ROMANIAN JOURNAL OF INFORMATION SCIENCE AND TECHNOLOGY
Volume **17**, Number 1, 2014, 63–75

A Region-based Color Image Segmentation Method Based on P Systems

Hong PENG[1], Yufan YANG[1], Jiarong ZHANG[1], Xiaoli HUANG[1], Jun WANG[2]

[1] Center for Radio Administration and Technology Development, Xihua University, Chengdu, 610039, China

E-mail: ph.xhu@hotmail.com

[2] School of Electrical and Information Engineering, Xihua University, Chengdu, 610039, China

Abstract. Region growing-based color image segmentation approaches suffer from expensive computation cost. In order to overcome this issue, a novel region-based color image segmentation method based on P systems is proposed in this paper. A tissue-like P system is designed in such a way that an adaptive selection of target regions is achieved. The proposed method is evaluated on several real-life color images.

Key-words: Membrane computing; Tissue-like P systems; Color image segmentation; Region-based segmentation

1. Introduction

Image segmentation is an important problem in computer vision and video applications. It is a process of dividing an image into several regions according to specific rules [1]. These regions are mutually disjoint, well-defined and have the same properties. The purpose of segmenting an image is to identify regions that are then utilised to recognize and understand the image. In the past decades, a large number of image segmentation algorithms have been developed [2, 3, 4]. These algorithms can be roughly classified into three categories: threshold-based segmentation methods, edge-based segmentation methods and region-based segmentation methods. The threshold-based segmentation method is one of the oldest. It is a simple and popular technique for image segmentation, which uses the image histogram to select the appropriate threshold(s), in accordance with some criteria, in order to divide an image into two or more pixel collections. Its underlying assumption is that an image consists of different regions corresponding to the gray-level ranges. It has been used widely as a tool to segment the gray images, but only a few works on color image segmentation have been reported. The main advantage of this technique lies in its simple computation approach. However, the threshold-based segmentation method ignores the spatial relationship information. The edge-based segmentation method is extensively utilized for gray-level image segmentation, which is based on the detection of discontinuity in the gray level. An edge or boundary is a place where there is a more or less abrupt change in the gray level. Amongst the most used edge detection operators are Roberts operator, Sobel operator, Guass-Laplace operator and Canny operator. There are two key approaches regarding the region-based segmentation method: region growing and splitting-merging. Region growing polymerizes image's pixels or sub-regions that are considered as seeds into larger regions according to some criteria [5]. The characteristics of pixels and the adjacency of spatial distribution are fully considered in region growing. However, because of its iterative computational process, region growing has a high computing cost.

Membrane computing, as a branch of natural computing, is a class of computing models inspired by the structure and functioning of living cells as well as from the cooperation between cells in tissues and organs [6]. The computing models are also known as P systems. Generally, a P system consists of three characteristics: (i) membrane structure, (ii) multisets of objects and (iii) evolution rules. The multisets of objects are placed in compartments surrounded by membranes, and evolving by the use rules [7]. According to the membrane structure, P systems can be roughly classified into three categories: cell-like P systems, tissue-like P systems and neural-like P systems. A variety of P systems have been proposed [8, 9, 10, 11, 12, 13]. Tissue-like P systems are inspired by the intercellular communication and cooperation between cells, where the cells are considered as nodes (processors) and communications of objects between the cells reflects their connection. Thus, a tissue-like P system can be considered as a net of processors dealing with symbols and communicating them along the specified channels. In addition to the advantage of distributed parallel computing, tissue-like P systems have evolution and communication mechanisms of objects, which allow the evolution of objects as well as the exchange and sharing of objects between elementary membranes.

Recently, some works on the use of membrane computing to image segmentation have been reported. Díaz-Pernil et al. [14] developed an image segmentation method on 2D images using P systems, which was applied to medical image segmentation. This method regarded the pixels in an image as the objects in the designed membranes. Christinal et al. [15] presented an image segmentation method based on tissue-like P systems, which segmented the images using the 4-neighborhood relation of pixels in the 2D-image. However, they only addressed the segmentation results of artificial images rather than real-life images. Wang et al. [16] proposed an optimal single-level thresholding method based on P systems. Peng et al. [17] presented a three-level thresholding method based on cell-like P systems for image segmentation. Zhang et al. [18] developed an infrared object segmentation method with membrane computing, which was used to obtain the optimal parameters quickly. Peng et al. [19] proposed an optimal multi-level thresholding method based on tissue-like P systems and fuzzy entropy. Díaz-Pernil et al. [20] proposed a parallel implementation of a new algorithm for segmenting images with gradient-based edge detection by using techniques from membrane computing. Yang et al. [21] developed a region-based segmentation method with membrane computing, which effectively segmented gray images. However, the method cannot be extended to color images.

