A region segmentation method for region-oriented image compression

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ABSTRACT

In order to obtain homogeneous regions and smooth contours for region-oriented image compression, gradient-coupled spiking cortex model is designed and applied to digital image segmentation. Inspired by the knowledge of visual cortex, the model is composed of neurons with spike coupling and gradient enhancement, and it is same as the one in the visual cortex which can distinguish some objects in real scene through capturing boundary information. The model smoothes pixels within regions and enhances pixels at boundaries by creating a fitting function. Outputs of the model are the desired segmented image after connection components label. Experiments show that the method not only detects regions of original image, but also remains succinct effective contours, so it is suitable for region-oriented image compression.

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1. Introduction

Digital image processing is a subject about 2D discrete signal processing in which a digital image is represented as a matrix and the value is called as gray intensity. Image segmentation is to divide an image into some connected components based on the location and its gray intensities. While image compression is to represent images with the shorter bits and the more information. Region-oriented image compression technique handles images based on regions as contours of objects but regular rectangles as processing units.

Segmented image coding (SIC) is considered as one of region-oriented image compression technology [1], which divides an input image into two parts: contours and regions with slowly varying image intensity. The contours are coded with a method while the homogeneous regions are represented by linear combination of orthogonal basis functions. Here, segmentation of regions is one of key problems to be solved. The actual performance of image compression depends highly on the segmentation algorithm. As proposed by Christopoulos et al. [2], the segmented image is expected as the one that has the controlled number of regions, perfect homogeneity within a region, less small-region and smooth contours.

In order to represent images effectively, segmented regions are expected as homogeneous as possible, and the number of small regions should be limited [3]. Furthermore, many experiments show that quite a few of bits are spent for coding contours in SIC. Hence, the number of contour pixels is essential for compression ratio of the image compression method [4]. The segmented algorithm should not only classify similar neighbor pixels into same regions, but also contour objects with the least pixels. Those properties are essential but no existing methods could meet.

Generally, there are two approaches [5] to partition an image into regions: region-based segmentation and edge detection. For region-based segmentation, all pixels with similar attributes are grouped together and marked as a region. Pixels are selected based on the similarity of some attributes, for a gray image, the basic attributes are gray intensity and spatial distance. Pixels may be partitioned into the same region if they have similar gray intensity and adjacent space distance. Edges are crucial local information of regions and they generally occur at the common border of two or more regions. Edge detection aims to form a boundary to separate different regions and it implements through looking for the discontinuity of the image intensity. There are many edge detection algorithms such as Canny, Sobel, Prewitt, Laplace and so on [5], but edges detected by this method always are not closed.

Splitting and merging technology [6] is a region-based method, which starts with a unit in an image, and then the units split and/or merge together with some criteria until the desired result. This approach could obtain preferable segmented image but the process of splitting or merging is difficult to control. For region-oriented
image compression. Christopoulos et al. [2] proposed a segmented method based on splitting and merging technology. The method produces an over-segmented image firstly by splitting, and then merges some regions based on the difference of their gray mean intensity and a cost function. The cost function is founded on the gradient information, the size of the segments and the shared contour length of adjacent segments. The over-segmented image is to reduce the risk of losing important edges and the merging is to classify some small segments into its neighboring regions, but the merging is unruly, and the optimal segmented image can be obtained by trial and error. Furthermore, the segmented image contains many unconsidered tiny texture or noise and it is a contradiction because if the over-segmented image is excessive, the important edge is captured but more useless textures are contained. Contrarily, the important edge information is lost. The clustering method [7–9] is another region-based approach and it regards image segmentation as common data classification to process through feature extraction and decision [10, 11], and the decision step provides final segmented images, therefore, the definition of feature space is significant and difficult for different kinds of images.

Active contour model is an effective edge detection method, which is based on variational method and be widely applied to SAR, medical image segmentation and so on. At present, depending on the curve expression, active contour model can be classified as parametric active contour model and geometric active contour model. Those models achieve its segmentation through minimizing the objective energy function and evolving the initial curve toward the edges of objects. The C-V model [12] is a classical geometric active contour model based on level set and curve evolution and it takes full advantage of global gray intensity, but the result is not good because the edge positioning accuracy is not high. In recent years, various models have been proposed, for example, active contour with shape prior [13], fast global minimization of active contour model [14], GVF snake [15] and methods based on level set [16].

Furthermore, a variety of hybrid methods appear; for example, watersheds method [17] which considers the border of local minima as watershed and segments the regions into catchment basins. It is better at the weak border, so the over-segmentation may emerge where there is noise. Graph cut [18], which considers an image as graph with nodes and edges, received considerable attention as a method for image segmentation. It could separate the object from a scene but the background is not homogeneous because some textures still hide in. Further, contours are not smooth enough. In [19], minimum description length principle is introduced into image segmentation. Images are modeled as Gaussian random fields with piece-wise homogeneous mean and variance. Based on the changes in the mean and/or variance, the edges can be detected.

For the past few years, artificial neural network has already become a well-known technology used in computer vision, of course, it is widely used in image segmentation. Motivated by a histogram clustering approach to image segmentation, Buhmann et al. [20] proposed a network of leaky integrate-and-fire neurons to segment gray image. The firing rate of class neurons is employed to encode image segmentation because the connection between neighboring neurons can smooth adjacent similar neighbors. Mehtah et al. [21] applied spiking neural network model for image segmentation and edge detection, and addressed the issue of parameter selection by an unsupervised learning method.

