Color Image Segmentation Method Based on Improved Spectral Clustering Algorithm

Dong Qin
Yancheng Institute of Technology, Yan Cheng, China
Email: dongqin011@163.com

***Abstract*—Contraposing to the features of image data with high sparsity of and the problems on determination of clustering numbers, we try to put forward an color image segmentation algorithm, combined with semi-supervised machine learning technology and spectral graph theory. By the research of related theories and methods of spectral clustering algorithms, we introduce information entropy conception to design a method which can automatically optimize the scale parameter value. So it avoids the unstability in clustering result of the scale parameter input manually. In addition, we try to excavate available priori information existing in large number of non-generic data and apply semi-supervised algorithm to improve the clustering performance for rare class. We also use added tag data to compute similar matrix and perform clustering through FKCM algorithms. By the simulation of standard dataset and image segmentation, the experiments demonstrate our algorithm has overcome the defects of traditional spectral clustering methods, which are sensitive to outliers and easy to fall into local optimum, and also poor in the convergence rate.**

***Index Terms*—Spectral Clustering; Segmentation; Intimate Matrix; Scale Parameter; KFCM**

I. INTRODUCTION

Color image segmentation based on data clustering is to take the whole image as an integral data. The predetermined defined distance measure method is used to calculate the similarity relation of pixel point to determine different regions of image. During past dozens of years, people apply many different clustering algorithms into image segmentation such as means algorithm [1, 2]. Since K means algorithm only fits data in spherical space and many data structures in reality are not this shape, segmentation results which are caused by these methods cannot be satisfied. Recently, spectral clustering based on spectral graph theory [3, 4, 5] has attracted people's focus of research. Compared to traditional algorithm, it has obvious advantages. This algorithm can operate in sample space with random shape and converge in global optimization and this characteristic extensively adapts to data. In addition, by means of spectral clustering, Gauss kernel needs to be applied to calculate similarity between random two points to form similarity matrix for clustering. When the scale of data set is large, computational complexity and memory capacitance of eigenvector decomposition which is performed by L matrix obtained from similarity matrix will become bottleneck. Meanwhile, parameter ξ in Gauss kernel has the largest influence on similarity between two points. However, there is not any effective method in current theory to automatically select the most appropriate value [6]. The value can only be set according to human experience. If data set type is different, ζ value is also different so it causes instable clustering results. On the basis of above analysis, there are two points which can be generalized from problems in this method: (1) Clustering is very sensitive to parameter; (2) Large time complexity and space complexity.

Towards above problems, scholars constantly study and effectively combine ensemble learning methods and spectral clustering [7, 8] to improve the robustness of clustering method and to avoid parameter selection troubles. Meanwhile, through many studies, it has been proved that the performance of clustering ensemble is superior to single clustering algorithm when it performs data-clustering with random shape and scale [9]. In 2003, Dudoit and J.Fridlyand [10] applied BOOTSTRAP sampling technology of data to generate different subsets of data and used the same algorithm to cluster on these different subsets so as to form a group of clustering. In 2005, Tang Wei and Zhou Zhihua [11] applied generating method of selective clustering member. They used BOOTSTRAP sampling method to obtain different data subset and cluster in this data subset with clustering algorithm to get different clustering members. Muna and Domeniconi [12] used different parameters of Locally Adaptive Clustering algorithm to generate diversified clustering members. Through certain selective strategy, Fern and Lin [13] selected some of clustering results to ensemble. In 2009, Hore, etc divided large dataset into non-overlapping data subset and clustered each data subset. The obtained diversified data is divided and BIPARTITE and METIS methods are used to integrate. Jia [14] applied the nearest neighbor method to select suitable clustering member to obtain integration result. Through above introductions, we can see that scholars adopted different methods to study based on image segmentation and obtain satisfied results to some extent. The implementation clustering method to study image segmentation attaches scholars' more and more attentions.

Therefore, this paper uses spectral clustering method to deeply study the image segmentation and clustering integration technology to further improve the performance of image segmentation. We attempt to

doi:10.4304/jmm.9.8.1024-1031

excavate available prior information in amounts of non-category data and apply semi-supervised algorithm to solve and excavate rare class problems. As image segmentation method is too sensitive to parameter selection, ensemble learning method with robustness and strong generalization ability can be applied. A self-adaptive semi-supervised fuzzy spectral clustering algorithm is proposed. This algorithm does not need to determine clustering category and it computes the value of scale parameter σ according to the distance between two points. Through the analysis on the spectral clustering algorithm and the problems of super-boundary integration method, K-MEANS algorithm in spectral clustering is replaced by FKCM algorithm. The fuzzy cluster validity function is introduced in algorithm to optimize cluster number. Membership matrix formed by FCM will extend "0" and "1" in super boundary fusion method to range [0,1] and cluster new super boundary so as to obtain final image segmentation result. Finally, by means of simulation experiment of data sets and image segmentation, the result shows that clustering effect of this algorithm is perfect.

