A New Color Image Segmentation Algorithm Combining Mean Shift and Hierarchical Clustering

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Abstract

A new color image segmentation method combining mean shift and hierarchical clustering algorithm is presented in this paper. The proposed algorithm preprocesses an input image by mean shift algorithm to form segmented regions that preserve the desirable discontinuity characteristics of image. The number of segmented regions, instead of the number of image pixels, is considered as the input data scale of hierarchical clustering algorithm. On the stage of hierarchical clustering, the average of the color vectors in each region is considered as a cluster. The proximity between each cluster is calculated to form the proximity matrix, and then ward algorithm is employed to obtain the final segmentation results. Experimental results illustrate that the proposed algorithm has superior performance and less computational costs compared to the traditional clustering algorithm.

Keywords: Color Image Segmentation; Hierarchical Clustering; Mean Shift

1 Introduction

Clustering analysis is an important means of data mining, and involves many research fields including statistics, biology and machine learning, etc. There are many clustering methods such as K-means algorithm [1], K-center algorithm [2], EM algorithm [3], hierarchical clustering [4], fuzzy clustering [5], clustering based on density [6], spectral clustering [7], etc.

In computer vision, a lot of clustering algorithms are not proper to be applied if the processed image data set is too large. Because the data of digital image processing in computer vision is often great and the complexity of the image itself is unpredictable, the process of image segmentation often takes more time and lacks of precision or may be unrealistic. Therefore, how to realize the real-time automatic quick image segmentation is still extremely important and the problems are
not yet to be solved effectively. Hierarchical clustering, same as K-means clustering, is one of the classic clustering algorithms and widely used because of its simplicity and efficiency though it is relatively old compared to other new clustering algorithm. However, hierarchical clustering needs huge calculating time and requires large space, it often fails to solve the problem of real-time processing of large-scale data set.

To overcome these shortcomings, we propose a new image segmentation method which combines mean shift (MS) and hierarchical clustering in this paper. Firstly, we perform image region segmentation by using the MS algorithm, and then we treat these regions as the input data points of hierarchical clustering. The final step is to apply the hierarchical clustering to partition these regions. MS algorithm is an unsupervised clustering-based segmentation method, where the number and the shape of the data cluster are unknown. Moreover, the termination of the segmentation process is based on some region-merging strategy applied to the filtered image result, and the number of regions in the segmented image is mainly determined by the parameters $h$ and $M$. $M$ stands for the least pixels number of the division area and $h$ stands for bandwidth. If $h$ and $M$ are bigger, MS algorithm will smooth off some details area, and the integral area will be less. If $h$ and $M$ are smaller, the number of segmentation regions by MS algorithm will be more, which means that MS algorithm will be over-segmentation for image. Therefore, we usually can not get ideal image segmentation results by using MS algorithm alone. This paper combines MS algorithm and hierarchical clustering algorithm, and utilizes the advantages of the two algorithms, avoids the shortcomings of the two algorithms respectively and obtains better image segmentation results.

2 Relative Works

2.1 MS algorithm

MS algorithm was first proposed by Fukunaga and Hostetler [8] in 1975. Comaniciu [9] employed the MS algorithm successfully in feature space analysis. MS algorithm was also used in image smooth and image segmentation, and got good performance. MS algorithm is defined as

$$M_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i G \left( \frac{x_i - x}{h} \right)}{\sum_{i=1}^{n} G \left( \frac{x_i - x}{h} \right)} - x,$$

where $x$ is the center of the kernel (window), and $h$ is a bandwidth parameter. Therefore, the MS algorithm is the difference between the weighted mean, using kernel $G$ as the weight and $x$ as the center of the kernel (window). The MS algorithm is guaranteed to converge to a nearby point where the estimate has zero gradients. The center position of kernel $G$ can be updated iteratively by

$$y_{j+1} = \frac{\sum_{i=1}^{n} x_i G \left( \frac{x_i - y_j}{h} \right)}{\sum_{i=1}^{n} G \left( \frac{x_i - y_j}{h} \right)}, j = 1, 2, \cdots$$

where $y_1$ is the center of the initial position of the kernel.
2.2 Hierarchical clustering algorithm

Hierarchical clustering algorithm is a non-parametric estimation algorithm, and groups data with a sequence of nested partitions, either from singleton clusters to a cluster including all individuals or vice versa. The former is known as agglomerative hierarchical clustering, and the latter is called divisive hierarchical clustering. Hierarchical clustering organizes data into the hierarchical structure based on proximity matrix. The proximity is defined as the distance between any two points that are not in the same cluster. The results of hierarchical clustering are usually depicted by a binary tree or dendrogram. Agglomerative hierarchical clustering starts with \( N \) clusters, each of which includes exactly one data point. The closest pair of clusters is then merged in each step until only one cluster (or \( K \) clusters). Compared to agglomerative hierarchical clustering, divisive hierarchical clustering proceeds in the opposite way. In the beginning, the entire data set belongs to one cluster, and a procedure successively divides it until all clusters are singletons.

