www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

# SPECTRAL CLUSTERING WITH SPATIAL COHERENCE PROPERTY JOINTING TO ACTIVE CONTOUR MODEL FOR IMAGE LOCAL SE GMENTATION

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***Submitted: Jan.6, 2016*** ***Accepted: Oct.4, 2016*** ***Published: Dec.1, 2016***

***Abstract- Local Segmentation is the fundamental task for image processing. Consider to the problem of low segmentation precision and contour control instability for image local segmentation, a local segmentation theory is researched that based on SSCACM (spectral clustering with spatial coherence property jointing active contour model). First, by applying spatial coherence property constraint of image pixels to spectral clustering, an adaptive similarity function is constructed and the corresponding spectral clustering algorithm is used to extract initial contour of the local region of an image. Then, the NBACM (narrow band active contour model) is combined with the priori information of initial contour to evolve contour curve to get the segmentation result. At last, the local segmentation experiment is realized on synthetic images and medical images. The experimental results show that the method proposed can extract contour accurately and can improve the effectiveness and robust for image local segmentation.***

**Index terms*:* Adaptive similarity function, Spatial coherence property constraints, Adaptive speed operator, Spectral clustering, Active Contour model.**

## I. INTRODUCTION

Image segmentation always is an interesting work in the fields of digital image processing, pattern recognition and computer vision. In practice, image local segmentation is often defined as partitioning special region of interesting in an image for user. For example, medical diagnosis often ask for segmenting some special tissues of the putamen, cerebellum under magnetic resonance imaging and texture images that are required the accurate boundaries of the particular region with noises.

With the development of the image segmentation theory, there are many segmentation methods based on knowledge integration in different application fields.

(1) Segment images that uses gray-scale distribution modeling based on statistics. The classical model is HMM (Hidden Markov Model) based on multi-scale analysis which mainly segments the statistical images in spatial domain and wavelet domain and expands the local segmentation theory from the view of multiple scale analysis [1-2]. But the segmentation method based on multi-scale analysis is higher calculation complexity and lower boundary detection ability which can lead to error segmentation of region boundary.

(2) Segment images that uses machine learning based on multi-agent images data interpretation. The method designs multiple structure nodes with different functions. Every structure node represents an agent. The method can improve image segmentation effects by cooperative work among multi-agents [3]. The niftiest thing about the method is that it can use the priori information of image regions obtained in the process of machine learning of multi-agents node to do image local segmentation.

(3) Segment images that use multi-classes partitions based on clustering algorithm [4-6]. The various clustering algorithms including unsupervised clustering and semi-supervised clustering also belong to machine learning. The C-mean cluster is the most common algorithm in the current unsupervised clustering algorithms, but it usually fails because it has not taken the advantage of spatial dependency relationship of image pixels if the image data structure is non-convex and the data points are serious overlapping each other. SC (Spectral Clustering) is an unsupervised clustering algorithm proposed in paper [5]. It overcomes the drawbacks of the mean

clustering algorithm, recognizes the non-convex data structure, gets the prior knowledge and converge the best global results.

(4) Extract local information of an image that uses boundary method based on ACM (Active Contour Model). ACM is an effective method which can do image segmentation, edge extraction and target tracking. There are many improved strategies which have been noticed by many researchers in local segmentation. For example, Mile proposed a narrow ACM [7] and Hu Yuhui proposed a local sub-region ACM [8]. But, neither resolves the interference of pixels spatial distance to signed distance function in the algorithms. These valuable ACMs often was applied some specific image segmentation which was determined initial contour artificially. Moreover, it needs longer time to evolve the contour curve. It is a challenge how to obtain a better initial contour in the process of local segmentation using ACMs.

In order to integrate the excellent machine learning strategy to ACMs and use the spatial distance property, we expend the SC theory, apply spatial coherence property of image pixels constraints to SC, propose an image segmentation method based on spatial coherence property under SC framework, which can eliminate the error segmentation of image local regions, get the prior knowledge of the morphological structure and image represent on local property and oriental property. Thus, our method can resolve above puzzles. For the poor popularity of many ACMs, we design a novel adaptive speed operator under ACM framework which expands application scope of ACMs. The experiments on synthetic images and medical images show that our method can realize image local segmentation effectively.