This paper focuses on the use of the inherent mechanisms and parallel behavior of tissue-like P systems to overcome the drawbacks of the existing region-based color image segmentation methods, and propose a novel region-based color image segmentation method based on tissue-like P systems.

The rest of this paper is organized as follows. In Section 2, we review the definition of a tissue-like P system. In Section 3, we firstly review the principle of region segmentation used in this work, and then describe the proposed image segmentation method based on tissue-like P systems. Experimental results are provided in Section 4. The conclusions are discussed in Section 5.

2. Tissue-like P systems

In this section, we briefly review the definition and mechanisms of tissue-like P systems. More detailed descriptions of tissue-like P systems can be found in [7, 8, 22, 23].

Formally, a tissue-like P system (of degree $d \geq 1$) with symport/antiport rules is a construct

$$\Pi = (\Gamma, \Sigma, \mathcal{E}, \omega_1, \ldots, \omega_d, R, i_o) \tag{1}$$

where

(1) Γ is the alphabet of objects.

(2) $\mathcal{E} = \Gamma - \Sigma$ is the alphabet of objects in the environment.

(3) w_i, $1 \leq i \leq d$, are finite sets of strings over Σ associated with the regions $1, 2, \ldots, d$. The environment is labeled by 0. They represent multisets of objects initially present in the regions.

(4) R is a finite set of rules, which includes rules of three types:

   (a) Evolution rule: $u \to v$, where $u, v \in \Gamma^*$.

   (b) Division rule: $[\ ]_i \to [\ ]_i [\ ]_{s_1} \cdots [\ ]_{s_i}$, where $i, s_1, \ldots, s_i \in \{1, 2, \ldots, q\}$.

   (c) Communication rules: $(i, u/v, j)$, where $u, v \in \Gamma^*$, $i \in \{0, 1, 2, \ldots, q\}$.

(5) i_0 is a label of a membrane, which indicates the output region of the system.

The tissue-like P system consists of d cells, which are placed in the environment. Objects are processed by the evolution rules. Each membrane usually contains one or more evolution rules of form $u \to v$, $u, v \in \Gamma^*$. The application of the rule $u \to v$

means that u will be evolved to v. In order to deal with some real-world problems, the evolution rules usually need to be specially designed according to the domain knowledge.

The objects are moved between cells by the use of the communication rules. Objects are also exchanged with the environment. The object communications implicitly reflect the connection relationships between these cells. There are two types of communication rules: symport and antiport rules. A symport rule is of the form $(i, u/\lambda, j)$ with $i \neq 0, j \neq 0$. This shows a direct connection between cell i and cell j. The application of the rule means that u will be communicated from cell i to cell j. A communication rule $(i, u/v, j)$ is called an antiport rule, $u \neq \lambda$ and $v \neq \lambda$. An antiport rule $(i, u/v, j)$, with $i \neq 0, j \neq 0$, shows a direct connection between i and j. The application of this rule means that the multisets represented by u and v will be interchanged among the two cells. In this context, the environment can be considered as a virtual node of the graph such that its connections are defined by communication rules of the form $(i, u/v, j)$, with $i = 0$ or $j = 0$.

In addition, there are also other kinds of rules, such as division rule. The division rule is used to split a membrane into several membranes.

A computation in a tissue-like P system is a sequence of steps which start with the cells $1, \ldots, d$ containing the multisets $w_1, \ldots, w_d$ and where, in each step, one or more rules are applied to the current multisets of symbol objects. A computation is successful if and only if it halts. When it halts, it produces a result in output cell.

The inherent mechanisms of tissue-like P systems provide a great flexibility in dealing with real-world problems. In this work, we will apply this model to define a region-based color image segmentation method.

3. The proposed region-based color image segmentation method

3.1. The method for automatic target point selection

We consider a pixel as target point if it satisfies two criteria given below. In this work, we use a target points method which is a modified version of the method described in the current literature [24].

1st criterion: The similarity of the pixel with its neighbors is higher than a threshold value T_1.

For a color image, the similarity of a pixel with its neighbors is calculated as follows. As shown in Fig. 1(a), if we want to calculate the similarity of the pixel at (i, j), we consider the eight pixels in red.

