Segmentation based on Genetic Algorithm

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1. Problem

Image segmentation is a challenging task in many fields. Image segmentation aims at partitioning an image into certain regions satisfying a homogeneity criterion that takes into account one or more pixel features, such as color, texture, intensity, and so on. It can be used as pre-process for pattern recognition, auxiliary tool for medical image analysis, modelling method for 3-D printing and so on. Therefore, a well-designed segmentation method is very important and practical to our life.

2. What I have done in this project

Firstly, when implementing the framework of method [1], I have encountered some problems about local optimization. It is hard to find the global solution when the individuals become too similar after a long time searching.

Secondly, I introduce the hybridism framework with a two-level GA to make sure the diversity of individuals. In the low level GA, the different local areas are evolved independently, and the best elites are selected from these areas after long-time evolution. After that, in the high level GA, the selected elites are grouped into a new community, and start new cross-breeding until finding the best result.

Thirdly, in the high level GA, I improve the Evaluation Function by introducing bi-evaluation standard to make sure community diversity. Here, I combined the WNCut evaluation function with distance information between individual and best solution. This strategy avoids the inbreeding. Make sure the diversity to a large extent.

3. Problem Definition

The image is defined as a graph G = (V, E, w), where V is the set of *n* nodes of graph G, E is the set of edges, and w: E->R is a function that assigns a value to graph edges. Each node corresponds to a pixel in the image, and a graph edge (i, j) connects two pixels i and j, provided that these two pixels satisfy some suitably defined property. The weight w(i, j) associated with an edge (i, j) represents the likelihood that pixels i and j belong to the same image region. The original definition of weight between two pixels is defined as follow:

$$\mathrm{w(i, j)} = \begin{cases} e^{-\max_{x \in \mathrm{line}(i,j)} ||\mathrm{Edge}(x)||_2^2 / 2a^2} & \text{if } ||X(i) - X(j)||_2 < r, \quad i \neq j \\ 0 & \text{otherwise} \end{cases}$$

where $\mathrm{a} = \left(max_{y \in I} \left|\left|\mathrm{Edge(y)}\right|\right|\right) \times \delta$, Edge(x) is the image edge strength at position x, line(i, j) is a straight line between i and j.

The original evaluation function defined by [1] is as follow:

$$\mathrm{WNCut} = \sum_{i=1}^{k} \frac{\mathrm{cut}(A_i, V - A_i)}{\mathrm{assoc}(A_i, V)} + \frac{\mathrm{cut}(A_i, V - A_i)}{\mathrm{assoc}(V - A_i, V)}$$

Where “*cut()” and “assoc()”* is defined as:

$$cut(A, B) = \sum_{i \in A, j \in B} w(i, j).$$

$$\mathrm{assoc}(A, V) = \sum_{i \in A, t \in V} w(i, t)$$

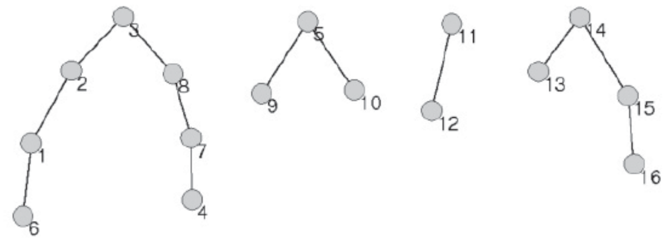
4. How to play Evolutionary in Image Segmentation

4.1 Representation in GA

In the task, an individual of the population consists of *n* genes $g_1, g_2, \dots, g_n$ and each gene can assume value in the range{1,…,n}. For example, if node *i* connects with node *j*, the $g_i = j$ is set (As Fig. 2(a) shows).

pixel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
neighbor	2	3	8	7	9	1	4	7	5	5	12	11	14	13	14	15

(a)



(b)

$$\begin{Vmatrix} r_1 & r_1 & r_1 & r_1 \\ r_2 & r_1 & r_1 & r_1 \\ r_2 & r_2 & r_3 & r_3 \\ r_4 & r_4 & r_4 & r_4 \end{Vmatrix}$$

(c)

Figure 2: (a) Locus-based representation of individual J_1. (b) Corresponding segmentation of the graph G of Figure 1(d) in four segments composed by the pixels $r_1 = \{1, 2, 3, 4, 6, 7, 8\}$, $r_2 = \{5, 9, 10\}$, $r_3 = \{11, 12\}$, and $r_4 = \{13, 14, 15, 16\}$. (c) Image partitioning.