## II. IMAGE LOCAL SEGMENTATION USING SC AND ACM

### a. Spectral Clustering

SC is an image segmentation method based on graph whose computing processes are that construct weighted graph with pixels as vertex and with similarity between pixels as weight, construct similarity matrix of the weighted graph, do clustering analysis of vertexes of graph by computing the similarity matrix or the eigenvectors and eigenvalues of the correlation matrix. So, we can realize image segmentation using above results.

a.i Construction graph and measure rule of SC

We should first construct an adjacency graph of pixels, then need measure the adjacency graph by selecting an appropriate partitioning rule when we segment image using SC algorithm.

Set the pixel $p_i$ in an image as a vertex in the adjacency graph, and set the side $E_{ij}$ connecting vertex $v_i$ and $v_j$ as weight $W_{ij}$ according to the similarity between the pixels $p_i$ and $p_j$, a weight graph(adjacency graph) is gotten by $G=(V,E,W)$. There are several common adjacency graphs described as follows: $\varepsilon$ neighborhood domain graph, $k$-nearest neighborhood graph, complete junction graph and so on [9-10].

To measure the adjacency graph is to determine the partitioning rules of the graph, which can affect the clustering result directly. We divide the graph $G$ given weight $W$ to two sub-sets $A$ and $B$, $A\bigcup B=V, A\bigcap B=\varnothing$. The evaluation function is defined as

$$cut(A,B)=\sum_{u\in A,v\in B} w(u,v). \tag{1}$$

We can get the best adjacency graph of graph $G$ if the evaluation function $cut(A,B)$ is minimized. There are several common partitioning rules listed as follows: MCut(Minimum Cut), RCut(Ration Cut), ACut(Average Cut), NCut(Normalized Cut) and so on [11-14]. The NCut rules proposed in paper [14] is a better partitioning rule because it can not only measure the minimum similarity between sub-graph data sets but also can measure the maximum similarity inner sub-graph data set. Thus, the clustering effect using the NCut rule to segment an image is better than others.

a.ii Similarity matrix and clustering analysis of SC

Mathematically, to describe the best excellent adjacency graph is to compute similarity matrix or spectral decomposition of Laplacian matrix, and then we may do clustering analysis using the eigenvectors calculated by spectral decomposition.

1970s, Donath and Hoffman [15] related the graph partitioning with the eigenvectors of similarity matrix theoretically. Fiedler [16] researched the eigenvectors and eigenvalues of Laplacian matrix composed by similarity matrix. Later, Shi and Malik [14] created the NCut rule on the graph partitioning and translated the NP puzzle (i.e. the best graph partitioning) into computing the generalized eigenvectors and eigenvalues related with Laplacian matrix of the graph.

Clustering analysis is to cluster class by analyzing the degree of closeness between objects chosen an appropriate distance function or constructed a new distance function. Many effective algorithms proposed in [4] that can realize special image segmentation and have their advantages and disadvantages respectively. Image segmentation algorithms based on spectral clustering are adopted by many researchers. NJW(Ng-Jordan-Weiss) algorithm proposed in paper [5] shown an effective segmentation result whose working processes were to choose the corresponding eigenvectors for the first $k$ maximum eigenvalues of normal Laplacian matrix, let above eigenvectors map the corresponding original data into $k$ dimension space in where clustering was done.

Although these image segmentation methods based on spectral clustering have gotten better segmentation effects, there are many puzzles need to study that are described as follows.

(1) How to choose an appropriate measure rule for the adjacency graph.

(2) How to construct an effective similarity matrix.

(3) How to ensure the spatial coherence of the near pixels.

(4) How to improve computing efficiency.

b. Description of ACM

ACM proposed by Kass [17] is one of the classical image segmentation methods which basic idea is to minimize the given energy functional by iterating.