According to the 3×3 neighborhood, the standard deviations of Y, C_b, C_r components are calculated respectively by:

$$\sigma_x = \sqrt{\frac{1}{9} \sum_{i=1}^{9} \left(x_i - \bar{x}\right)^2}, \tag{2}$$

where x_i can be Y or Cb or Cr, and $\bar{x} = \frac{1}{9}\sum_{i=1}^{9} x_i$ is the average value of all the nine pixels in the 3×3 window. The standard deviation of each pixel is calculated by:

$$\sigma = \sigma_Y + \sigma_{C_b} + \sigma_{C_r} \tag{3}$$

Next, the standard deviation of each pixel is normalized as follows:

$$\sigma_x^{'} = \sigma_x / \sigma_{max} \tag{4}$$

where σ_{max} is the maximum value of standard deviations of all sliding windows. Finally, the similarity value H_x of each pixel to its neighborhood is defined as:

$$H_x = 1 - \sigma_x^{'} \tag{5}$$

We get the threshold value T_1 using usual Otsu's method. The between-class variance of the sliding window is seen as the threshold value T_1.

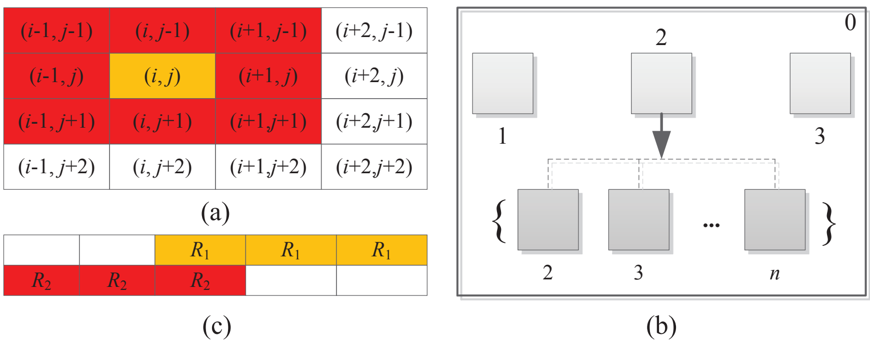

Fig. 1. (a) the yellow point is the pixel that will be calculated; (b) membrane structure of the tissue-like P system; (c) the yellow part is the target region marked by 'R_1', the red part is the target region marked by 'R_2', but the yellow part and the red part should belong to the same region.

2^{nd} criterion: The maximum distance of the pixel to its neighbors is less than a threshold value T_2.

The relative Euclidean distances of a pixel to its neighbors are calculated as follows:

$$d_i = \sqrt{\frac{(Y - Y_i)^2 + (C_b - C_{bi})^2 + (C_r - C_{ri})^2}{Y^2 + C_b^2 + C_r^2}} \tag{6}$$

where $i = 1, 2, \ldots, 8$. Thus, the maximum distance of the pixel to its neighbors is calculated by

$$d_{max} = \max_{i=1}^{8}\{d_i\} \tag{7}$$

In our experiment, the value T_2 will be determined empirically. For a color image, if a pixel of the image satisfies the two conditions above, it is regarded as a target point.

3.2. The processing of target regions

After the selection of target points, we label the target regions by $A_1, A_2, \ldots, A_n$, where A_i represents the ith region and its area is denoted by S_i. When the size of a target region is smaller than 1/500 of the whole image, we will discard this target region. The processing way of target regions is suitable for using the designed tissue-like P system to achieve the region-based segmentation.

Based on the selected target points, the pixels which have a certain similarity with the seed points are merged to form new seed regions. The process of growing the target regions can be described as follows:

(1) Set the flags of all target points to be 1 to determine the initial seeds regions.

(2) Scan the whole image line by line. For each pixel, if its flag is 1, each pixel in its 8-adjacent neighborhood is processed as follows: set its flag to be 1 and put it into the corresponding seed region when it is similar with the seed point and its flag is 0.

(3) Repeat step (2) until all seed regions are no longer growing.

If the relative Euclidean distance of a pixel to its neighbor is less than the threshold value T_2, we say that the pixel is similar with its neighbor.

3.3. The proposed segmentation algorithm based on P systems

The region-based image segmentation method proposed in this paper is based on a tissue-like P system. The tissue-like P system applies its evolution rules and communication rules to achieve target region selection for color image segmentation. Therefore, for a color image, the tissue-like P system is able to complete image segmentation automatically. With the advantage of parallel computing of P systems, the proposed image segmentation method can effectively overcome the large computation cost problem of traditional region-based image segmentation method. The main components of the tissue-like P system for color image segmentation are described in detail as follows.