II. PRELIMINARY WORKS

A. Image Segmentation Models

Image segmentation technology has become a research spot in the field of image processing to be studied by most scholars recently. Thousands of image segmentation algorithms have been proposed so far and hundreds of research results will be published every year. Since most image segmentation algorithms are put forward for special problems, there are big limitations and pertinence [15]. Related researchers have proposed an accepted definition for image segmentation based on the set theory [16]:

The images to be segmented are looked as a set denoted by R. The process of segmentation is equivalent to segment R into several sub-sets $R_1, R_2, ..., R_n$ by different algorithms. The sub-sets should satisfy the following conditions:

(a) $\bigcup_{i=1}^{n} R_i = R$

(b) $R_i \cap R_j \neq \Phi$

(c) $P(R_i) = TRUE, i = 1,2,...,n$

(d) $P(R_i \cup R_j) = FALSE, i \neq j$

(e) R_i is connected area, $i = 1,2,...,n$

In the above points, (a) means the segmented images set can be used to revert to original images; (b) means there are not overlapped parts among the segmented sub-sets; (c) means each of the segmented sub-sets should be non-empty; (d) means different segmented sub-sets are independent each other in character or feature; (e) means any of segmented sub-sets is connected.

B. Implementation of Spectral Clustering Algorithm

The idea of spectral clustering algorithm originates from spectra division theory and it takes clustering as a multi-channeled division problem of undirected graph. Original sample data is mapped to k-dimension space. Then, clustering algorithms such as traditional k-means, kernel c-means, etc are applied to cluster in k-dimension space.

We assume a dataset X, $X = \{x_1, x_2, ..., x_k\}$ is considered as an undirected weighted graph $G(V, E, A)$. V is vertex set, E is side set, A is intimacy matrix set which denotes the side weight set to connect two vertex. We choose Gauss kernel function to define the intimacy matrix

$$\bar{k}_{ij} = \exp(-\frac{\| x_i - x_j \|^2}{\sigma^2}), i \neq j \quad (1)$$

$\bar{k}_{ij}$ is kernel of Gauss, σ is kernel radius which controls the attenuation speed of $\bar{k}_{ij}$. According to spectrum theory the value of σ is given and the line vector of $\bar{k}_{ij}$ will surround them for clustering which distribute on the hypersphere of k-dimension space. D is diagonal matrix and

$$D_{ij} = \sum_{j=1}^{n} \bar{k}_{ij} \quad (2)$$

$$k_{ij} = \frac{\bar{k}_{ij}}{\sqrt{D_i D_i}} \quad (3)$$

Calculate corresponding eigenvectors of the first k maximum eigenvalues in matrix K to establish matrix $Y[n \times k]$. Each line of matrix Y is unitized to get matrix V

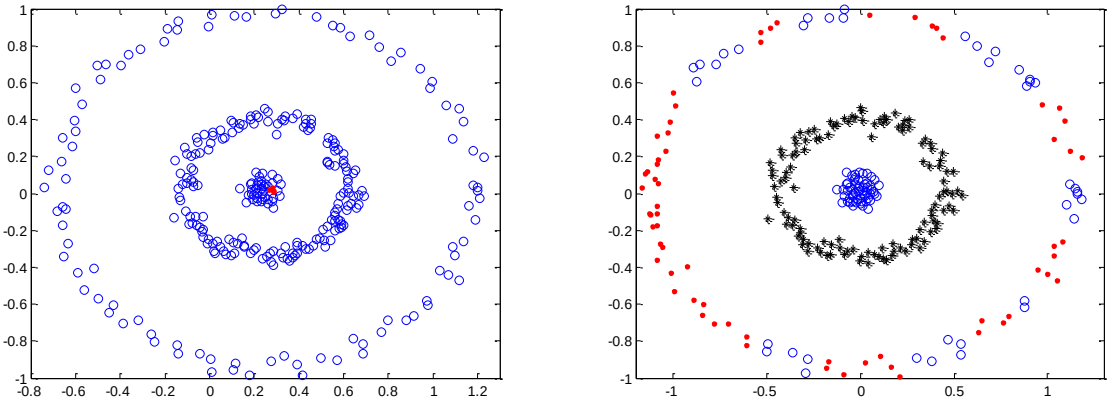
$$V_{ij} = Y_{ij} / (\sum_j Y_{ij}^2)^{\frac{1}{2}} \quad (4)$$

All the line vectors in V are considered as points of R^n-dimension space. These data points are clustered with k-means or other clustering methods. If and only if the i_{th} behavior is clustered as j, the original data point x_i is the j_{th} class.