Set $C: v(s)=(x(s),y(s)), s\in[0,1]$ is the sets of image contour curve. The energy functional of the curve is defined as follow.

$$E_{sn}=\int_0^1 (E_{\text{int}}(v(s)+E_{ext}(v(s))ds. \qquad (2)$$

Where, $v(s)$ is the 2D coordinate point, $E_{\text{int}}$ is the inner potential energy, $E_{ext}$ is the outer potential energy.

In order to attract contour curve to the ideal location, the computing expression is defined as follow.

$$\begin{cases} E_{\text{int}}(v(s))=\dfrac{\alpha(s)\left|v^{'}(s)\right|^2+\beta(s)\left|v^{''}(s)\right|^2}{2}, \\ E_{ext}(v(s))=-\zeta(G_\sigma(v(s))*\nabla^2 v(s))^2 \ . \end{cases} \qquad (3)$$

Where, $v^{'}(s)$ and $v^{"}(s)$ are the variation rate of active curve length and curvature, respectively. $\alpha(s)$ is an elastic coefficient to control the shrinking rate of the active curve. $\beta(s)$ is an strength coefficient to control the variation speed of active curve along the normal direction to the ideal location. $\zeta_{ext}$ is a weighting coefficient to represent the ratio of outer potential energy in the curve variation. $G_{\sigma}(v(s))$ is an Gaussian function whose standard deviation is $\sigma$. We can smooth the object contour which satisfies image local features if minimizing the energy functional $E_{sn}$.

Now, there are many ACMs who are global traversal, that is, it need compute iteratively on whole image. Obviously, it reduces segmentation efficiency certainly. An update way is that, we set a narrow band around object region in advance and constraint the ACM in the given narrow band of the local region which can improve the local segmentation ability of the ACM [18].

Let $I(x):\Omega \to R$ is a given image, $C = \{x \mid \phi(\mathrm{x}) = 0\}$ is the sets of image contour curve, the narrow band region function is defined as follow.

$$\delta(\phi(x)) = \begin{cases} 1 & \phi(x) = 0 \\ \dfrac{1}{2\varepsilon}\left\{1 + \cos(\dfrac{\pi\phi(x)}{\varepsilon})\right\} & 0 < |\phi(x)| \le \varepsilon . \\ 0 & |\phi(x)| > \varepsilon \end{cases} \quad (4)$$

Feature function $B(x, y)$ is used to label the local neighborhood.

$$B(x, y) = \begin{cases} 1 & \|x - y\| < r \\ 0 & otherwise \end{cases}. \quad (5)$$

If we ensure $\delta(\phi(x))$ around the zero level set, the narrow band is controllable, we can get the object contour accurately.

With the research to ACM, in order to get more accurate image contour, there are some problems.

(1) How to create better initial contour.

(2) How to use the prior knowledge of the initial contour in ACM effectively.

(3) How to improve the efficiency of the local segmentation integrating ACM with machine learning.

## III. DESCRIPTION OF SSCACM

### a. Constructing initial contour

In general, in order to improve image quality and collect more useful image information, the image should be pre-process such as denoising or filtering.

#### a.i Spectral clustering

It should construct the adjacency topology graph and choose measure topology rules before spectral clustering analysis. In our paper, we use complete junction graph to create the adjacency topology.

NCut rule mentioned in paper [10] is better than ACut or MCut in spectral clustering. According to the rules that sub-graph is minimum if pixels spatial coherence, we set NCut rule as measure rule for the adjacency topology graph. Constraint sample sets $Y$ with $y^{'}WI = y^{'}DI = 0$, we minimize the evaluation function of NCut as follow.

$$\min Ncut(A,B) = \min_y \frac{y^{'}(D-W)y}{y^{'}Dy}. \qquad (6)$$

Where, $I$ is an identity matrix, $W$ is a similarity matrix, $D$ is a diagonal matrix and $D(i,i) = d_i = \sum_j w(i,j)$. We relax the vector $y$ to the continuous domain [-1, 1], equation (6) is transformed as follow.

$$\arg \min_{y^{'}DI=0} \frac{y^{'}(D-W)y}{y^{'}Dy}. \qquad (7)$$

Equation (7) conforms to Rayleigh quotient acceleration rule of vector $y$, therefore, the convergence problem of (7) is equivalent to solve generalized feature equation as follow.

$$(D-W)y = \lambda Dy. \qquad (8)$$

From Laplacian matrix, we know that the corresponding eigenvectors of the second minimum eigenvalues in (8) represent a solution of the best topology partitioned, then, after applying Rayleigh quotient acceleration rule to (8), the second minimum eigenvalues in (8) will be converged rapidly. It improves computing speed of (8) and the best partitioning information of the topology graph must be included in the corresponding eigenvectors. The Spectral clustering algorithm is described in the following steps.