In the pixel connection, only pixels satisfying the h-Neighborhood are regarded as neighbors. This h-Neighborhood definition not only considers the spatial closeness, but also the pixel affinity. Within the distance radius *r*, only pixels with top-h highest weight are regarded as a pixel's neighbor. For example in Fig. 1(c) and Fig. 6, if we define the h =2, for node 3, the top-2 highest weight are 1.0 and 0.9, so the node 2, 4, 7, 8 are kept as its neighbor and node 6 (w=0.7) is removed.

$1 \to \{(2; 1.0), (6; 0.7)\}$
$2 \to \{(1; 1.0), (3; 1.0), (7; 0.9)\}$
$3 \to \{(2; 1.0), (4; 1.0), (7; 0.9), (8; 0.9)\}$
$4 \to \{(3; 1.0), (7; 0.9), (8; 0.9)\}$
$5 \to \{(6; 0.5), (9; 1.0), (10; 1.0)\}$
$6 \to \{(1; 0.7), (2; 0.7), (3; 0.7), (7; 0.6)\}$
$7 \to \{(2; 0.9), (3; 0.9), (4; 0.9), (8; 1.0)\}$
$8 \to \{(3; 0.9), (4; 0.9), (7; 1.0)\}$
$9 \to \{(5; 1.0), (6; 0.5), (10; 1.0)\}$
$10 \to \{(5; 1.0), (6; 0.5), (9; 1.0)\}$
$11 \to \{(7; 0.8), (8; 0.8), (12; 1.0)\}$
$12 \to \{(7; 0.8), (8; 0.8), (11; 1.0)\}$
$13 \to \{(9; 0.4), (10; 0.4), (14; 1.0)\}$
$14 \to \{(9; 0.4), (10; 0.4), (13; 1.0), (15; 1.0)\}$
$15 \to \{(10; 0.4), (14; 1.0), (16; 1.0)\}$
$16 \to \{(11; 0.3), (12; 0.3), (15; 1)\}$

(a)

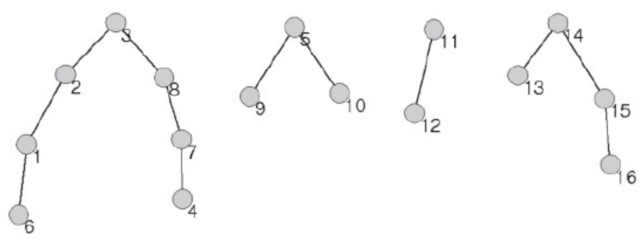
Figure 6: Nearest neighbors nn_i^h for $1 \leq i \leq 16$ and $h = 2$.

4.2 Crossover and Mutation

Provided there are two parent-individuals J_1 and J_2 as follow:

pixel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
neighbor	2	3	8	7	9	1	4	7	5	5	12	11	14	13	14	15

(a)



(b)

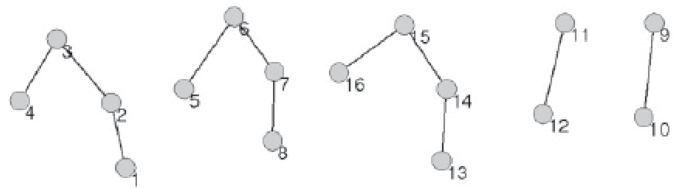
$$\left\Vert \begin{matrix} r_1 & r_1 & r_1 & r_1 \\ r_2 & r_1 & r_1 & r_1 \\ r_2 & r_2 & r_3 & r_3 \\ r_4 & r_4 & r_4 & r_4 \end{matrix} \right\Vert$$

(c)

Figure 2: (a) Locus-based representation of individual J_1. (b) Corresponding segmentation of the graph G of Figure 1(d) in four segments composed by the pixels $r_1 = \{1, 2, 3, 4, 6, 7, 8\}$, $r_2 = \{5, 9, 10\}$, $r_3 = \{11, 12\}$, and $r_4 = \{13, 14, 15, 16\}$. (c) Image partitioning.

pixel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
neighbor	2	3	4	3	6	7	8	7	10	9	12	11	14	13	14	15