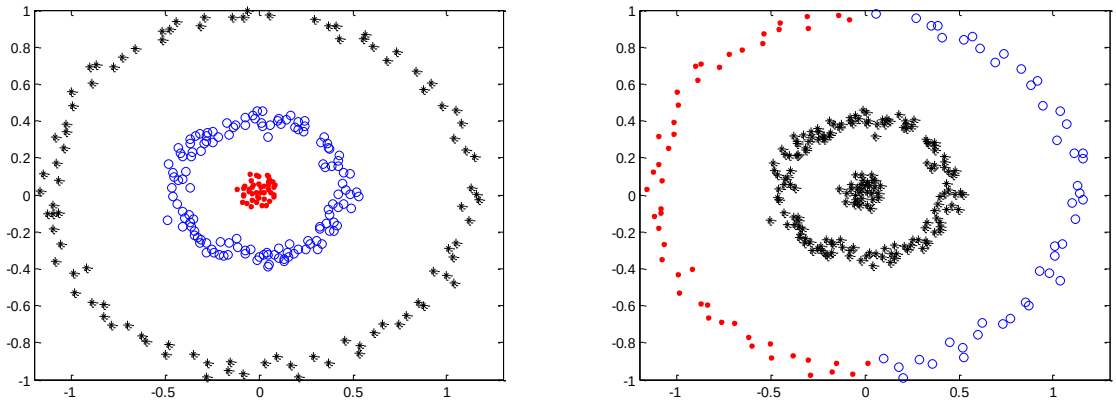
Spectral clustering often constructs weighted graph using the image pixels as convexes when segmenting images. The weight of side reflects the similarity among the pixels. By analysis on the eigenvectors and eigenvalues of weighted matrix whose elements are the side weight of graph, the vertexes can be clustered to segment the image. For a piece of image, the principle rules for segmentation are to make maximum internal similarity of k sub-images and minimum similarity among these sub-images. So we can calculate the value of RAssoc [17] to determine the performance of segmentation.

$$RAssoc(G) = \max_{v_1,...,v_k} \sum_{c=1}^{k} \frac{link(V_c, V_c)}{|V_c|} \quad (5)$$

$$link(A, B) = \sum_{i \in A, j \in B} W_{ij}$$



(a) $\sigma = 0.00001$ (b) $\sigma = 0.02$



(c) $\sigma = 0.087$ (d) $\sigma = 0.3$

Figure 1. Influence on clustering results of selection for σ

$$\deg ress(A) = link(A,V)$$

W_{ij} denotes the connected weight among the pixels.

III. Adaptive Fuzzy Semi-Supervised Spectral Clustering Algorithm

A. Optimization of Scale Parameter

It is san important procedure to establish intimate matrix in spectral clustering algorithm. Usually Gauss kernel function is used to define the intimate matrix. For the scaling parameters the given kernel radius will directly affect the clustering results. The scaling parameter may be looked as a measuring standard to judge whether two data points are the same, as is considered in data processing. While there are not corresponding provided standard to process the data belonging to different fields. So the determination of kernel radius will influence the final results by scaling parameter σ, as shown in the following experiments.

It can be seen that the clustering results are different with different σ, so the choice of σ can not be ignored. The relation between c and clusters number is: when σ has smaller value, which means each data object has smaller effect on around areas. w_{ij} appears to the sum of spike-like functions who takes n data points as the center. The clustering result will generate many clusters. The most extreme case is that each data point aggregates into a cluster respectively, which is obviously pointless. On the contrary, when σ takes a larger value, each data object has bigger effect on around areas. w_{ij} appears to the sum of function composed by n data points, changing slowly with large width. In the most extreme case, all the points are aggregated into one cluster. Therefore, to acquire clustering results as accurate as possible, the decision of σ should embody the distributed features of original data.

Zelnik-Manor proposed an adaptive SC algorithm in [18] to solve the problem of σ. The optimal determination of σ in spectral clustering can be performed as the searching method directly on original data. The cross-validation may be used to avoid the problem caused by single choice of scaling parameter σ. In this paper we will replace the calculation of σ with local σ_i of each data point. So the distance between x_i and x_j is $d(x_i, x_j)/\sigma_i$ and the contrary from x_j to x_i is $d(x_j, x_i)/\sigma_i$. Then the distance between two points is defined as:

$$d^2(x_i, x_j) = \frac{d(x_i, x_j)d(x_j, x_i)}{\sigma_i \sigma_j} \tag{6}$$

The intimate matrix is:

$$k_{ij} = \exp[-\frac{1}{\sigma_i \sigma_j} d^2(x_i, x_j)] \quad (7)$$

Its diagonal matrix and Laplacian matrix are:

$$D_{ii} = \sum_{j=1}^{n} k_{ij} \quad (8)$$

$$K_{ij} = \frac{k_{ij}}{\sqrt{D_i D_j}} \quad (9)$$

We use a special scaling parameter which permits them to adaptively regulate the distance between the points according to the ne local statistics of neighborhood. The choice of σ_i can be determined by the research on local statistics of data point x_i. So σ_i is calculated as:

$$\sigma_i = d(x_i, x_m) \quad (10)$$

x_m is the m_{th} neighbor point of x_i and $d(x_i, x_m)$ is the distance between x_i and x_m.

B. Determination of Validity Index

The clustering number c is closely related to the clustering quality: larger value will make the clustering results complicated and hard to explain and analyze; smaller value will cause information loss and misleading to the final decision. The validity index can be used to determine reasonable clustering numbers, to ensure more effective clustering results of the algorithm. To acquire better fuzzy kernel c-means results, we choose the kemelized AmineM.Bensaid validity index. It is defined as:

$$V_{KBsaid}(U,V;c) = \sum_{i=1}^{c}[\frac{\sum_{j=1}^{n} u_{ij}(1-K(v_i, x_j))}{n_j \sum_{i=1}^{c}(1-K(v_i, v_j))}] \quad (11)$$

$n_j = \sum_{j=1}^{n} u_{ij}$, $\sum_{j=1}^{n} u_{ij}(1-K(v_i, x_j))$ are used to measure the compactness inside the class. The smaller this value is, the more compact the element in the class is; $n_j \sum_{i=1}^{c}(1-K(v_i, v_j))$ is to measure the separation among the classes.