Step 1 Map sample sets $Y$ into the adjacency topology graph $G$, create matrix $W$ and matrix $D$ by $G$.

Step 2 Solve the second minimum eigenvalues in (8) and the corresponding eigenvectors.

Step 3 Look up the partitioning point $i$ among the corresponding eigenvectors from step 2, on which $Ncut(A,B)$ is the minimum. Then, we partition the points greater than or equal to $i$ as one class, the points less than $i$ as another class.

Step 4 Iterate step 3 until clustering is end.

a.ii Spectral clustering constraining with spatial coherence

It will simplify the computation of the spectral clustering if we apply spatial coherence property of pixels with the image segmentation. We constrain spatial coherence property with one neighborhood pixel of one pixel in the image according to the spatial relationship among image pixels. Then, we propose an adaptive similarity function who has considered the pre-segmentation information and neighborhood information for every pixel while computing similarity measure rules and we can get the prior knowledge of the image segmentation by our spectral clustering.

Given two pixels $i$ and $j$ in an image who are at their respective neighborhood, there is a great probability that they are same cluster: $W(i,j) \to 1$. The key problem is how to define the similarity degree between pixels $i$ and $j$ if

$M_i \neq M_j \ (M_i, i = 1,2,...,N, \ represent \ the \ preclassification \ of \ i \ )$.

Therefore, we propose the adaptive similarity functions as follows.

$$W(i,j) = W_C(i,j) W_{N_j}(i). \tag{9}$$

$$W(j,i) = W_C(i,j) W_{N_i}(j). \tag{10}$$

$$W(j,i) = W_C(i,j) W_{N_i}(j). \tag{11}$$

Where, $S_i$ is the color feature of the pixel $i$. $l(i,j)$ is an extremal function.

$$l(i,j) = \begin{cases} 0, & i \ and \ j \ are \ same \ cluster \\ 1, & i \ and \ j \ are \ not \ same \ cluster \end{cases}.$$

$W_{N_j}$ is a influence factor between neighborhoods that is a constraint using spatial coherence.

$$W_{N_j} = \sum_{N_j} \exp(-l(i, j_k)\lambda). \tag{12}$$

Where, $j_k$ is the pixel in the Neighborhood $N_j$ of the pixel $j$. The parameter $\lambda$ is a scale parameter that represents a constraint ability of spatial information to influence factor. A higher value of $\lambda$ indicates a higher neighborhood scale that will lead to null clustering. A lower value of $\lambda$ indicates a lower neighborhood scale that will lead to excessive clustering. In generally, the value of $\lambda$ should be [0.001, 0.01] for different images by experiments. The constraint functional indicates that the pixels around $j$ that are same class with $i$ are more, the more probability that $i$ is same cluster with $j$. Notice: For the pixel $i$, the similarity functional is (9). For the pixel $j$, the similarity functional is (10). In generally, $W_{N_j}(i)$ is not equal to $W_{N_i}(j)$, conversely, $W(i, j)$ is not equal $W(j,i)$. We let $\max(W(i, j), W(j,i))$ as our adaptive similarity functional according to the spatial coherence property.