2.3 The proposed algorithm

The image segmentation result is not ideal to use the MS algorithm alone, and hierarchical clustering algorithm has high time and space complexity which is not suitable for dealing with large image data sets segmentation. Therefore the proposed algorithm first applies MS algorithm to pre-segment the image, and sets bandwidth \( h \) and region minimum number of pixels \( M \) reasonably. Then we get the coarse segmented image. The region number after MS algorithm is far less than that of the original image pixels points, and far more than that of the final segmentation region number. Finally hierarchical clustering is applied to partition these regions and obtain the final segmentation results.

Hierarchical clustering algorithm gets the clustering results according to the proximity between data points. When processing the image datasets, we need to define the feature space before calculation the proximity. The feature of an image can be the color, texture, shape and statistical characteristics, etc. In this paper, we choose color information as the main feature. For color images, the color of each point are represented by a 3 dimension vector \( X_i = (X_{1i}, X_{2i}, X_{3i}) \), the color difference between pixels (Euclidean distance) is as follow:

\[
d_{ik} = \|X(i) - X(k)\|^2
\]  

(3)

Suppose that the image is divided into \( m \) regions \( R_i, i = 1, ..., m \) by MS algorithm, the color vector in each region is \( X_{R_i} = (\bar{x}_{1i}, \bar{x}_{2i}, \bar{x}_{3i}) \), where \( \bar{x}_{1i}, \bar{x}_{2i}, \bar{x}_{3i} \) are the mean pixel intensities of the \( i \)th region in the three different color spaces respectively. Then the color difference between regions after MS segmentation is as follow:

\[
d_{R_{ik}} = \|X_{R_i} - X_{R_k}\|^2
\]  

(4)

At the stage of hierarchical cluster in the proposed algorithm, the average value of the color vector \( X_{R_i} \) after MS algorithm pre-segmentation is considered as a cluster, and the proximity matrix is formed by calculating the differences (Euclidean distance) between each cluster. Then ward algorithm is employed to merge the closest two clusters and obtain final K clusters. Ward algorithm merges the two adjacent clusters each time according to the minimum of SSE between the two clusters. The updating formula of proximity between two clusters \( C_i, C_j \) is as follow:

\[
u^* = \frac{n_i u_i + n_j u_j}{n_i + n_j} = u_i + \frac{n_j(u_j - u_i)}{n_i + n_j} = u_j + \frac{n_i(u_i - u_j)}{n_i + n_j},
\]  

(5)
where $u^*$ is the centroid of the cluster $C^*$ after merging, $n_i, u_i, n_j, u_j$ are the size and mean of cluster $C_i, C_j$.

$$SSE_{C^*} = \sum_{x \in C_i} \| x - u^* \|_2^2 + \sum_{x \in C_j} \| x - u^* \|_2^2$$

$$= SSE_{C_i} + \frac{n_i n_j^2}{(n_i + n_j)} \| u_i - u_j \|_2 + SSE_{C_j} + \frac{n_j n_i^2}{(n_i + n_j)} \| u_i - u_j \|_2$$

(6)

So the distance between cluster $C_i$ and $C_j$ is

$$d(C_i, C_j) = \sqrt{\frac{n_j n_i}{n_i + n_j} \| u_i - u_j \|_2}$$

(7)

The proposed algorithm procedure is as follows:

(1) Preprocess the input target image by MS algorithm;

(2) According to the results after MS algorithm, compute the color average value of all regions, and regards the color average value of each region as an input data point of hierarchical clustering algorithm;

(3) According to hierarchical clustering algorithm, regard each input point as a cluster and calculate the proximity matrix;

(4) Merge the closest two clusters and update the proximity matrix according to the definition of the distance function;

(5) Repeat Step 3 ∼ 4, until only K clusters remain.

3 Experimental Results

The code was implemented in MATLAB 2007b and run on a PC machine with an Intel (R) core (TM) 2 Quad CPU Q6600 2.40 GHz and 4 GB memory. In the experiments, the parameter of MS algorithm are set to be $h = (h_r, h_s) = (6, 8)$, $M = 50$. The comparison of the segmentation results by MS algorithm, K-means algorithm and the proposed algorithm are shown in Fig. 1 respectively. The used images are from Berkeley standard image library BSDS500 [10]. The size of all images is $240 \times 160$.

