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Research on Image Segmentation based on Clustering Algorithm

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Abstract

Hierarchical clustering (HC) algorithm can obtain good clustering results, but it needs large storage and computational complexity for large image processing. Anew color image segmentation algorithm based on mean shift and hierarchical clustering algorithm named MSHC is presented in this paper. MSHC algorithm preprocesses an input image by MS 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 HC algorithm. The proximity between each cluster is calculated to form the proximity matrix, and then ward algorithm is employed to obtain the final segmentation results. MSHC algorithm is employed on color image and medical image segmentation.

Keywords: *image segmentation, clustering analysis, mean shift, Hierarchical clustering*

1. Introduction

Currently the clustering method often used for segmenting large-scale images performs pre-treatment of images, which can be implemented with less complicated clustering algorithm or others; then it makes the second clustering separation with such other clustering algorithms like the combined approach of watershed algorithm and spectral clustering algorithm [1-3], mean shift algorithm and Ncut algorithm [4], marked watershed and region merging algorithm [5], combined texture image segmentation of EHMM-HMT and MSWHMT [6], combined color image segmentation of EFD and Ncut [7], MRI medical image segmentation based on FCM and Level Set [8], infrared image segmentation based on contourlet transform and improved fuzzy C-means clustering [9]. The basic idea of those methods is to divide images to small domains with less complicated clustering algorithm, then with them as data samples, choose properly some features of them for the second clustering till complete the final partition of images. This type of methods reduces the volume of data for the second clustering through pre-processing, degrading greatly the overall complexity of the algorithm and improving drastically the efficiency. As seen, those methods are feasible for segmentation of massive image data.

Watershed algorithm and mean shift algorithm are both common pre-treatment algorithms. The former is simple and efficient. However it easily leads to over-segmentation for too many and refined partitions caused after segmenting. The afterward treatment based on that is not satisfactory. Mean shift (MS) algorithm has two steps by avoiding the estimation of probability density function: discontinuous preserving filter and mean shift clustering. But its segmented results are affected by the size of kernel, *i.e.*, parameter h and M, where h is bandwidth of kernel function; M is the number of fewest pixel points in divided region; appropriate h and M are not always easily determined. Hence, if the two parameters are set not reasonably, there will cause over-segmentation or under-segmentation of images (no sufficient information acquired because some detailed regions smoothed). The results of segmentation with mere use of MS algorithm are not desirable.

Here we keep to the idea of multi-layered clustering: firstly use less complicated algorithm like MS algorithm to pre-cut images; then based on pre-segmenting results, choose quality clustering method for the second clustering and merging. We do like that in order to cut large-scale images in a rapid and efficient manner and overcome the problems of high computational and temporal complexities, which are found in some high quality clustering algorithms when they're clustering images in pixel level. On this case, we discuss about why some high quality clustering algorithms are hardly applied to process the segmentation of massive image dataset when they're challenged with costly computing complexity and tremendous memory requirement in solving image cutting problem. A multi-clustering algorithm is proposed here for image segmentation. Considering hierarchical clustering algorithms are impossibly utilized to treat large image data due to high temporal and spatial complexities, we develop the image segmentation algorithm based on both MS algorithm and hierarchical clustering (HC), which is MSHC algorithm in short. It's also used in segmenting color images and medical images and makes good effects, together with enhanced cutting efficiency.

2. Pre-Segmentation by Mean Shift Algorithm

In image segmentation by mean shift algorithm, we introduce firstly smoothing because segmentation can be regarded as extension of smoothing. For the processing of color images, it's required to process simultaneously image's color information and spatial location information. So inputting any pixel of the image is described as one 5D information vector, in the expression $x=(x^s,x^r)$; where x^s is 2D spatial location coordinate; x^r is 3D color feature vector. The kernel function is expressed as follows:

$$K_{h_s,h_r}=\frac{C}{h_s^d h_r^p}k\left(\|\frac{x^s}{h_s}\|^2\right)k\left(\|\frac{x^r}{h_r}\|^2\right) \tag{1}$$

In it, C is a normalized constant; ρ and d refer to space dimension(ρ =3,d=2); h_s is radius of the kernel function, indicative of space's kernel size; h_r is radius of feature space, the kernel size of value range.