(a)



(b)

$$\left\| \begin{matrix} r_1 & r_1 & r_1 & r_1 \\ r_2 & r_2 & r_2 & r_2 \\ r_3 & r_3 & r_4 & r_4 \\ r_5 & r_5 & r_5 & r_5 \end{matrix} \right\|$$

(c)

Figure 3: (a) Locus-based representation of another individual J_2. (b) Corresponding segmentation of the graph G of Figure 1(d) in five segments composed of the pixels $r_1 = \{1, 2, 3, 4\}$, $r_2 = \{5, 6, 7, 8\}$, $r_3 = \{9, 10\}$, $r_4 = \{11, 12\}$, and $r_5 = \{13, 14, 15, 16\}$. (c) Image partitioning.

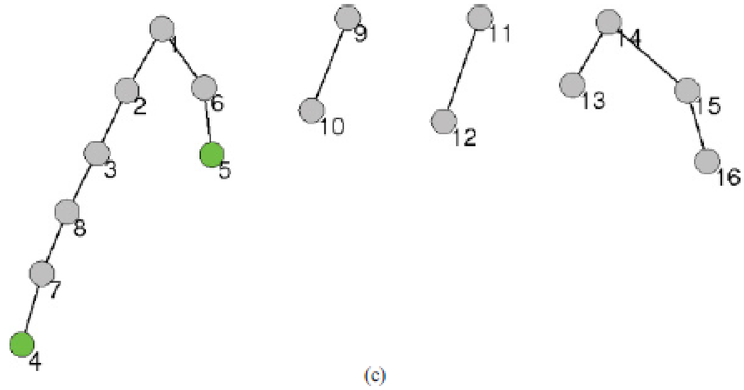
The crossover is implemented by an exquisite definition of mask that is generated randomly (As Fig. 4(a)). If mask[i] is 0, the g_i is selected from J1; otherwise, g_i is selected from J2. As Fig. 4 show, after crossover between J1 and J2, the segmentation of image is composed of the pixels {1, 2, 3, 4, 5, 6, 7, 8}, {9, 10}, {11, 12} and {13, 14, 15, 16}.

mask	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
	1	0	0	0	1	0	0	1	1	1	0	0	0	1	1	0

(a)

pixel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
neighbor	2	3	8	7	6	1	4	7	10	9	12	11	14	13	14	15

(b)



(c)

$$\begin{Vmatrix} r_1 & r_1 & r_1 & r_1 \\ r_1 & r_1 & r_1 & r_1 \\ r_2 & r_2 & r_3 & r_3 \\ r_4 & r_4 & r_4 & r_4 \end{Vmatrix}$$

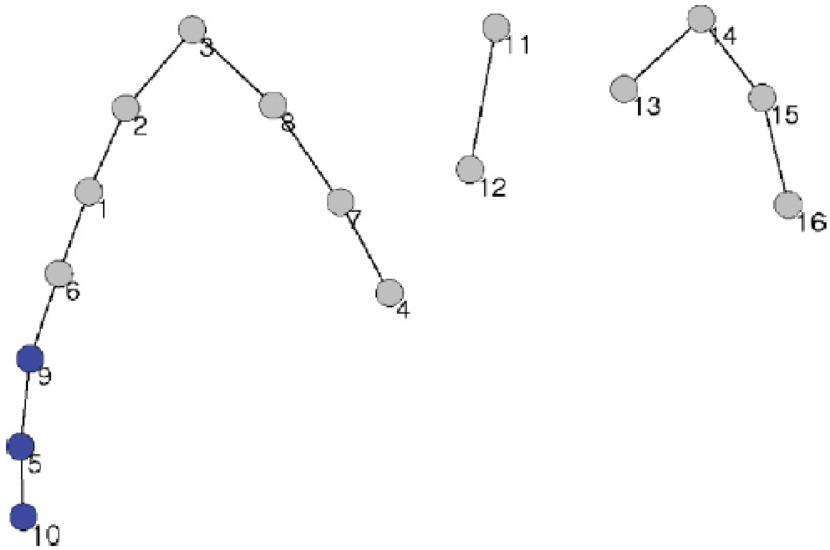
(d)

Figure 4: Crossover between the two individuals J_1 and J_2 of Figures 2–3. (a) Random mask generated. (b) Offspring generated from J_1 and J_2. (c) Corresponding segmentation of the graph G of Figure 1(d) in four segments composed of the pixels $r_1 = \{1, 2, 3, 4, 5, 6, 7, 8\}$, $r_2 = \{9, 10\}$, $r_3 = \{11, 12\}$, and $r_4 = \{13, 14, 15, 16\}$. (d) Image partitioning.