Membrane structure. The tissue-like P system consists of three elementary membranes, which are labeled by 1, 2 and 3, respectively. Fig. 1(b) shows its membrane structure. As usual in tissue-like P systems, the environment is labeled by 0. Each elementary membrane contains a number of objects and evolution rules. The communication rules between elementary membranes perform the exchange of objects. In the tissue-like P system, membrane 1 deals with the automatic selection of the target points, while membrane 2 processes the target regions. Membrane 2 can be split into $n+1$ membranes. The value n is determined according to the objects in the system. Membrane 3 is the output membrane of the system. When the system halts, the objects in the output membrane are the result of the whole system.

Objects in membranes. Usually, a tissue-like P system processes the information through evolution and communication rules applied to objects. In this paper, these mechanisms of tissue-P systems are used to achieve a region-based segmentation. For an image with $n \times m$ pixels $(n, m \in N)$, let $C \subseteq N$ be the set of all the value levels (Y is in [16, 235], and C_b and C_r are in [16, 240]) and they are in a certain order. There are five types of objects in our tissue-like P system:

(1) Object a_{ij}, $1 \le i \le m, 1 \le j \le n, a \in C$. The object a_{ij} denotes the pixel with value Y or C_b or C_r at (i, j), $a \in C$.

(2) Object H_{ij}, $1 \le i \le m, 1 \le j \le n, H \in E$. Each pixel corresponds to a similarity value, which indicates the degree of similarity of the pixel with its neighboring pixels. Therefore, the similarity value can be seen as the feature value of the pixel, which is encoded by H_{ij}. Here, $E \subset R$ denotes the set of these feature values. Initially, set $H_{ij} = 0.0$.

(3) Object D_{ij}, $1 \le i \le m, 1 \le j \le n, D \in F$. Each pixel corresponds to a distance value, which indicates the maximum distance of the pixel to its neighboring pixels. Similarly, the distance value can be seen as another feature value of the pixel, which is encoded by D_{ij}. Here, $F \subset R$ denotes the set of these feature values. Initially, set $D_{ij} = 1000.0$.

(4) Object $A_{ij}^{R_t}$, $1 \le i \le m, 1 \le j \le n, t \in C$. $A_{ij}^{R_t}$ is the output object of the whole system, and it will be communicated into membrane 3 as an output object when object a_{ij} is identified as a target point or a point in some target regions. The label R_t indicates that the point A_{ij} is in the tth target region. Initially, set $t = 0$.

(5) Object c, $c \in N$. The object c is used to count the target regions. It is changed by the evolution rules during the processing of the target regions. Initially, set $c = 0$.

The designed tissue-like P system. For each color image with $n \times m$ pixels $(n, m \in N)$ we design a tissue-like P system of degree $d = 3$ to achieve a region-based segmentation. The tissue-like P system can be described as follows:

$$\Pi = (\Gamma, \Sigma, \mathcal{E}, \omega_1, \omega_2, \omega_3, R, i_o) \tag{8}$$

where,

(1) Γ is the alphabet of objects, $\Gamma = \Sigma \bigcup \{A_{ij}^{R_t} \mid 1 \le i \le n, 1 \le j \le m, A \in C, t \in C\}$, where $\Sigma = \{a_{ij} \mid 1 \le i \le n, 1 \le j \le m, a \in C\} \bigcup \{H_{ij} \mid 1 \le i \le n, 1 \le j \le m, H \in E\} \bigcup \{D_{ij} \mid 1 \le i \le n, 1 \le j \le m, D \in F\}$.

(2) $\mathcal{E} = \Gamma - \Sigma$ is the alphabet of objects in the environment.

(3) $\omega_1 = \Sigma$, $\omega_2 = a_{ij}$, $\omega_3 = \emptyset$ are initial multisets of objects.

(4) R is a finite set of rules, which includes the following rules of three types:

(a) Evolution rules:

(i) The Eq. (5) and Eq. (7) are used as evolution rules of objects. Membrane 1 achieves automatic selection of target points according to the evolution rules (5) and (7). The role of the evolution rules is to compute the similarity value H_{ij} and the distance value D_{ij} of each pixel here.