C. KFCM Algorithm

Given limited samples set $x_k \in R^n$, kernel function Φ is used to map the samples set on high-dimension space H, that is, $\Phi: R^n \to H$. The topology structure of samples in the original space keeps unchanged and $\Phi(x_k)$ denotes the k_{th} class center of feature space H. Then the target function of FKCM clustering is:

$$\begin{aligned} J &= \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{\alpha} \| \Phi(x_i) - \Phi(v_i) \|^2 \\ &= \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{\alpha}[K(x_j, x_j) - 2K(x_j, v_j) + K(v_i, v_i)] \end{aligned} \quad (12)$$

v_i denotes the class center of the i_{th} class; $\alpha > 0$ denotes the weight index; $\Phi(v_i)$ denotes the image of this center in corresponding kernel space and it is described as:

$$\Phi(v_i) = \frac{\sum_{j=1}^{n} u_{ij}^{\alpha} \Phi(x_j)}{\sum_{j=1}^{n} u_{ij}^{\alpha}} \quad (13)$$

Satisfying following constricts:

$$\begin{cases} 0 \le \mu \le 1, i = 1, 2, ..., n, \ j = 1, 2, ..., k \\ \sum_{j=1}^{k} \mu_{ij} = 1 \\ 0 < \sum_{i=1}^{n} \mu_{ij} < n \end{cases}$$

In the feature space H, the membership function is:

$$\mu_{ij} = \frac{1}{\sum_{g=1}^{c}(\frac{Q_{ij}}{Q_{gi}})^{\frac{1}{\alpha-1}}} \quad (14)$$

$Q_{ij} = K(x_j, x_j) - 2K(x_j, v_j) + K(v_i, v_i)$ is the Euclidean distance from the j_{th} sample to the center of the i_{th} class.

$$K(x_k, v_i) = \Phi(x_k)\Phi(v_i) = \sum_{j=1}^{n} u_{ij}^{\alpha} K(x_j, x_k) / \sum_{j=1}^{n} u_{ij}^{\alpha} \quad (15)$$

$$K(v_i, v_i) = \Phi(v_i)\Phi(v_i) = \sum_{j=1}^{n}\sum_{l=1}^{n} u_{ij}^{\alpha} u_{il}^{\alpha} K(x_j, x_l) / [\sum_{j=1}^{n} u_{ij}^{\alpha}]^2 \quad (16)$$

So we get

$$Q_{ik} = K_{kk} - (2/N)\sum_{j=1}^{n} \mu_{ij} K_{kj} + (1/N_i^2)\sum_{j=1}^{n}\sum_{l=1}^{n} \mu_{ij}\mu_{il} K_{jl} \quad (17)$$

Bezdek introduces the weighted index m, called smoothing factor either, to control the sharing degree among the fuzzy clustering. Thus, to acquire the fuzzy clustering we must choose suitable m. Since the selection of optimal m lacks theoretic instruction, Bezdek and Hathway study the conclusion about sample number n which is related to the value of m, from the convergence of algorithm. They advice $m > n/(n-2)$. In Pal's research, in the experiments of clustering effectiveness, the conclusion is that the optimal range of m should be [1.5, 2.5] and $m = 2$ is generally adopted.

The detail of KFCM algorithm is described as the follows:

Step 1: Given the number of clustering class $c(2 \le c \le k)$. k is the number of samples. Assuming the iteration ending threshold $\varepsilon = 0.01$ and the algorithm iteration calculator $t = 1$. Choose the kernel function K and its parameters;

Step 2: Initializing the membership matrix;

Step 3: Computing the distance from samples to the clustering center according to equation 17;

Step 4: Recalculating the membership degree of each sample according to equation 14;

Step 5: If $\max_{i,j} | \mu_{ij}^{t} - \mu_{ij}^{t-1} | > \varepsilon$, go to step 3;

Step 6: If $V_{KBsald}^{t} > V_{KBsald}^{t-1}$, the validity index is the optimal clustering number c; otherwise $c = c + 1$ and go to step3.

D. Adaptive Fuzzy Spectral Clustering Algorithm

The adaptive semi-supervised fuzzy spectral clustering algorithm proposed by our paper is using the data information of tag to adjust the distance matrix formed by the distance among the points. It makes the points distribution inside the clustering as close as possible and the clustering as separated as possible each other. When adjusted matrix adopts the spectral clustering algorithm for clustering, we should make the distance between the K_{th} and $(K+1)_{th}$ eigenvalue of matrix K as large as possible, to acquire better clustering results.