The mutation operator, analogous to the initialization process, randomly assigns to a neighbor node *i*. For example in the Fig. 5, the node 9 is chosen at random and its neighbor 5 is substituted by the other neighbor 6. As Fig. 5 show, after mutation from J1, a new segmentation in three components constituted by {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}, {11, 12} and {13, 14, 15, 16}.

allele	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
gene	2	3	8	7	9	1	4	7	6	5	12	11	14	13	14	15

(a)



(b)

$$\begin{Vmatrix} r_1 & r_1 & r_1 & r_1 \\ r_1 & r_1 & r_1 & r_1 \\ r_1 & r_1 & r_2 & r_2 \\ r_3 & r_3 & r_3 & r_3 \end{Vmatrix}$$

(c)

Figure 5: (a) Mutation on individual J_1 of Figure 2 where 9 is the randomly chosen node. Its neighbor 5 is substituted with 6. (b) The new generated individual corresponds to the segmentation of graph G of Figure 1(d) in three segments composed of $r_1 = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$, $r_2 = \{11, 12\}$, and $r_3 = \{13, 14, 15, 16\}$. (c) Image partitioning.

5. Improvement

5.1 Hybridism

To avoid the local optimization, in the implementation of GA module, I introduce the idea of hybridism. Make full use of the advantages of geo-insulation to avoid local optimization. The illustrations of hybridism are presented in the Figure 7 and Figure 8.