(ii) $[a_{ij}A_{ij}^{R_0}a_{i-1j-1}a_{ij-1}a_{i+1j-1}a_{i-1j}a_{i+1j}a_{i-1j+1}a_{ij+1}a_{i+1j+1}]_2 \xrightarrow{c=c+1}$ $[a_{ij}A_{ij}^{R_c}a_{i-1j-1}a_{ij-1}a_{i+1j-1}a_{i-1j}a_{i+1j}a_{i-1j+1}a_{ij+1}a_{i+1j+1}]_2$, where $1 \leq i \leq n, 1 \leq j \leq m$.
These evolution rules are used to mark which target region the point at (i,j) is in while its neighbors are not target points. The value of the object 'c' is the count of the marked target regions.

(iii) $[a_{ij}A_{ij}^{R_0}a_{kl}A_{kl}^{R_0}a_{pq}]_2 \xrightarrow{c=c+1} [a_{ij}A_{ij}^{R_c}a_{kl}A_{kl}^{R_c}a_{pq}]_2$, where $1 \leq i \leq n,\ 1 \leq j \leq m,\ k,p \in \{i-1,i,i+1\},\ l,q \in \{j-1,j,j+1\}$.
These evolution rules are used to mark which target region the point at (i,j) is in while its neighbors are not target points or the marked target points. The object a_{pq} is optional. The value of the object 'c' is the count of the marked target regions.

(b) Division rule: $[]_2 \rightarrow []_2\underbrace{[]_4[]_5[]_6\ldots[]_{c+3}}_{c}$.

This division rule means that the membrane 2 is divided into c membranes. c is the number of the target regions. Note that the membrane 2 still exists in the system. The objects in the membrane 2 do not change and there is no object in the membranes $4, 5, \ldots, c+3$.

(c) Communication rules:

(i) $(1, H_{ij}D_{ij}/A_{ij}^{R_0}, 0), 1 \leq i \leq n, 1 \leq j \leq m$. The triggering condition of the rule is $H_{ij} > T_1$ and $D_{ij} < T_2$.
This rule is used to select target points. It will be executed when the similarity value H_{ij} of the pixel at (i,j) with its neighboring pixels and the distance value D_{ij} of the pixel at (i,j) to its neighbors satisfy the trigger condition above. The execution of the rule means that object a_{ij} is marked as a target point.

(ii) $(1, A_{ij}^{R_0}/\lambda, 2), 1 \leq i \leq n, 1 \leq j \leq m$.
This rule is used to communicate the target points marked in membrane 1 into membrane 2. In the tissue-like P system, the function of membrane 1 is automatic selection of target points while the function of membrane 2 is to achieve the region-based segmentation.

(iii) $(2, a_{ij}A_{ij}^{R_t}a_{kl}A_{kl}^{R_0}/a_{ij}A_{ij}^{R_t}a_{kl}A_{kl}^{R_t}, 0),\ 1 \leq i \leq n, 1 \leq j \leq m$, $k \in \{i-1,i,i+1\}, l \in \{j-1,j,j+1\}, a \in C, t \in C$.
This is a communication rule between membrane 2 and the environment. For a marked target point a_{ij}, if there exists an unmarked adjacent target point object, the adjacent target point will be marked in the same region with the target point.

(iv) $(2, a_{ij}A_{ij}^{R_s}a_{kl}A_{kl}^{R_t}/a_{ij}A_{ij}^{R_t}a_{kl}A_{kl}^{R_t}, 0)$, $1 \le i \le n, 1 \le j \le m$, $k \in \{i-1, i, i+1\}, l \in \{j-1, j, j+1\}, a \in C, t \in C$.
For a marked target point a_{ij} which is in the region R_s, if there exists a marked adjacent target point a_{kl} in the region R_t, the point a_{ij} will be marked in the region R_t. In selection method of target points, there may be the case shown in Fig. 1(c). So we use this rule to correct those mislabeled regions.

(v) $(2, a_{ij}A_{ij}^{R_t}a_{kl}/a_{ij}A_{ij}^{R_t}a_{kl}A_{kl}^{R_t}, 0)$, $1 \le i \le n, 1 \le j \le m, k \in \{i-1, i, i+1\}, l \in \{j-1, j, j+1\}, a \in C, t \in C$.
The triggering condition of the rule is that the relative Euclidean distance of a_{kl} to a_{ij} is less than T_2.

(vi) $(2, A_{ij}^{R_t}/\lambda, t+3), 1 \le i \le n, 1 \le j \le m, t \in C$.
This rule is used to transport the target point to the corresponding membrane. The target point which belongs to the region t is moved to the membrane $t+3$.