In the semi-supervised clustering process, the tag data provided by users have two kinds commonly [19]: Tag data with class; pair of point limit (marking whether two points are from the same class). The tag data of the latter form is some kind of weaker tat data, but the former is more reasonable for tag data with classes. We can turn it into equivalent pair point limit, but not vice versa. In our algorithm, the data form of tag is pair point limit. There are

There are two sets $M = \{(x_i, x_j)\}$ and $C = \{(x_i, x_j)\}$ (x_i, x_j of C belong to different cluster), $Y = [y_1^T, y_2^T, ..., y_k^T]$. Matrix V is acquired by the normalization of matrix Y.

$$\cos\theta_{ij} = \frac{y_i^T y_j}{\| y_i \| \| y_j \|} = \begin{cases} 1, (x_i, x_j \in M) \\ 0, (x_i, x_j \in C \end{cases} \quad (18)$$

y_i is the i_{th} line vector of Y. According to above theories, we may calculate the quality S_k with the clustering results.

$$S_k = \sum_{c=1}^{k} \frac{1}{N_c} \sum_{i,j \in M_c} \cos\theta_{ij} \quad (19)$$

M_c is the data point set in class c and N_c is the number of data points. When the values of S_k is bigger, the similarity of data point in each class if higher. So the value of k makes maximum S_k is the optimal clustering number.

For spectral clustering algorithm, we only need the distance function satisfy the symmetry. When $x_i, x_j < M$, adjust $D_i = D_j = 0$. To ensure the distance among the points is a reasonable norm, we adopt the shortest path algorithm to modify the distance among all the related points in matrix; when $x_i, x_j < C$, adjust $D_i = D_j = \infty$. We adjust the distance matrix according to the tag data and use the adjusted matrix for spectral clustering. Since original distance matrix is the Euclidean distance in space, it satisfies the triangle inequality. So any two points which need to adjust the distance between 2 points must be the point via set I ($I = \{i : \exists j \ne i, (i, j) \in M\}$). Then the algorithm of acquired the shortest path can be obtained rapidly.

During the process of spectral clustering, when matrix Y is performed FCM clustering, we can determine the original point as the following method: Select a point as the center point of the first cluster randomly. Choose the points which are orthogonal to all the center points possibly as the center point for the next clustering, until the k_{th} original center points is found. The procedures of improved algorithm are show as follows:

Step 1: Calculate the scaling parameter σ_i of each data point $x_i \in X$;

Step 2: For any $x_j \in X$, calculate the euclidean distance of two points D_{ij};

Step 3: Add pair limit information and adjust the distance matrix D according to tag data;

$$\begin{cases} D_{ij}, D_{ji} = 0, \ if (x_i, x_j) \in M \\ D_{ij}, D_{ji} = \infty, if (x_i, x_j) \in C \end{cases}$$

Step 4: Establish similarity matrix $\hat{\hat{k}}_{ij}$ based on adjusted D;

Step 5: For $k = 2$ to $k_{\max}$

a) Establish matrix K and calculate the corresponding eigenvectors to the previous k_{th} maximum eigenvalues of $\hat{\hat{k}}_{ij}$ $\{ v_1, v_2, ..., v_k \}$;

b) Establish matrix Y and normalize K to Y;

c) Calculate $\cos\theta_{ij}$ and S_k;

Step 6: Fine suitable k_{opt} to make the maximum S_k;

Step 7: Set each line in Y as some point in R^k and clustering it into k_{opt} class with FCM;

Step 8: If the i_{th} line of Y belongs to the j_{th} class, then divide original point x_i into the j_{th} class.

IV. EXPERIMENTAL RESULTS

A. Standard Datasets

Experimental data are mainly from Iris data set and Wine data set in UCI. Iris data set is the most famous UCI real data set to inspect clustering algorithm and validity index performance. Corresponding to Iris data set, Wine is another famous data set in UCI database. This

dataset is made up of 178 samples in 3 types and each sample has 13 attributes. Towards high dimensional data set, the determined optimal clustering number in the whole range of $m<[1.5,2.5]$ is stable. Restricted numbers are from 0 to 299 in all experiments. Each given limited number is performed 20 experiments. Since selected restriction of output average results is different, clustering algorithm attribute will have large influence. Following methods are adopted to produce limitations for experimental equality: the same limited number will produce 100 groups of different limitations. For this reason, different random generator of seeds initialization is performed. Seed number increases from 1 to 110 so different limited sets under the same limited number can be obtained.