Above proof may be interpreted by Bayesian posterior probability. Let the prior classification of the $ith$ pixel in an image as $\{M_1, M_2, ..., M_h\}$ and the classification numbers of NCut is $\{l_1, l_2, ..., l_m\}$, then the Bayesian posterior probability is defined as follow.

$$P(l \mid M_i) = \frac{P(M_i \mid l)P(l)}{\sum_{l'=1}^{m} P(M_i \mid l')P(l')}. \tag{13}$$

Where, $l$ denotes one class in the NCut classification and $l'$ denotes another. Let $P(M_i \mid l) = \omega_{il}$, then

$$\sum_{l'=1}^{m} P(M_i \mid l')P(l') = \sum_{l'=1}^{m} \omega_{il'}. \tag{14}$$

Where, $P(l)$ is the priori probability of $M_i$ belong to $l$. Now, We constraint $P(l)$ with spatial coherent property, let it meet uniform distribution [19].

$$P(l) = 1/m. \tag{15}$$

$M_i$ must be one NCut classification. Thus, $\sum_{l'=1}^{m} \omega_{il'} = 1$ is a constant.

$P(M_i \mid l)$ is a conditional probability defined as follow.

$$P(M_i \mid l) = \frac{\left| x_i \in M_i \cap x_i \in l \right|}{\left| M_i \right|}. \tag{16}$$

Therefore,

$$P(l \mid M_i) = \frac{|x_i \in M_i \cap x_i \in l|}{m|M_i|} \Leftrightarrow \frac{|x_i \in M_i \cap x_i \in l|}{|M_i|}. \tag{17}$$

Where, $|\bullet|$ denotes pixel numbers. $M_i$ will be partition to the cluster whose posterior probability is the highest after computer ends.

By above proof, we know that the result classification may be different with the given classification if we do not constrain with spatial coherence property. The main reasons why are that if there is a classification including several NCut classifications who is assigned to one NCut classification, it must be lead to these classifications maybe been combined together, then lead to classification failing. By constraining spectral clustering with spatial coherence property, our adaptive similarity function can adjust classification automatically and separate NCut classification combined. The method will reduce classification error and obtain the prior knowledge of the initial contour on image local region.

a.iii Extracting initial contour

Our extracting algorithm is described as follows.

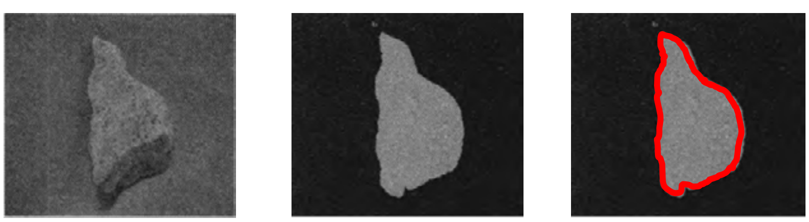
Step 1 Construct the adjacency topology graph and choose measure topology rules for the image $I$ using the algorithm described in III.a.i.

Step 2 Do spectral analysis constraining with spatial coherence property using the algorithm described in III.a.ii.

Step 3 Adjust our adaptive similarity function and optimize the corresponding eigenvectors.

Step 4 Segment the image $I$ by iterate step 3 until getting the initial contour.

The initial contour for image local segmentation using our method is shown in Figure 1.



(a) (b) (c)

(a) Original image. (b) Binary iamge. (c) Initial contour.

Figure 1. The segmentation performance of the initial contour

b. Constructing result contour using ACM modified

In order to modify the problems mentioned in II.b, we have designed an adaptive similarity function constraining spectral clustering with spatial coherence property and have gotten the initial contour for image local segmentation. Next, we will construct the result contour on the basis of the initial contour using ACM. We introduce a novel adaptive speed operator who joints the narrow band region function proposed in the paper [18] to expand ACM to a general framework for image local segmentation. Using our modified ACM, we will optimize the initial contour to draw the more accurate result contour as same time improves segmentation robust.

b.i Adaptive speed operator

From (4), we know that the evolving contour curve can close the object contour rapidly if we design a controllable narrow band around the initial contour. Using the theories of the binary level sets and morphologic computing, we set $\phi(x)$ in (4) be 1 and -1, i.e.

$$\phi(x)=\begin{cases}1 & x\in\Omega_0\\ -1 & x\in\Omega\setminus\Omega_0\end{cases}. \tag{18}$$

Where, $\Omega_0$ is the subset of $\Omega$ (image defining domain).