Set the number M of the fewest pixels in divided region. Suppose x_i is dot in one d-dimension original input image; z_i is dot in the image after mean-shift pre-processing. The smoothing is implemented as follows:

(1) Initializing Make j=1 and $y_{i,1}=x_i$; start from the first pixel point of input image to traverse the whole image; and write down central positions of changing kernel function during the shift;

(2) Employ mean shift algorithm mentioned above to calculate $y_{i,j+1}$ till the iteration meets converging condition; end convergence and write down convergence value $y_{i,c}$;

(3) Assignment of $z_i=(x_i^s,y_{i,c}^r)$ zi, *i.e.*, assign the spatial position of point i and color information of i's convergence point to the smoothed point.

For image segmentation, mean shift algorithm uses similar principle with smoothing; that is, cutting image on the basis of image smoothing; to put it simply, clustering all pixels converged by one maximum value point of the same density in the input image and assigning cluster's label to all points in the cluster; any one cluster with point number smaller than M after segmentation should be removed. Mean shift algorithm implements the segmentation in following steps:

The image receives smoothing processing by mean shift algorithm; 5D vector's convergence point $z_i = (x_i^s, y_{i,c}^r)$ is recorded during the implementation of mean shift; pixels in the same class are converged to one point;

The division follows this criterion: as per h_s and h_r, categorize all points z_i whose spatial domain distance shorter than h_s and feature space distance shorter than h_r to respectively one class; they're finally sorted as class ρ; It is indicated by $\{C_\rho\}_{\rho=1,\dots,m}$

Mark the image; $L_i = \{\rho \mid z_i \in C_\rho\}$

Merge the region where it's pixels fewer than M to its neighboring small region.

The result of mage segmentation by mean shift is shown in Figure 1. After pre-segmentation, the image is parted to lots of small regions. From the picture, we see target objects are cut finely after pre-treatment and edge information is well conserved.

(a) original (b) The segmentation results of Mean shift

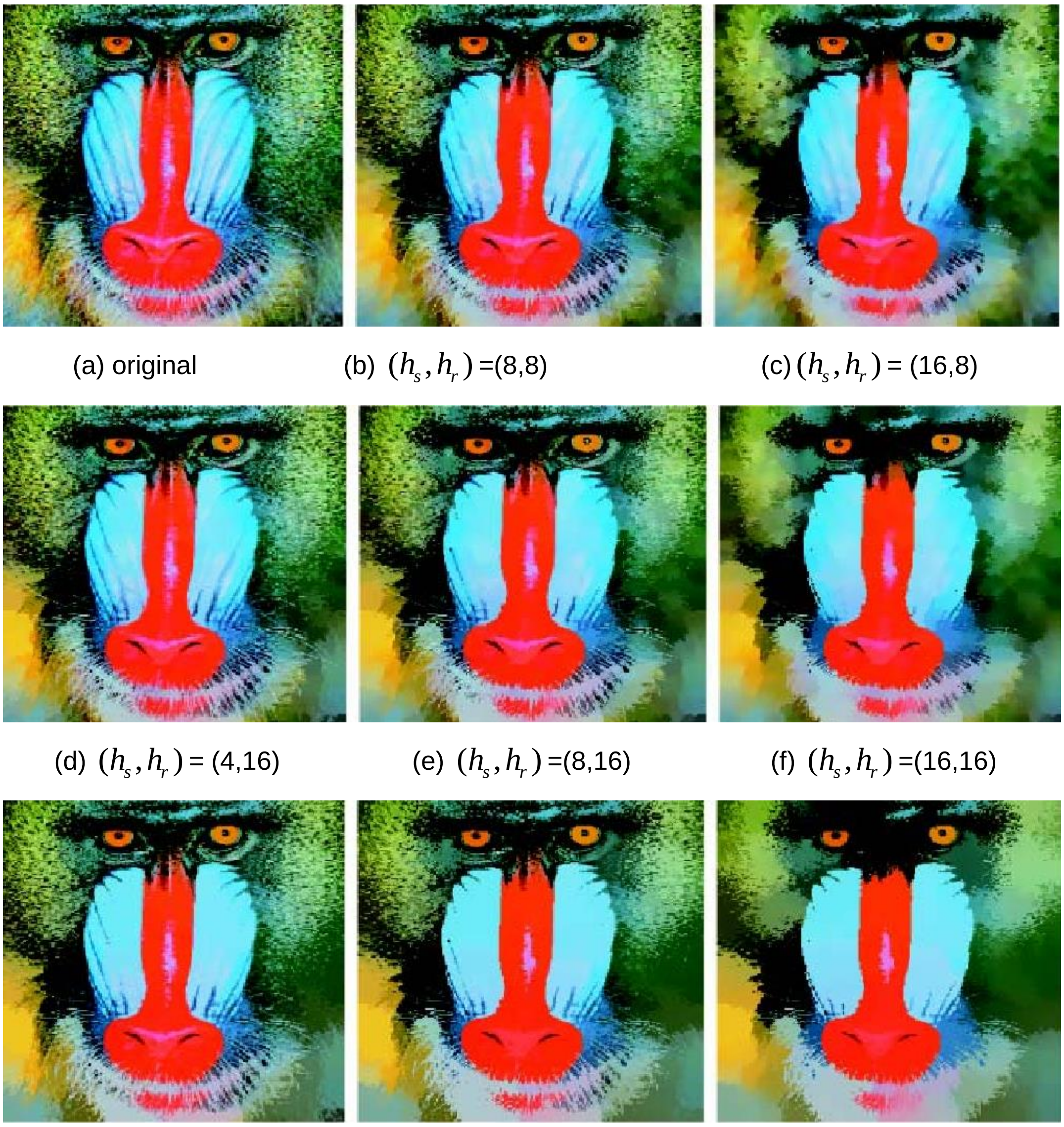
Figure 1. Mean Shift Preprocessing Result