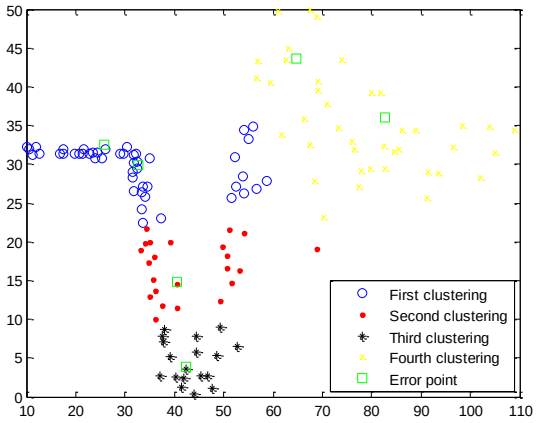


Figure 2. Clustering result of improved algorithm

This experiment applies three clustering methods. The first clustering method adopts traditional k-means clustering and makes 10 times of iterations. Each obtained clustering result is respectively compared to classification result of data set in UCJ database and average value of accuracy sum from these 10 times clustering results are taken as its final clustering accuracy. The second clustering method adopts NJW spectral clustering algorithm. 10 a values are randomly selected from 0 to 10. Each obtained clustering result is individually compared to classification result of data set in UCI database and the average value of accuracy sum from these 10 times clustering results is taken as its final clustering accuracy. The third clustering method adopts EBSC method proposed in this paper without manually setting scale parameter 6. The obtained clustering result is compared to classification result of data set in UCI database to calculate its clustering accuracy.

TABLE I. CLUSTERING ACCURACY OF 3 ALGORITHMS IN UCI DATASET

Dataset	k-means	NJW	ASC
Iris	57.33	59.33	63.33
Wine	57.30	61.24	62.66
Parkinsons	73.85	74.87	76.30
Musk	51.68	57.98	60.05
Spectf	62.55	67.19	68.65
Breast-cancer	85.41	76.09	79.20
Average rate	64.69	66.12	68.37

The experimental results are shown as table 1. We can see that our algorithm is superior to previous two algorithms on clustering average accuracy. The improved algorithm operates normally and the clustering result does not rely on careful selection of user parameter, which has effective robustness.

B. Standard Image Segmentation

In order to testify algorithm effectiveness, we will carry out experiment on real image and compare it with algorithm result in reference [9]. Figure 5 presents segmentation results comparison of these two algorithms. Figure 5(a) is source image with size of 340×500, figure 5(b) is the segmentation result of reference [9] and figure 5(c) is the algorithm segmentation result in this paper.

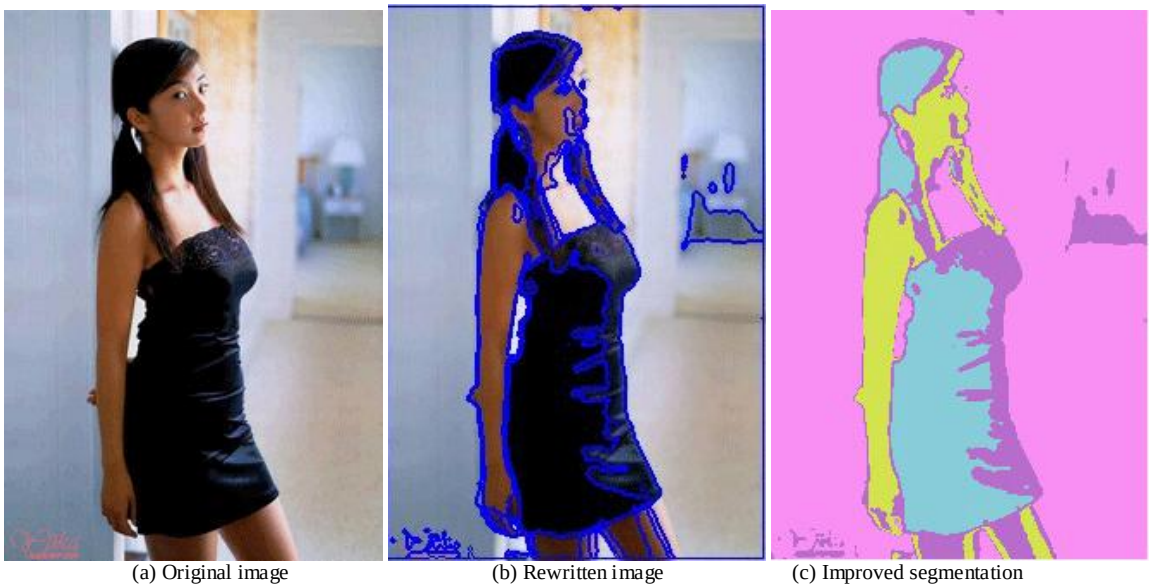
From the experimental results we know, on image segmentation and under the condition of the same category number, the time consumption of algorithm in reference [9] and our algorithm is very large but the result of the improved algorithm is obviously better. Limited artificial information is applied during experiment. That is, the limited points are clicked on image to mark relationship between corresponding regions, so as to satisfy the given limited accurate image segmentation result. We can discover from experiment that consumed time and pixel value are rising in linearity. The selected image pixel value in this paper is approximately 180000. When this image size is smaller than 100×150, the consumed time to calculate intimacy matrix is smaller than 15. The consumed time of selected image to calculate intimacy matrix is 10.3281s in this paper. Our algorithm also has disadvantages during experiment process. Such as large pixel figures, when the eigenvector and eigenvalue of weighted matrix are calculated, their operations are a bit slow in comparison with smaller images. We can see from this result that each block is mutually independent region which can express comprehensive information and conveniently extract high-level information

Table 2 is the comparison of these two algorithms in consumed time and RAssoc value. From this table, this paper introduced weighted fuzziness to reduce consumed time. In addition, RAssoc value refers to interior approximate degree of sub-image. The larger the value, the higher the approximate degree inside sub-image, the better the segmentation result. Obviously, segmentation results of the improved algorithm are superior to those in reference [9].

