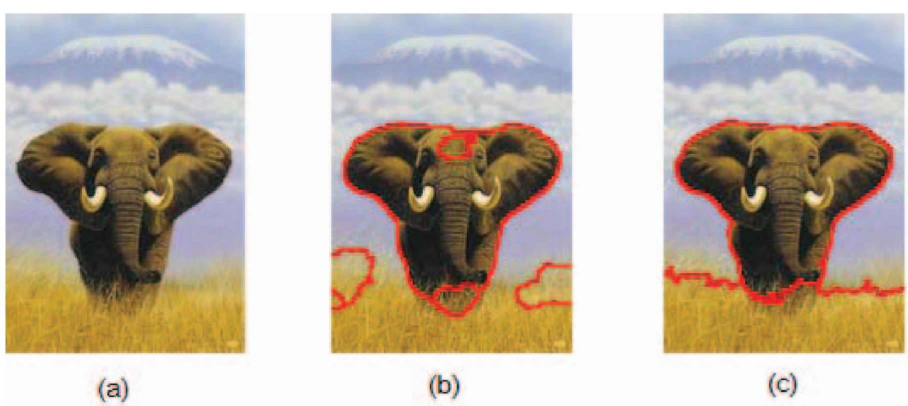


**Fig. 5**. Elephant. (a) Original image. (b) Result by Jing's approach. (c) Result by our approach.