After drawing the narrow band, all points in the narrow band region will be update to close the object contour using given speed function. We introduce a novel adaptive speed operator by modifying the classical speed function. There are variation adaptive speed operators which can fit different image segmentation by modifying items in speed operator. In other words, our method can be named an adaptive NBACM (Narrow Band Active Contour Model).

Given, $I(x)$ is the image whose initial contour has been extracted by above method mentioned in III.a, $C$ is the closing curve. The inner region of $C$ from (4) and (5) is defined as $H_{in}=(\phi(x)+1)/2$, The outer region of $C$ from (4) and (5) is defined as $H_{out}=(1-\phi(x))/2$. Thus, the local means of the image gray can be defined as follows.

$$u(x)=\frac{\int_{\Omega_y} B(x,y)\,H_{in}(y)\,I(y)dy}{\int_{\Omega_y} H_{in}(y)dy}. \tag{19}$$

$$v(x) = \frac{\int_{\Omega_y} B(x, y) H_{out}(y) I(y) dy}{\int_{\Omega_y} H_{out}(y) dy}. \tag{20}$$

From above, our adaptive speed operator is defined as follow.

$$F(x) = (I(x) - v(x))^2 - (I(x) - u(x))^2. \tag{21}$$

Only do we compute the local means $u(x)$ and $v(x)$ of the corresponding image gray, the adaptive speed operator can be gotten by (21) respectively.

b.ii Local segmentation

Based on the initial contour gotten by the spectral clustering constraint with spatial coherence property, we propose the framework for image local segmentation in follows.

Step 1 Pre-process the given image according to the real situation.

Step 2 Design the adaptive similarity function $W$ using (9) and (10), do spectral clustering analysis constraining with spatial coherence property, get prior knowledge of the local segmentation and construct the initial contour for the image local segmentation.

Step 3 Design the adaptive speed operator $F$ using (20), update the NBACM to optimize the initial contour.

Step 4 Iterate to update the given adaptive operator $F$ according to the following formula: $\phi^{n+1} = \phi^n + \Delta t \cdot F$ .

Step 5 If the updated NBACM is convergence, then the image local segmentation is ended, otherwise, go to Step 4.

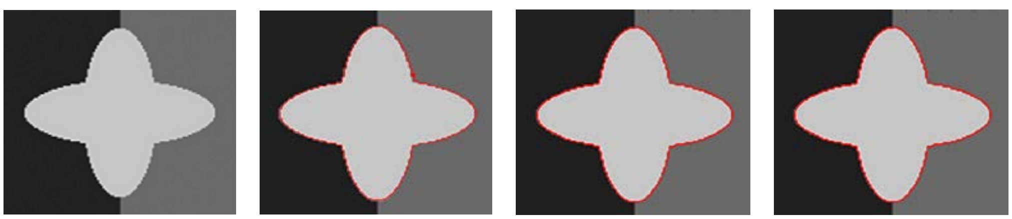
From the above framework, we know that the accuracy of the initial contour decides the next evolution speed for the NBACM. The more accuracy the spectral clustering computes, the more closing the object boundary the initial contour is, the faster speed the NBACM evolve. Thus, It can improve the efficiency and robust of image local segmentation using our method. Moreover, our designing procedure for the adaptive speed operator is a dynamic procedure. We can design the corresponding adaptive speed operator for different image local segmentation, so can update the corresponding ACM and can expend the application of the ACM.

## IV. EXPERIMENT RESULTS

In order to verify the effect of our method in image local segmentation, we segment synthetic image and medical image using NJW spectral clustering algorithm mentioned in the paper [5], NBACM algorithm mention in the paper [7] and our method, respectively. All the experiments circumstance is the same with that Windows 7 OS (I5 CPU/2G memory) and Matlab8.0.

### a. Experiment on synthetic image

The local segmentation result of a connected region synthetic image is shown in Figure 2. The original image is shown in Figure 2 (a). The local segmentation result using NJW spectral clustering algorithm is shown in Figure 2 (b). In NJW, we select neighborhood window size $k = 3$ and the iteration ending value is $\varepsilon = 0.0001$. The local segmentation result using NBACM algorithm is shown in Figure 2 (c). In NBACM, we select the theories of the binary level sets and morphologic computing as curve smooth scheme and set the radius size of feature function $B(x, y)$ to label neighborhood as 2. Our result is shown in Figure 2 (d). The computing times of these three methods are presented in Table 1.