TABLE II. COMPARISON OF THE ALGORITHM PARAMETERS

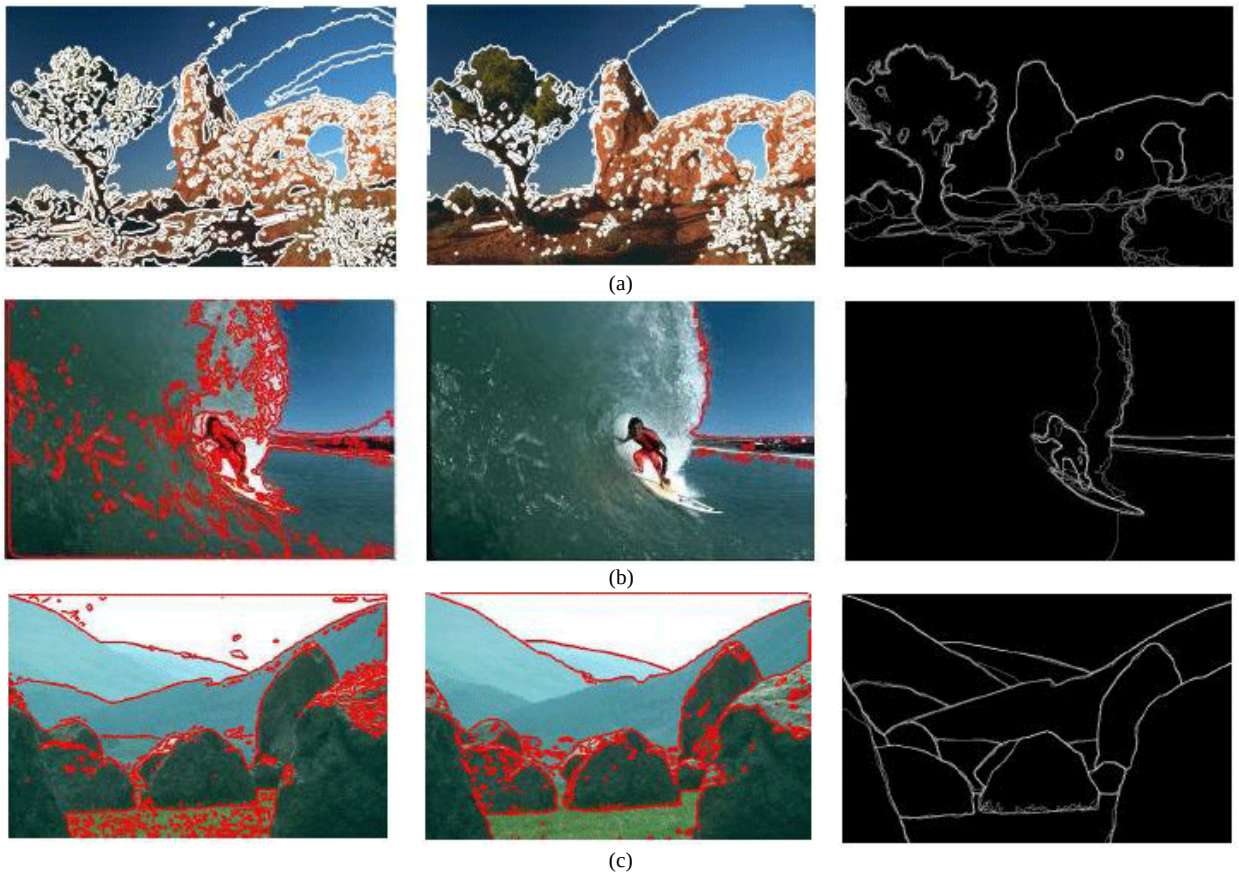
Algorithm	*Consumed time*	*Rassoc*
Adaptive spectral clustering	8.339	15.997
Algorithm in reference [9]	117.898	15.825

To testify the performance of clustering integration method on large size of image segmentation, the available images in experiment are shown as figure 6. Image (a) and (b) are images taken on their own, the image size is 1024×768 (modified as 480×320 in experiment). Others are from Berkeley image segmentation database and image size is 480×320 (source image is 481×321). Ncut



(a) Original image (b) Rewritten image (c) Improved segmentation

Figure 3. Segmentation results comparison



(a)

(b)

(c)

Figure 4. The results of three segmenting algorithms

method in experiment and method in previous experiment are used for reference. They show the experimental results. Image (a), (b), (c) respectively refer to integrated segmentation result of images, Ncut segmentation result, Ncut segmentation result and segmentation result based on blocking technology segmentation algorithm. In this experiment, $m = 2$, ζ is randomly selected in $[0.01\ 0.09]$ and the clustering member number is 7.