(vii) $(t+3, A_{ij}^{R_t}/\lambda, 3), 1 \le i \le n, 1 \le j \le m, t \in C$. The triggering condition of the rule is $S_{t+3} > \dfrac{n \times m}{500}$, where S_{t+3} is the number of objects in $(t+3)$th membrane.
This rule is used to communicate target objects or objects in target regions in membrane $t+3$ into membrane 3. In this system, membrane 3 is the output membrane. The objects in membrane 3 is the output results of the whole system when it halts.

(5) $i_o = 3$. It indicates that membrane 3 is the output membrane of this system. When the whole system halts, the objects in membrane 3 are the result of the computation.

4. Experimental results

In our experiment, several color images randomly collected from the Internet are used to evaluate the proposed image segmentation method based on tissue-like P systems.

Figure 2 shows the selection of target points and segmentation result of the proposed region-based segmentation method. The red parts in Fig. 2(b) are the target points selected in membrane 1, which can represent the target regions. After the processing of the target regions in membrane 2, we can get the final result by outlining the target regions. In these pictures the target regions are not full. The reason is that the values H and D of the center pixel are computed by using the eight adjacent pixels. That is to say, if a pixel is located on the edge of a region, its H value is lower and its D value is higher than the values corresponding to pixels within the region.

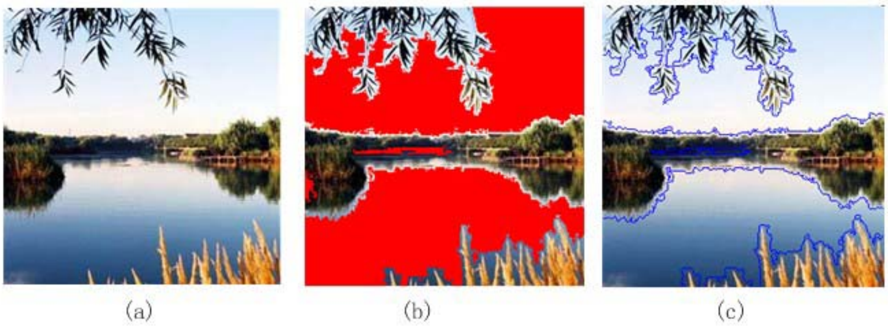

Fig. 2. Example of target point selection: (a) original color image Lake, (b) the target image, and (c) the result image.

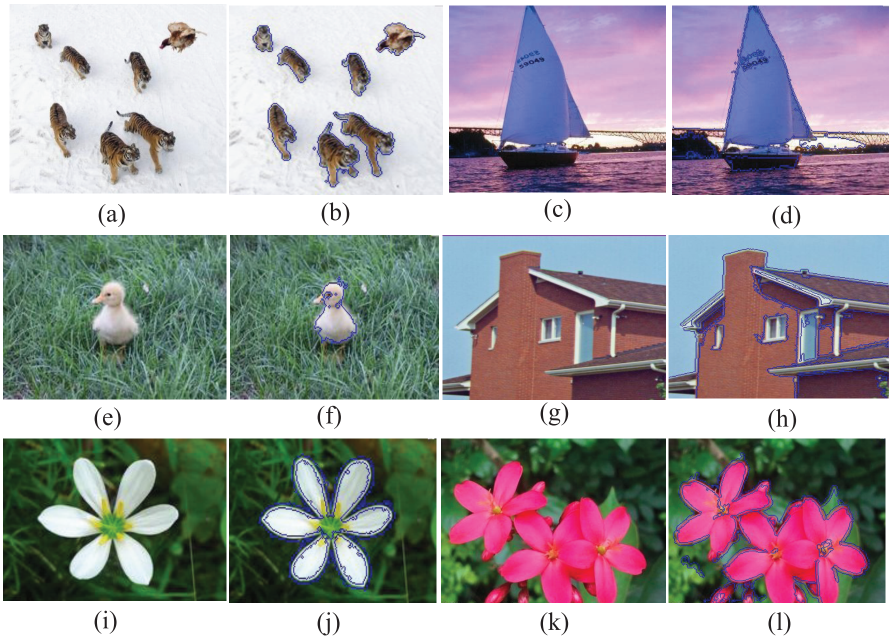

Fig. 3. The segmentation results of the proposed segmentation method on the tiger, sailing boat, two flowers, little duck and house images: (a)(c)(e)(g)(i)(k) original images, (b)(d)(f)(h)(j)(l) result images.