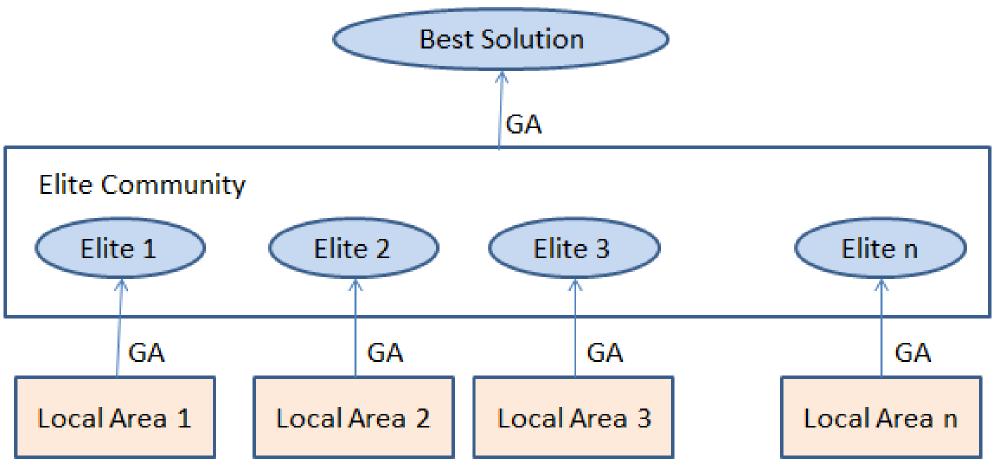


Figure 7: The illustration of hybridism

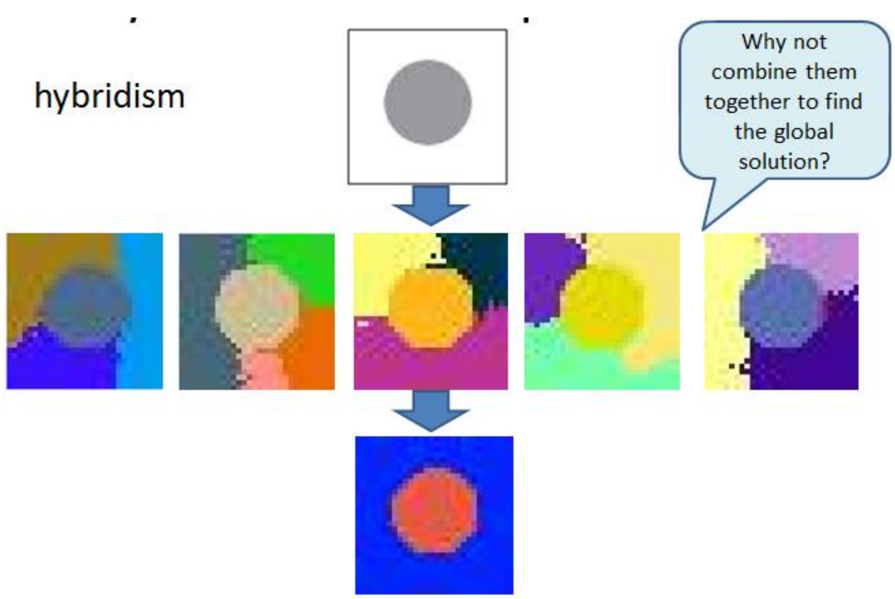


Figure 8: The samples of hybridism.
First line is the original input. Second line is the optimal solutions generated from different local areas. Third line is the final solution.

5.2 Distance Information

To avoid falling in local optimization in high level GA again, I introduce the distance information to avoid the inbreeding phenomenon. Give the differential individuals higher survival rights. This strategy makes the elite community with a higher special diversity. The definition of survival evaluation function is defined as follow:

$$V_{survival} = \alpha * e^{di} + (1 - \alpha) * e^{-|WNCut_i - WNCut_{best}|}$$

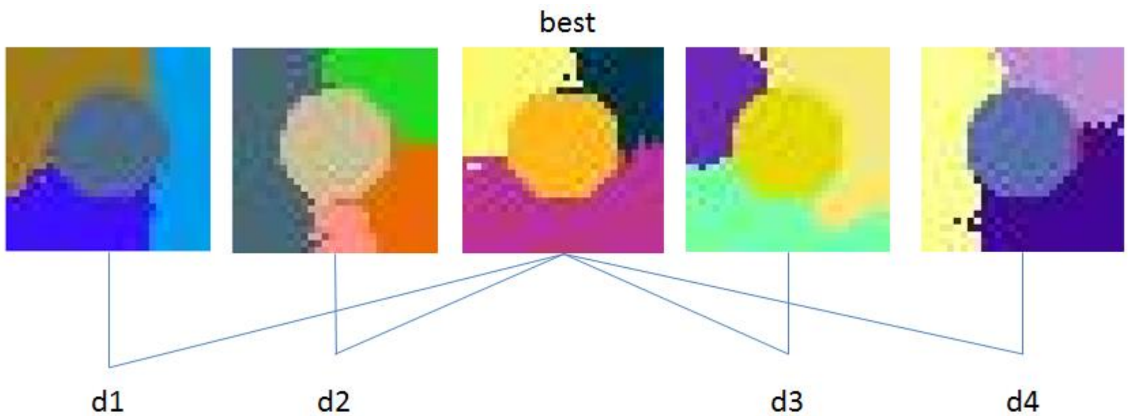


Figure 9: Illustration of Distance Information. d is the distance definition of between the best solution and individual