Fig. 1(a)∼(e) are respectively the original images, segmentation results by MS algorithm, segmentation contours by the proposed algorithm, segmentation results by the proposed algorithm and segmentation results by K-means algorithm. From Fig. 1(b), we can see that the segmentation results are over segmented by MS algorithm alone. The region number after MS algorithm is far less than that of the original image pixel point, and far more than that of the final segmentation area number. Then hierarchical clustering is applied to obtain the final segmentation results. From Fig. 1 (c) (d), we can learn that the segmentation results by the proposed algorithm are much better than those by K-means (shown in Fig. 1(e)). The first image of Fig. 1(a), after K-means segmentation, the segmentation results of the mountain part in the image are very poor.
and exist many isolate points and out group points. Furthermore, the cloud in the sky is not segmented out. In addition, for more complex image, such as the third image shown in Fig. 1(a), the person and background are mixed together after K-means segmentation, and there are more isolate points and out group points, too. The segmentation results by K-means algorithm are not stable, and the edges are not smooth. The proposed algorithm gives full consideration to the integrity of the image, isolate points and out group points are fewer and the edges are much smoother. The segmentation results are more superior.

Fig. 2 are the segmentation results comparison between the proposed method and human segmentation. From Fig. 2, we can learn that the segmentation results by the proposed method are satisfied and much closer to the human segmentation.

<table>
<thead>
<tr>
<th>Image No. (from top to bottom)</th>
<th>Region num. of MS</th>
<th>Region num. of proposed algorithm</th>
<th>Region num. of K-means</th>
<th>Time of MS(s)</th>
<th>Time of hierarchical clustering(s)</th>
<th>Time of K-means(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>89</td>
<td>6</td>
<td>6</td>
<td>0.729</td>
<td>0.093</td>
<td>0.682</td>
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<td>73</td>
<td>3</td>
<td>3</td>
<td>0.737</td>
<td>0.092</td>
<td>0.405</td>
</tr>
<tr>
<td>3</td>
<td>104</td>
<td>10</td>
<td>10</td>
<td>0.725</td>
<td>0.095</td>
<td>1.146</td>
</tr>
</tbody>
</table>

Computation time comparison of the proposed algorithm and K-means algorithm is shown in Table 1. From the Table 1, we can see that the main time consumption of the proposed algorithm is in MS step. After MS pre-segmentation, run time of hierarchical clustering algorithm is very short, basically just 0.1s. Because time complexity of K-means clustering algorithm is linear to the cluster number, so when the cluster number is few, the time consumption of K-means algorithm is less than that of the proposed algorithm. Such as the second image in Fig. 1(a), the cluster number is 3, the total time consumption of the proposed algorithm is about 0.829s, while the time consumption of K-means algorithm is only 0.405s. When the number of segmentation region
is much more, the time consumption of K-means algorithm is more than that of the proposed algorithm. Such as the third image in Fig. 1(a), the number of segmentation region is 10, and the total time consumption of the proposed algorithm is about 0.820s, while the time consumption of K-means algorithm is up to 1.146s. So, the efficiency of the proposed method is higher.

For the size of the image is $240 \times 160$, the data point number is 38400. For so large data scale, if hierarchical clustering algorithm is applied to segment the image directly, it is time-consuming and need a lot of memory space, even the ordinary PC may not realize. However, after pre-segmenting the image by MS algorithm, the proposed algorithm reduces the size of the input data of hierarchical clustering algorithm by replacing the number of the pixels in original image to the number of segmentation regions. Compared to hierarchical clustering algorithm, the proposed algorithm reduces the time and space complexity of calculating the proximity matrix and gets higher efficiency. The experimental results show that the proposed algorithm has the ability of dealing with large image data set and gets better segmentation results than traditional clustering algorithms.

4 Conclusions

This paper presents a new color image segmentation method combining mean shift and hierarchical clustering algorithm. The proposed algorithm first uses MS method to pre-segment the
image and get the over-segmentation results, and then employs hierarchical clustering algorithm to obtain the final segmentation results. Hierarchical clustering algorithm considers global information, but it has high complexity and running time. Therefore the proposed algorithm combines the advantages of MS algorithm and hierarchical clustering algorithm for the color image segmentation. The experimental results show that the proposed algorithm can get better segmentation results and have higher efficiency than traditional clustering algorithms.

Acknowledgement

This work is supported by the Natural Science Foundation of China (60975042), the Doctor Foundation of Harbin University (HUDF2013-005), the Science and Technology Project Foundation of Heilongjiang Province Department of Education (12533043) and the Science and Technology Research Project of Harbin (2012DB2BG048). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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