Figure 3 gives the segmentation results of the proposed segmentation method on six real-life images. In these segmented images, the blue lines express the edges of the target regions. Due to the fact that the threshold value T_2 is not selected, the segmented results are determined according to the threshold values for the relative Euclidean distance. Figures 3(b) and (d) give the outlines of the tigers and sailing boat, respectively. It can be observed that two objects, the tigers and sailing boat, are segmented better. Figures 3(j) and (l) give the outlines of two different flowers. The segmentation results clearly indicate that the two flowers can be segmented better. Figures 3(f) and (h) provide the outlines of the little duck and house, respectively. However, the segmentation results are not so satisfactory due to some noise occurring in the results.

Figures 4(a)–(c) show the segmentation results of the proposed segmentation method on Lake image with different value T_2 for the relative Euclidean distance, which correspond to the thresholds T_2 =0.11, 0.05 and 0.02, respectively. When the threshold value is 0.02, the number of the target regions is bigger and the size of each target region is smaller compared with that of thresholds T_2 =0.05 and 0.11. The results indicate that the higher the threshold value T_2 is, the more target seeds will be obtained, and then the bigger the target regions are.

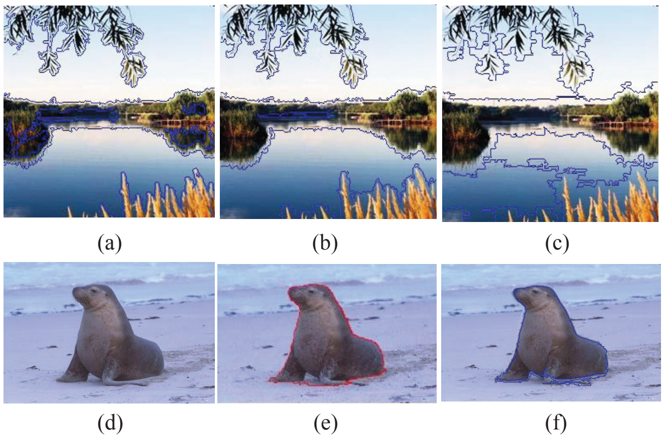

Fig. 4. The segmentation results of the proposed segmentation method on Lake image with different T_2 values: (a) $T_2 = 0.11$, (b) $T_2 = 0.05$, and (c) $T_2 = 0.02$. The comparison results: (d) original image, (e) the result of Shih's method [24], and (f) the result of the proposed segmentation method.

In order to evaluate the segmentation effect, the proposed segmentation method is compared with Shih's method [24], which is a region-based segmentation method developed recently. Figures 4(e) and (f) show segmentation results of the two methods on the sea lion image, which gives the outlines of the sea lion. The result of the proposed segmentation method is closer to the result of the artificial segmentation. But the proposed segmentation method has some noise in the result image.

5. Conclusions

A region-based color image segmentation method using tissue-like P systems is proposed in this paper. The tissue-like P system model takes advantage of evolution rules and communication rules to implement an adaptive region-based segmentation, in which three elementary membranes accomplish automatic selection of target points and target regional processing under the control of the parallel computing mechanism of the P systems. Therefore, the proposed image segmentation method based on tissue-like P systems has the advantage of fast segmentation. The experimental results show that the proposed image segmentation method has good segmentation effect and performance. The proposed image segmentation method expands the application of membrane computing in the field of image processing.

Acknowledgements. This work was partially supported by the National Natural Science Foundation of China (No. 61170030), Chunhui Project Foundation of the Education Department of China (No. Z2012025, No. Z2012031), Research Fund of Sichuan Key Technology Research and Development Program (No. 2013GZX0155), China.

References

[1] BALLARD D.H., BROWN C.M., *Computer Vision*, Prentice Hall, 1982.

[2] PAL N.R., PAL S.K., *A review on image segmentation techniques*, Pattern Recognition, **26**(9), pp. 1277–1294, 1993.

[3] LIU D., JIANG Z.H., FENG H.Q., *A novel fuzzy classification entropy approach to image thresholding*, Pattern Recognition Letters, **27**, pp. 1968–1975, 2006.

[4] CHENG H.D., JIANG X.H., SUN Y., WANG J., *Color image segmentation: advance and prospects*, Pattern Recognition, **34**, pp. 2259–2281, 2001.

[5] CHANG Y.-L., LI X., *Adaptive image region-growing*, IEEE Transaction on Image Processing, **3**, pp. 868–872, 1994.

[6] PĂUN GH., *Computing with membranes*, Journal of Computer System Sciences, **61**(1), pp. 108–143, 2000.