6. Experiment

6.1 Synthetic Image 1

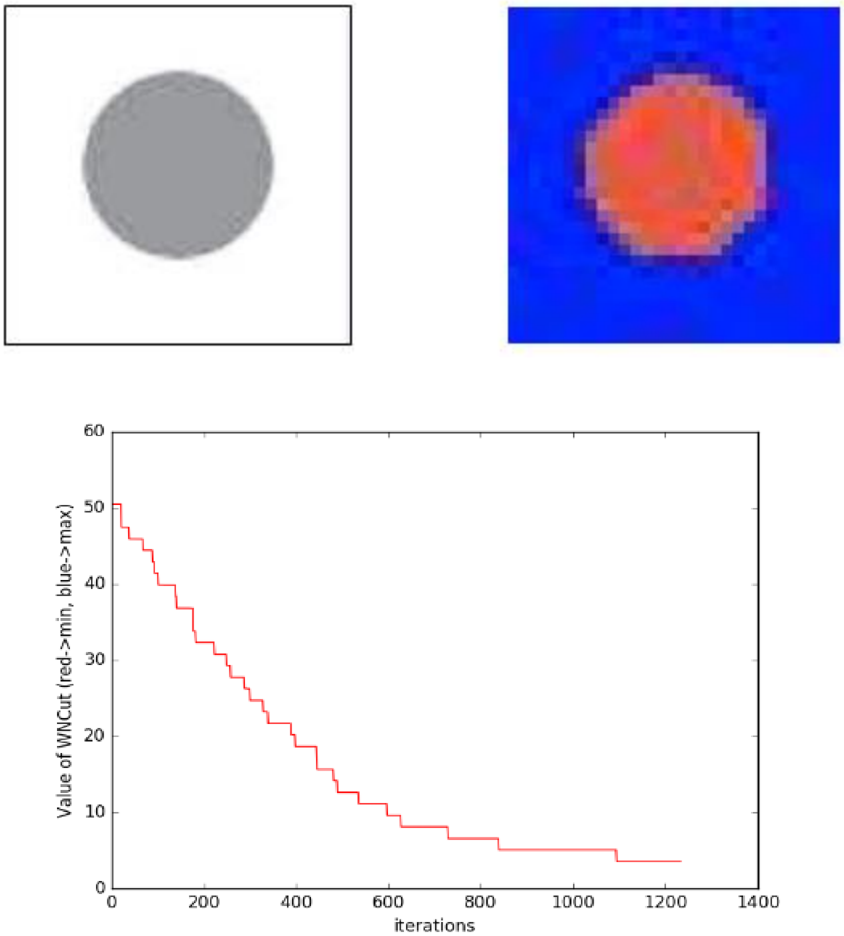
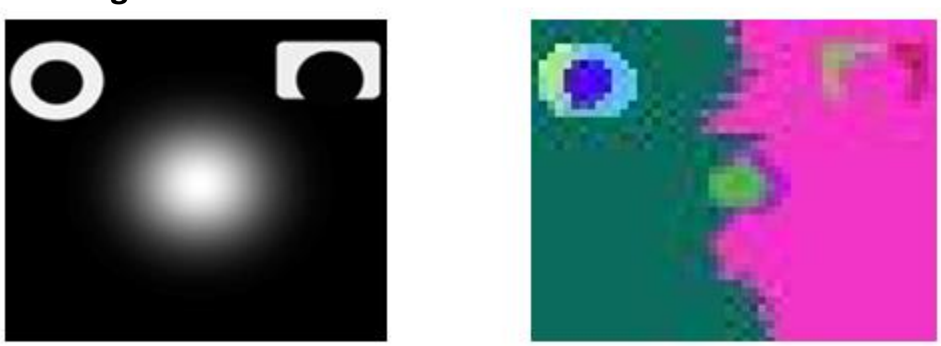


Figure 10: The result of Synthetic Image 1.
Top left is the original Image. Top right is the classified result. Below one is the relationship between the best WNCut and iterations.

6.2 Synthetic Image 2



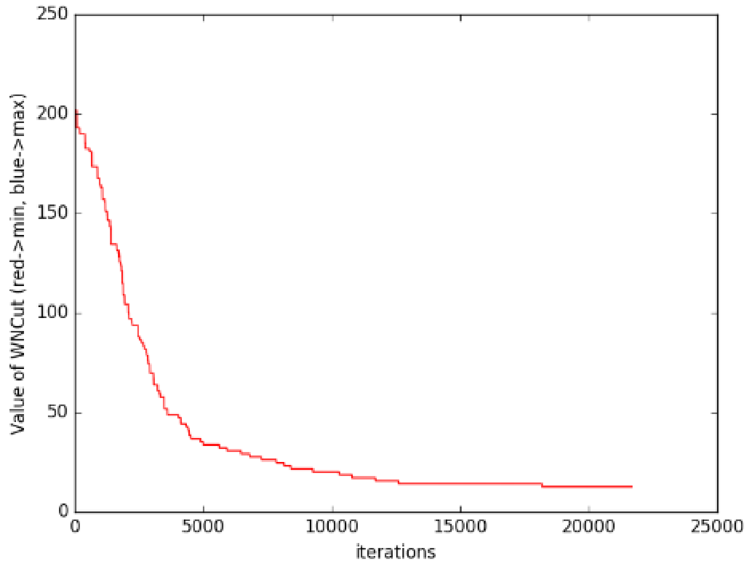


Figure 11: The result of Synthetic Image 2.
Top left is the original Image. Top right is the classified result. Below one is the relationship between the best WNCut and iterations.