(a) original (b) The segmentation results of Mean shift

Figure 2. Mean Shift Segmentation Result

Figure 2 shows for value $[h_s, h_r, M] = [8, 6, 1000]$ of the parameter, segmentation result by mean shift algorithm for Figure 1(a); Figure 2(a) gives normal segmentation result. Clearly, after division, the region number cuts down obviously; outer boundary of lotus has no big changes, except that fine grains on petals are smoothed; Figure 2(b) is overlapped picture of extracted edges and original image.

In the image cutting by mean shift method, h_r and h_s are very important parameters. They can be determined by required resolution in the experiment. Different h_r and h_s will have impacts on the ultimate segmentation results. See details in Figure 3.



(a) original (b) (h_s, h_r) =(8,8) (c) (h_s, h_r) = (16,8)

(d) (h_s, h_r) = (4,16) (e) (h_s, h_r) =(8,16) (f) (h_s, h_r) =(16,16)

(g) (h_s, h_r) = (4,32) (h) (h_s, h_r) =(8,32) (i) (h_s, h_r) =(32,16)

Figure 3. Segmentation Results with Different h_s, h_r

3. Image segmentation algorithm based on MSHC

3.1. Selection of Image Features

Hierarchical clustering algorithm performs clustering merging according to the proximity between data points and produce final clustering results. In processing image data, before calculating the vicinity between pixel dots, it needs to define feature space. Image's feature can be its color, texture, statistical characteristics and shape *etc*. Here we choose color information as the main feature. Regarding color image, the color of each point is expressed with one 3D vector as $X_i = (x_{1i}, x_{2i}, x_{3i})$. Then, the color difference *i.e.*, Euclidean distance between pixel points is:

$$d_{ik} = \| X(i) - X(k) \|^2 \tag{2}$$

Assume $R_i (i = 1, 2, ..., m)$ is one of the m regions after division of pre-processed images by MS algorithm. The color vector of point in each region is depicted as $X_{R_i} = (\overline{x}_{1i}, \overline{x}_{2i}, \overline{x}_{3i})$; where $\overline{x}_{1i}, \overline{x}_{2i}, \overline{x}_{3i}$ is mean value of all pixels' related color components in the ith area. To obtain better segmentation result, we need to select the color space whose color difference is associated with Euclidean distance. We take Luv color model which has linear mapping feature. This model is introduced previously. L means luminance; u and v refer both to chromaticity coordinate. The color difference *i.e.*, Euclidean distance between regions is:

$$d_{R_{ik}} = \| X_{R_i} - X_{R} \|^2 \tag{3}$$

3.2. Description of Image Segmentation Method based on MSHC

When MSHC implements image segmentation, in hierarchical clustering period, it regards the mean value X_{R_i} of point's color vector in each region after MS pre-cutting as one cluster and computes the difference degree (*i.e.*, Euclidean distance) between clusters to constitute proximity matrix; then, it merges with Ward algorithm to generate the final k clusters. Ward algorithm is an agglomerative hierarchical clustering algorithm utilizing global target function such as minimal SSE. Its acquired results are superior over other hierarchical clustering methods. Ward algorithm merges two most adjacent clusters in accordance to their minimal increment of sum of squared errors (SSE). Then, it updates proximity matrix. After n-k mergences, k clusters are produced. Hereunder is the equation for calculating the proximity of two clusters C_i and C_j. Mark the centroid u^* of cluster C^* after merging, and then:

$$u^* = \frac{n_i u_i + n_j u_j}{n_i + n_j} = u_i + \frac{n_j (u_j - u_i)}{n_i + n_j} = u_j + \frac{n_i (u_i - u_j)}{n_i + n_j} \tag{4}$$

Where, n_i, u_i, n_j, u_j respectively show the mean and size of clusters C_i C_j .

$$
\begin{aligned}
SSE_{C^*} &= \sum_{x\in C_i} \| x-u^* \|^2 + \sum_{x\in C_j} \| x-u^* \|^2 \\
&= \sum_{x\in C_i} \| x-u_i-\frac{n_j(u_j-u_i)}{n_i+n_j} \|^2 + \sum_{x\in C_j} \| x-u_j-\frac{n_i(u_i-u_j)}{n_i+n_j} \|^2 , \\
&= SSE_{C_i} + \frac{n_i u_j^2}{(n_i+n_j)^2} \| u_i-u_j \| + SSE_{C_j} + \frac{n_j u_i^2}{(n_i+n_j)^2} \| u_i-u_j \| \\
&= SSE_{C_i} + SSE_{C_j} + \frac{n_j u_i}{n_i+n_j} \| u_i-u_j \|
\end{aligned}
\tag{5}
$$

Clusters C_i C_j Distance is

$$
d(C_i, C_j) = \sqrt{\frac{n_j n_i}{n_i+n_j} \| u_i-u_j \|}
\tag{6}
$$

We use the sample data with six 2D points to compare all hierarchical clustering algorithms. Six points' coordinate x, y, Euclidean distance among them and spatial position are found in Table 1 and 2, as well as Figure 4. The clustering process is schematically shown in Figure 5-8.

Table 1. Coordinates of 6 Points

points	(x,y)
P1	(0.40, 0.53)
P2	(0.22, 0.38)
P3	(0.35, 0.32)
P4	(0.26, 0.19)
P5	(0.08, 0.41)
P6	(0.45, 0.30)

Table 2. Euclidean Distance Matrix for 6 Points

	P1	P2	P3	P4	P5	P6
P1	0.00	0.24	0.22	0.37	0.34	0.23
P2	0.24	0.00	0.15	0.20	0.14	0.25
P3	0.22	0.15	0.00	0.15	0.28	0.11
P4	0.37	0.20	0.15	0.00	0.29	0.22
P5	0.34	0.14	0.28	0.29	0.00	0.39
P6	0.23	0.25	0.11	0.22	0.39	0.00