[7] PĂUN GH., ROZENBERG G., SALOMAA A., eds., *The Oxford Handbook of Membrane Computing*, Oxford Unversity Press, New York, 2010.

[8] FREUND R., PĂUN GH., PÉREZ-JIMÉNEZ M.J., *Tissue-like P systems with channel-states*, Theoretical Computer Science, **330**, pp. 101–116, 2005.

[9] IONESCU M., PĂUN GH., YOKOMORI T., *Spiking neural P systems*, Fundamenta Informaticae, **71**(2–3), pp. 279–308, 2006.

[10] WANG J., ZHOU L., PENG H., ZHANG G., *An extended spiking neural P system for fuzzy knowledge representation*, International Journal of Innovative Computing, Information and Control, **7**(7A), pp. 3709–3724, 2011.

[11] PENG H., WANG J., PÉREZ-JIMÉNEZ M.J., WANG H., SHAO J., WANG T., *Fuzzy reasoning spiking neural P system for fault diagnosis*, Information Sciences, **235**, pp. 106–116, 2013.

[12] WANG J., SHI P., PENG H., PÉREZ-JIMÉNEZ M.J., WANG T., *Weighted fuzzy spiking neural P systems*, IEEE Transactions on Fuzzy Systems, **21**(2), pp. 209–220, 2013.

[13] WANG T., PENG H., *Adaptive fuzzy spiking neural P systems for fuzzy inference and learning*, International Journal of Computer Mathematics, **90**(4), pp. 857–868, 2013.

[14] DÍAZ-PERNIL D., MOLINA-ABRIL H., REAL P., GUTÍERREZ-NARANJO M.A., *A bio-inspired software for segmenting digital images*, 2010 IEEE Fifth International Conference of Bio-Inspired Computing: Theories and Applications (BIC-TA 2010), pp. 1377–1381, 2010.

[15] CHRISTINAL H.A., DÍAZ-PERNIL D., REAL P., *Region-based segmentation of 2D and 3D images with tissue-like P systems*, Pattern Recognition Letters, **32**, pp. 2206–2212, 2011.

[16] WANG H., PENG H., SHAO J., WANG T., *A thresholding method based on P systems for image segmentation*, ICIC Express Letters, **6**(1), pp. 221–227, 2012.

[17] PENG H., SHAO J., LI B., WANG J., PÉREZ-JIMÉNEZ M.J., JIANG Y., YANG Y., *Image thresholding with cell-like P systems*, in Garcia-Quismondo, M., Macías-Ramos, L.F., Păun, Gh., Pérez-Hurtado, I., Valencia-Cabrera, L. (eds.), *Proceedings of the Tenth Brainstorming Week on Membrane Computing*, Volume **II**, Seville, Spain, January 30-February 3, 2012, Report RGNC 01/2012, Fénix Editora, pp. 75–88, 2012.

[18] ZHANG Z., PENG H., *Object segmentation with membrane computing*, Journal of Information & Computational Science 9(17), pp. 5417–5424, 2012.

[19] PENG H., WANG J., PÉREZ-JIMÉNEZ M.J., SHI P., *A novel image thresholding method based on membrane computing and fuzzy entropy*, Journal of Intelligent & Fuzzy Systems, **24**(2), pp. 229–237, 2013.

[20] DÍAZ-PERNIL D., BERCIANO A., PEÑA-CANTILLANA F., GUTÍERREZ-NARANJO M.A., *Segmenting images with gradient-based edge detection using membrane computing*, Pattern Recognition Letters, **34**, pp. 846–855, 2013.

[21] YANG Y., PENG H., JIANG Y., HUANG X., ZHANG J., *A region-based image segmentation method under P systems*, Journal of Information and Computational Science, **10**(10), pp. 2943–2950, 2013.

[22] PĂUN GH., PÉREZ-JIMÉNEZ M.J., RISCOS-NÚÑEZ A., *Tissue P system with cell division*, in *Second Brainstorming Week on Membrane Computing*, Sevilla, Report RGNC 01/2004, pp. 380–386, 2004.

[23] DÍAZ-PERNIL D., GUTIÉRREZ M.A., PÉREZ-JIMÉNEZ M.J., RISCOS-NÚÑEZ A., *A uniform family of tissue P systems with cell division solving 3-COL in a linear time*, Theoretical Computer Science, **404**, pp. 76–87, 2008.

[24] SHIH F.Y., CHENG S., *Automatic seeded region growing for color image segmentation*, Image and Vision Computing, **23**, pp. 877–886, 2005.