6.3 Satellite Image 1

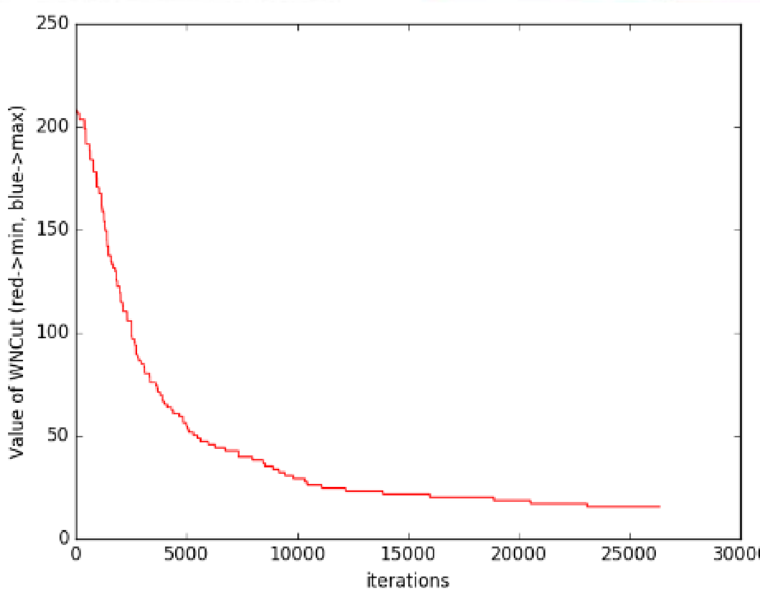


Figure 12: The result of Satellite Image 1.
Top left is the original Image. Top right is the classified result. Below one is the relationship between the best WNCut and iterations.