(a) (b) (c) (d)

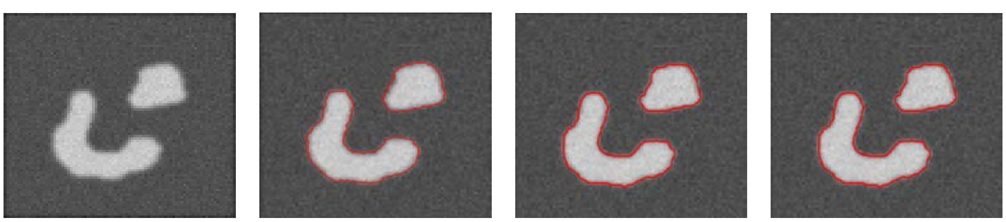
(a) Original image. (b) The segmentation result using NJW. (c) The segmentation result using NBACM. (d) The segmentation result using our method.

Figure 2. Segmentation performance for a connected region synthetic image

Table 1: Time comparison among NJW, NBACM and SSCACM (s)

| Cases | NJW | NBACM | SSCACM |
|---|---|---|---|
| 1 | 1.3230 | 1.3455 | 1.2898 |
| 2 | 1.3286 | 1.3485 | 1.2896 |
| 3 | 1.3397 | 1.3505 | 1.3040 |
| 4 | 1.4031 | 1.3182 | 1.2773 |
| 5 | 1.3530 | 1.3344 | 1.2960 |
| 6 | 1.3332 | 1.3651 | 1.2933 |
| 7 | 1.3463 | 1.3432 | 1.2865 |
| 8 | 1.3137 | 1.3542 | 1.2768 |
| 9 | 1.3636 | 1.3623 | 1.2770 |
| 10 | 1.3043 | 1.3231 | 1.2665 |
| Average | 1.3409 | 1.3445 | 1.2857 |

The local segmentation result of a separated region synthetic image is shown in Figure 3. The original image is shown in Figure 3 (a). The local segmentation result using NJW spectral clustering algorithm is shown in Figure 3 (b). In NJW, we select neighborhood window size $k = 3$ and the iteration ending value is $\varepsilon = 0.0001$. The local segmentation result using NBACM algorithm is shown in Figure 3 (c). In NBACM, we select the theories of the binary level sets and morphologic computing as curve smooth scheme and set the radius size of feature function $B(x, y)$ to label neighborhood as 2. Our result is shown in Figure 3 (d). The computing times of these three methods are shown in Table 2.



(a) (b) (c) (d)

(a) Original image. (b) The segmentation result using NJW. (c) The segmentation result using NBACM. (d) The segmentation result using our method.

Figure 3. Segmentation performance for a separated region synthetic image

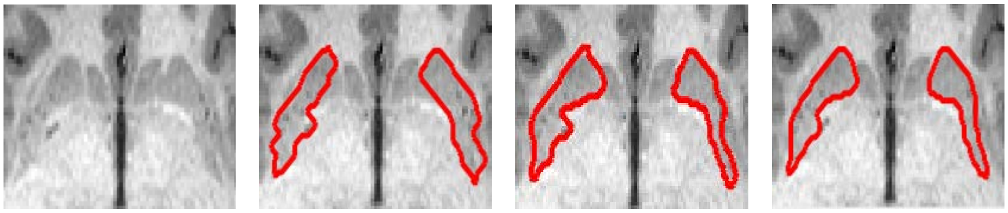
Table 2: Time comparison among NJW, NBACM and SSCACM (s)

| Cases | NJW | NBACM | SSCACM |
|---|---|---|---|
| 1 | 1.4186 | 1.4392 | 1.3207 |
| 2 | 1.4076 | 1.4188 | 1.3132 |
| 3 | 1.4628 | 1.5352 | 1.3322 |
| 4 | 1.4435 | 1.4458 | 1.3163 |
| 5 | 1.4315 | 1.4524 | 1.2910 |
| 6 | 1.3914 | 1.4333 | 1.2897 |
| 7 | 1.3997 | 1.4395 | 1.2889 |
| 8 | 1.4086 | 1.4486 | 1.3092 |
| 9 | 1.3910 | 1.4222 | 1.2712 |
| 10 | 1.4214 | 1.4525 | 1.2614 |
| Average | 1.4176 | 1.4488 | 1.2994 |