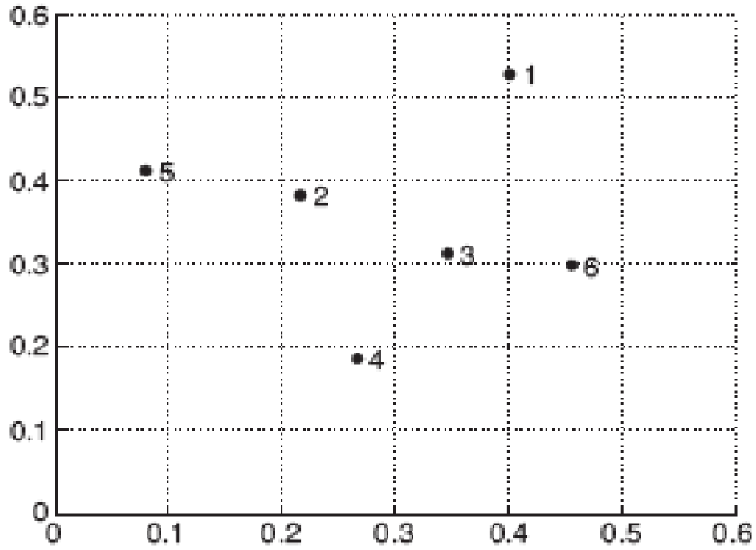
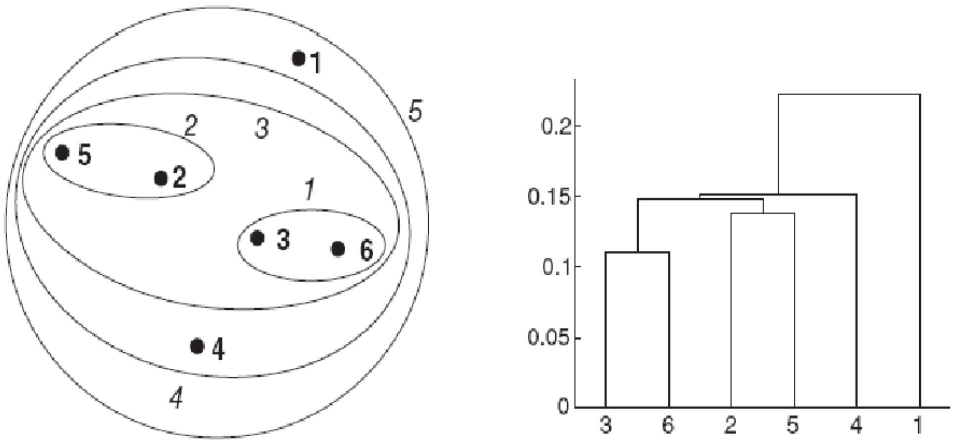
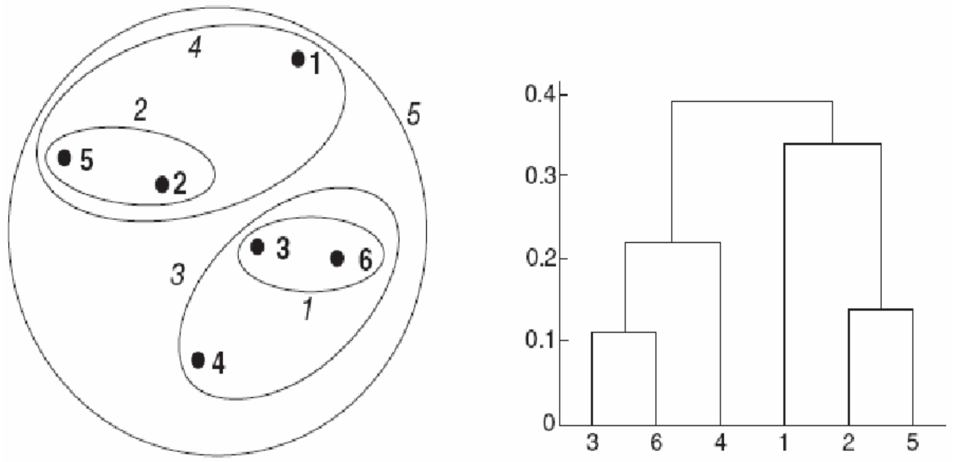