We can see that the method in this paper is not inferior to Ncut method and it is superior to Ncut in some details. For example, the detail of tree in 3a, the bear's outline detail in 4a and the architectural outline in 5a are all shown clearly. The most important point is that the processing speed of our method is obviously higher than Ncut. When image scale is large, Ncut time consumption is several times as much as this paper and this paper has ability to process large scaled image.

V. Conclusion and Future Work

The main work of our research is semi-supervised spectral clustering and its application in image segmentation. This paper mainly studies spectral clustering algorithm and application of fuzzy C-means algorithm in image segmentation technology. Based on characteristics and how to determine clustering quantity, this paper attempts to explore a combination algorithm between semi-supervised machine learning technique and spectral graph theory. For the improved self-adaptive semi-supervised fuzzy spectral clustering algorithm, its scale parameter optimizes through self-adaptive technology based on information entropy. Then through adding taged data, the taged data are used to regulate distance matrix, calculate similar matrix, discover suitable k and finally cluster through fuzzy c-means. By means of simulation experiments on standard data sets and image segmentation, experimental results show that the improved algorithm can effectively improve clustering quality.

We also need further improvements and studies and the following points are priorities for future research:

- To provide universal principles and construct similarity function
- To utilize knowledge of image segmentation and fuzzy theory and construct fuzzy segmentation target function
- According to practical problems, technologies in many fields are integrated specifically to improve classification performance.

References

[1] J. Shi, J. Malik, Normalized cuts and image segmentation. *IEEE Trans. Pattern Anal. Mach. Intell*, vol. 22, no. 8, pp. 888-905, 2000.

[2] U. von Luxburg. A tutorial on spectral clustering. *Statistics and Computing*, vol. 17, no. 14, pp. 395-416, 2007.

[3] X. R. Zhang, Spectral Clustering Ensemble Applied to SAR Image Segmentation. *IEEE Geoscienceand Remote Sensing Society*, vol. 46, no. 7, pp. 2126-2136, 2008.

[4] Toussi Soheila Ashkezari, Yazdi Hadi Sadoghi, Feature selection in spectral clustering, *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 4, no. 3, pp. 179-194, 2011.

[5] Liu Hanqiang, Jiao Licheng, Zhao Feng, Local manifold spectral clustering with FCM data condensation, *Proceedings of the International Society for Optical Engineering*, pp. 1009-1013, China, 2009.

[6] Xiaofei Li, Xuanjing Shen, Haipeng Chen, ElGamal Digital Signature Algorithm of Adding a Random Number, *Journal of Networks*, vol. 6, no. 5, pp. 774-782, 2011.

[7] Zhang Quan, Hu Yulan, Image Segmentation Algorithm Based on Spectral Clustering Algorithm, *Journal of Shenyang Ligong University*, vol. 31. no. 6, pp. 87-91.

[8] Meng Qingxia, Wen Xianbin, Xu Haixia, Improved synthetic aperture radar image spectral clustering algorithm, *Acta Optica Sinica*, vol. 32, no. 1, 2012.

[9] YIN Fang, CHEN Deyun, WU Rui, Improved method of image segmentation using spectral clustering, *Computer Engineering and Applications*, vol. 47, no. 21, pp. 185-187, 2011.

[10] J. Fridlyand, Bagging to improve the accuracy of a clustering procedure, *Bioinformatics*, vol. 19, no. 9, pp. 1090-1099, 2003.

[11] Tang W, Zhou ZH, Bagging-Based selective clusterer ensemble, *Journal of Software*, vol. 16, no. 4, pp. 496−502, 2005.

[12] M. Al-Razgan, C. Domeniconi, Weighted clustering ensembles, *Proceedings of the Sixth SIAM International Conference on Data Mining*, pp. 258-269. USA, 2006.

[13] A. Fred, A. K. Jain, Data clustering using evidence accumulation. *Proceeding of 16th Int'l Pattern Recognition*, pp. 276-280, USA, 2002.

[14] Yu Jin-hua, Wang Yuan-yuan, Shi Xin-ling, Image segmentation with two-dimension fuzzy cluster method based on spatial information, *Opto-Electronic Engineering*, vol. 34, no. 4, pp. 114-119, 2007.

[15] Mohamed Samar S., Salama Magdy M. A., Spectral clustering for TRUS images, *BioMedical Engineering Online*, vol. 15, no. 6, pp. 70-78, 2007.

[16] Yang Yuanfeng, Cui Zhiming, Wu Jian, Trajectory analysis using spectral clustering and sequene pattern mining, *Journal of Computational Information Systems*, vol. 8, no. 6, pp. 2637-2645, 2012.

[17] Jin HuiZhen, A Spectral Clustering-Based Algorithm for Gray Graph Segmentation, *Computer Systems & Applications*, vol. 4, no. 2, pp. 74-77, 2009.

[18] Bezdek J C, A physical interpretation of fuzzy ISODATA, *IEEE Transactions on Scientific Manpower Commission*, vol. 6, no. 3, pp. 2873-2890, 1976.

[19] Zhao Feng, Jiao Li-Cheng, Liu Han-Qiang, Semi-Supervised Eigenvector Selection for Spectral Clustering, *Pattern Recognition and Artificial Intelligence*, vol. 24, no. 1, pp. 48-56, 2011.