6.4 Satellite Image 2

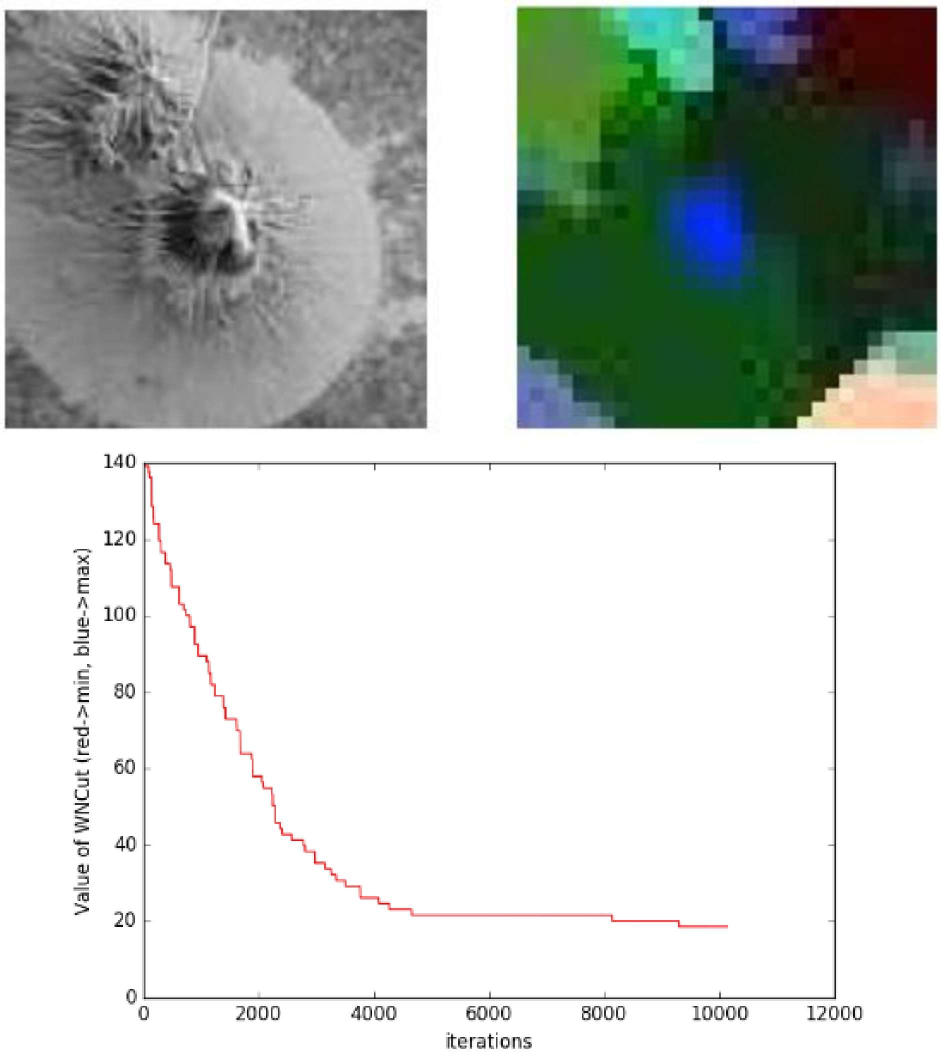


Figure 13: The result of Satellite Image 2.
Top left is the original Image. Top right is the classified result. Below one is the relationship between the best WNCut and iterations.

6.5 Biological Image 1

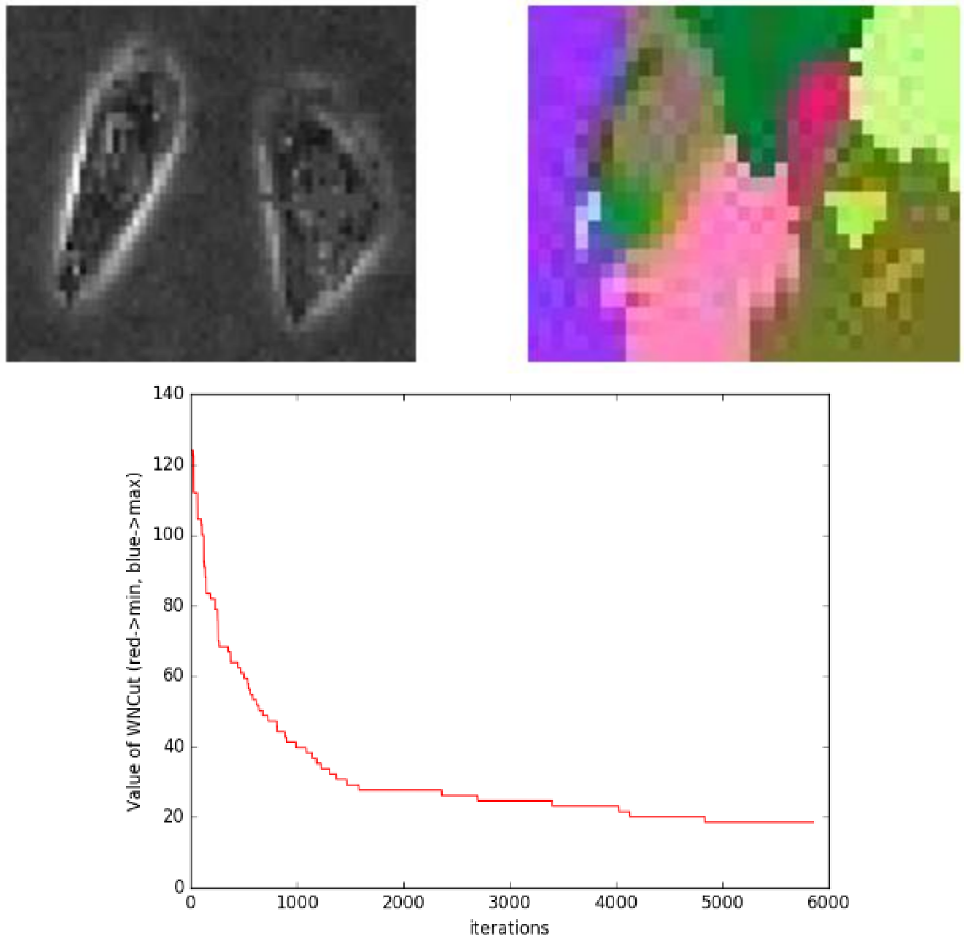


Figure 14: The result of Biological Image 1.
Top left is the original Image. Top right is the classified result. Below one is the relationship between the best WNCut and iterations.

Reference

[1] Amelio, Alessia, and Clara Pizzuti. "An evolutionary approach for image segmentation." *Evolutionary computation* 22.4 (2014): 525-557.