Figure 4. Set of 6 Two-Dimensional Points



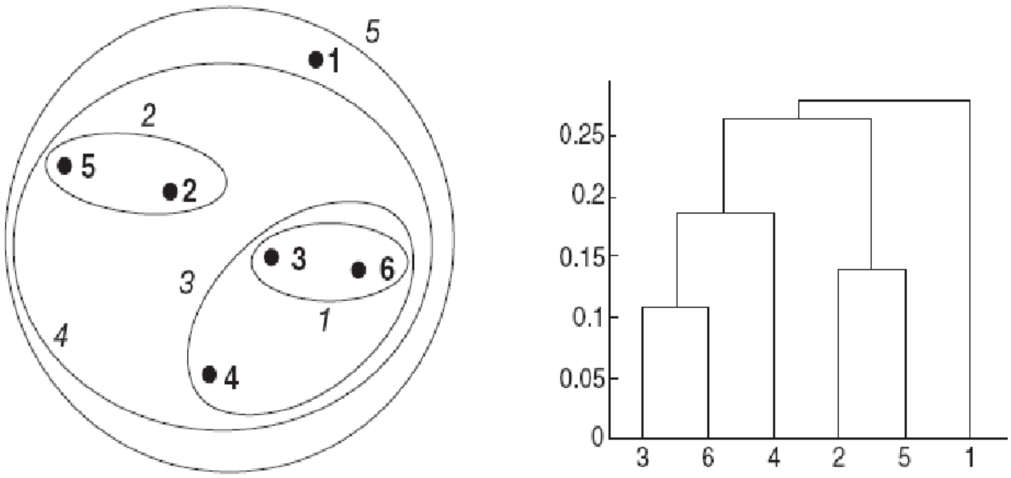
(a) Single Chain Cluster (b) Single Tree

Figure 5. Single Link Clustering of the 6 Points



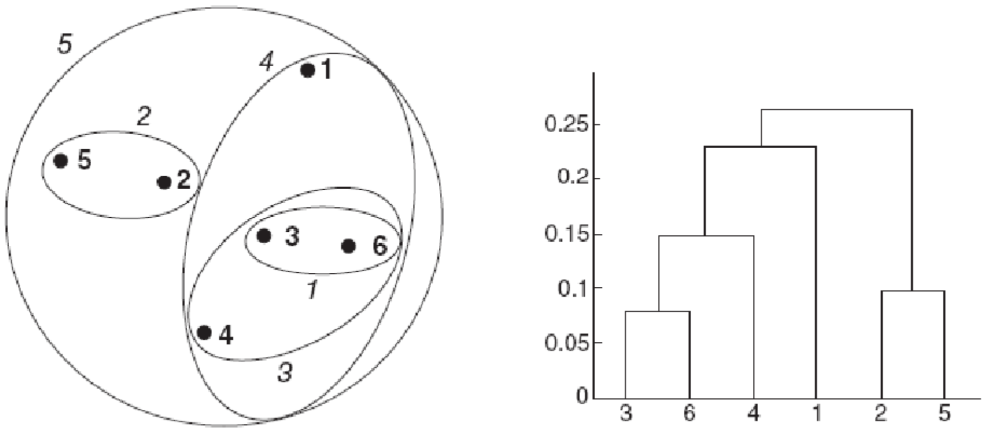
(a) the Whole Chain Cluster (b) the Whole Chain Tree

Figure 6. Complete Link Clustering of 6 Points



(a) Group Average Clustering (b) the Average Tree

Figure 7. Group Average Clutering of 6 Points



(a) Ward Cluster (b) Ward Tree

Figure 8. Ward Clustering of 6 Points

As observed, different distances cause different clustering results. Ward algorithm gets excellent clustering result.

After MSHC algorithm finishes clustering segmentation, isolated regions exist in images. So it’s necessary to make after-treatment of them. We introduce the simple quad adjacent point weighting to the algorithm. Weighting operator Θ is put in the expression:

$$\Theta = \frac{1}{8}\begin{bmatrix} 0 & 1 & 0 \\ 1 & 4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{7}$$

Through post-processing by the weighting, images are smoothed. More tiny noises are removed. Surely, other weighting methods are applicable for the work, like central weighted method.