From Figure 2, Figure 3, Table 1, and Table 2, we know, the computing speed of the NJW algorithm is faster because of its background of the machine learning theory, but the local segmentation effect of the NJW algorithm is easy to appear the deviation because there are many parameters must be given manually. The local segmentation effect of the NBACM is almost as well as our method. But the iteration times of the speed function of the NBACM depends on the gray uniformity of the image, the time complexity using NBACM to segment image will increase if the edges of the image local region are unclear. Our method extracts the initial contour using the spectral clustering with spatial coherence property firstly, and it overcomes the drawback of the NJW algorithm, gets the prior knowledge of the image local segmentation and decreases the time complexity of the NBACM.

b. Experiment on medical image.

The effect of the local segmentation of synthetic images is obvious while the time complexity is not obvious because its composition is simple. But for the medical images, because its composition is more complex, it will lead to the difference of the time complexity obviously. We use the local segmentation of the putamen in the brain structure under the cortex by MRI (Magnetic Resonance Imaging) as example to compare results to verify the efficiency of our method further. In MR image, the putamen is very similar with its near tissue like the claustrum or the isula. Especially, the distance between the putamen and the claustrum is very closing, and they must disturb each other when segmenting locally. Riklin-Raviv et al. [20] proposed that to improve segmentation efficiency that using the symmetrical information in the brain structure in the case of lacking the prior shape knowledge. But, the segmentation efficiency is bad usually using the classical method because the tissue of the MR image is not symmetrical strictly and there are more interference in the MR image. The original image is shown in Figure 4 (a). The segmentation results using three methods mentioned in IV.a are shown in Figures 4 (c) to figure 4 (e). The computing times of these three methods are shown in Table 3.



(a) (b) (c) (d)

(a) Original image. (b) The segmentation result using NJW. (c) The segmentation result using NBACM. (d) The segmentation result using our method.

Figure 4. Segmentation performance for a medical image

Table 3: Time comparison among NJW, NBACM and SSCACM (s)

| Cases | NJW | NBACM | SSCACM |
|---|---|---|---|
| 1 | 6.2230 | 6.5345 | 5.3322 |
| 2 | 6.2633 | 6.5641 | 5.3633 |
| 3 | 6.2015 | 6.5331 | 5.3001 |
| 4 | 6.2597 | 6.5739 | 5.3201 |
| 5 | 6.4022 | 6.2818 | 5.3163 |
| 6 | 6.3697 | 6.4728 | 5.2730 |
| 7 | 6.5714 | 6.5337 | 5.1442 |
| 8 | 6.5868 | 6.6624 | 5.2528 |
| 9 | 6.5373 | 6.2112 | 5.1401 |
| 10 | 6.4251 | 6.5981 | 5.2843 |
| Average | 6.3840 | 6.4966 | 5.2726 |

## V. CONCLUSIONS

In this paper, a novel spectral clustering with spatial coherence property jointing ACM method is proposed and is applied to image local segmentation. In order to depict the initial contour of the ACM accurately, we join the spectral clustering with spatial coherence property into the ACM to supplement the ACM. We have constructed an adaptive similarity function into the spectral clustering to provide the prior knowledge for the ACM. Moreover, we also propose an adaptive speed operator in the NBACM to expand the application scope of the ACM. Experiment results on both synthetic and MR images show that the proposed methods have better performance than the comparison methods.

Our future works are to integrate machine learning with image segmentation method sequentially, to reduce the artificial participation into the image segmentation by the classification of machine learning. We will study the potential of the ACM continually to expand the application scope of the ACM into the respective image segmentation.

## ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (61203320). The authors would like to thank the anonymous reviewers for their constructive comments.

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