MSHC algorithm includes these steps:

(1) Apply MS algorithm for pre-segmentation of input color images;

(2) As per results of pre-cutting by MS algorithm, calculate the mean value of all region's colors, with value of each region as one data point of HC algorithm input;

(3) Like hierarchical clustering algorithm, regard each data above as one cluster and estimate proximity matrix;

(4) According to predefined distance function, merge two closest clusters and update proximity matrix;

(5) Repeat 3~4 till the number of class meets the preset quantity and till only K clusters are left;

(6) Apply weighted operator Θ for post-processing.

What's to mention is in the algorithm, in the second clustering, MS pre-cut regions are used to replace numerous pixel points in the original images. So in step (5), it's required to reset the final clustering label, making it match with pixels of the original image.

4. Experiment Design and Discussion

The test is conducted in MATLAB2007b. The computer is configured to Intel (R) core (TM) 2 Quad CPU Q6600 2.40 GHz, 4G memory. In MS algorithm, make parameter $h=(h_r,h_s)=(6,8)$, M=50; h_r is bandwidth of value range; h_s is bandwidth of space range. All used images are in the range [10-11] collected from Berkeley's standard color image library BSDS500. To make better comparative tests, we make input images all at 160×240 or 240×160.

Figure 9 compares the color image segmentation results of MSHC, MS and k-means algorithm. It's seen that after MS cutting, the original image is divided into many regions and there's over-segmentation. The quantity of segmented regions is below pixel number of the original image but above the final cut region number. Then with hierarchical clustering, those regions are merged to get the ultimate clustering segmentation results. As seen in Figure 9(c), (d), results are pretty good. Figure 9(e) is segmentation result by K-means method, which is not so good. Like the first picture in Figure 9, after K-means segmenting, the segmentation of mountain in the image is on the whole very bad, with many isolated points and off-group points. Besides, clouds on the sky are not segmented. Regarding more complicated image, like the fourth picture in Figure 9, after K-means cutting, people and the background are mixed together, without complete separation. There're more isolated and noise points. Segmentation result is very inferior. The algorithm's input outcome is not stable and edges are not smooth. The proposed MSHC algorithm considers fully the image integrality, with fewer off-group points and smooth edges. The segmentation result is satisfactory. The proposed algorithm's time is mainly consumed by MS operation. After MS pre-segmenting, hierarchical clustering algorithm runs very short, only 0.1s, because K-means algorithm's time complexity is linearly related with the category number of clustering. When the segmented class number is very small, K-means method runs shorter than MSHC.

In Figure 9, the second image has 3 segmented classes, where MSHC runs 0.829s and k-means runs 0.405s. When the segmented class number is more, K-means algorithm takes more time than MSHC. As seen in Figure 9, the third image has 10 segmented categories, where MSHC algorithm runs 0.820s; K-means algorithm requires 1.146s. In general, MSHC algorithm has higher operational efficiency.

On this part we analyze the complex degree of MSHC. For one image at 240x160, it has 38400 data points. Regarding such a huge data scale, if we use directly hierarchical clustering algorithm for clustering segmentation, its proximity matrix will reach up to 38400x38400. The computation of ten-thousand dimensional matrix is considerably time-consuming and requires huge memory space. A common PC may not complete the operation. But the proposed MSHC algorithm uses the number of regions after MS pre-segmentation to substitute that of pixels in original image. After MSHC pre-segmentation, the number of regions is less than 200, apparently, 200<38400. MSHC algorithm decreases obviously the scale of hierarchical clustering algorithm input data by means of pre-segmentation, reducing running time and spatial complexity of proximity in the hierarchical clustering algorithm. MSHC algorithm's calculating efficiency is remarkably raised. It fully suggests that MSHC algorithm has the ability to process large-scale image dataset.

5. Conclusion

In the paper, it probed into the problem of multi-layered clustering segmentation of massive image dataset. In normal cases, the quality and speed of image segmentation are contradictory. The algorithm with good segmentation result would work inefficiently; while the efficient algorithm would cause poor precision of segmentation. Sometimes good quality is acquired at the cost of sacrificing speed; and sometimes in turn. The objective of the paper is to consider both quality and speed, for quick and good image segmentation within a certain range.

(a) The Original Image (b) MS Segmentation (c) MSHC Segmentation (d) MSHC Results (e) Kmeans Results

Figure 9. Segmentation Results Comparison among 3 Methods

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