In this paper, gradient-coupled spiking cortex model is proposed to segment gray images into homogeneous regions and smooth contours for SIC. The model is composed of neurons with spike coupling and gradient enhancement, and neurons imitate the ones in the visual cortex which can capture boundary information of the scene. Compared with others, the model smooths pixels within regions and enhances pixels at boundaries by creating a fitting function, so it could eliminate some noise or disturbances and emphasize functions of the similar neighbors on finding discontinuous of stimulus. Then, the stimulus is segmented by a series of dynamic thresholds and fitting curved-surfaces. The stimuli coupled with the spikes of neighbors turn into the internal state, those make a curved-surface and the dynamic threshold forms another curved-surface. At different times, transition of the multilayer curved-surfaces produces a series of binary matrices which contain the information of edge, region and texture. The time matrix of the neuronal spikes records object and boundary information of image. Outputs of the model are the desired segmented image after connection components label. Connected components labeling is implemented on those spike images to obtain regions and contours through fusing all the object information recorded in the spike images.

Considering a digital image as network, the network can achieve image segmentation through encoding the firing rate of similar neighboring neurons because of the local coupling among neighbors and decaying exponential. The method ensures that the results meet segmented image coding based on uniformity within a region and effectiveness of contour pixels.

In the model, an activated neuron may result in the synchronous excitation of its neighbors with approximate intensity. So, similar neighbors affect each other and could capture local information. It is called as spiking coupling. Another, the transition between stimulus is sharpened by gradient coupling and it is easy to find the discontinuous. In short, the model is convenient for showing the local discontinuous and smoothness of the network.

The organization of this paper is as follows: In Section 2, gradient coupling spiking cortex model and its properties for image processing is demonstrated. Section 3 is the segmentation method based on the proposed model. The experimental results will be shown in Sections 4 and 5 is conclusion.

2. Gradient-coupled spiking cortex model and its properties

Inspired by firing rate encoding of neuron network and the threshold segmentation method, a novel model is constructed to find the discontinuous of stimuli. In this section, we formulate the model and its properties when it is applied to image processing especially segmentation.

2.1. Gradient-coupled spiking cortex model

Based on the visual cortical model [22–24], gradient-coupled spiking cortex model is proposed as follows.

The fundamental component of the model also is leaky integrator. The basic form of the response is

\[ I(t) = Ve^{-t/\tau} \]

where \( V \) is the amplification factor, \( \tau \) is the decay time constant of the leaky integrator and \( I(t) \) is of exponential decay with time \( t \).

Each neuron is denoted with indices \((i, j)\), and its neighbors are denoted with indices \((k, l)\). Feeding and linking are combined together as internal activity. Neuron receives input signals from the stimuli and feedback synapse of its neighbors such that the output signal of a neuron modulates the activity of its neighbors. The internal activity \( U_i(n) \) of neuron in the model is modulated nonlinearly by feeding input and linking input as

\[ U_i(n) = U_i(n-1)e^{-t/\tau} + i_{in}(n) + i_{out}(n) + \sum_{\text{W}ij} W_{ij} Y_j(n-1) + S_i(n) \text{GRAD}_i(n) \]  

(1)
where $S_0[n]$ is the stimulus, $W_{ijk}[n]$ is the synaptic weight with which we could model excitatory or inhibitory connections through the value "1" or "0", $\tau_o$ is an internal activity time constant, and $\text{GRAD}_0[n]$ is the gradient field of the original image. The stimulus $S_0[n]$ is equal to the intensity $I_0$ of image pixel located at $(i,j)$, so $S_0[n] = S_0[n-1] = \ldots = S_0[0] = S_0$, $Y_0[n-1]$ are the previous spikes and one neuron couples with its neighbors only if it is activated, otherwise it gives no contribution.

If set $1 + \sum W_{ijk}Y_0[n-1] + \text{GRAD}_0[n] = X$ and the initial value of $U_0[0]$ as $S_0[n]$, then

$$U_0[n] = U_0[n-1]e^{-\tau_o/\tau} + S_0[n]X$$
$$= (U_0[n-2]e^{-\tau_o/\tau} + S_0[n-1])Xe^{-\tau_o/\tau} + S_0[n]X$$
$$= S_0[0](e^{-\tau_o/\tau} + Xe^{-\tau_o/\tau} + \ldots + Xe^{-\tau_o/\tau} + X)$$
$$= S_0 \left( e^{-\tau_o/\tau} + X \frac{1 - e^{-\tau_o/\tau}}{1 - e^{-\tau_o/\tau}} \right) \quad (2)$$

In (2), the internal activity is partitioned as two parts, the former is exponential decaying of initial value while the latter is the effects from neighbors. The dynamic threshold $E_0[n]$ is composed of a leaky integrator and spike modulation. It is described as

$$E_0[n] = E_0[n-1]e^{-\tau_o/\tau} + V_y Y_0[n-1] \quad (3)$$

where $V_y[n-1]$ is the spike signal and $V_y$ is the amplification of spike modulation. The dynamic threshold is decaying exponentially with time constant $\tau_o$ and it increases to a bigger value when a spike is produced. If we set the initial value of $E_0[n]$ as zero, in the interval between the first and the second firing of the neuron, the threshold could be rewritten as

$$E_0[n] = V_y e^{-\tau_o/\tau} \quad (4)$$

Along with time, when the internal activity $U_0[n]$ exceeds its dynamic threshold $E_0[n]$, a spike $Y_0[n]$ is produced by transfer-function as shown

$$Y_0[n] = \begin{cases} 1 & \text{if } U_0[n] > E_0[n] \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

here sigmoidal neurons are employed which apply a sigmoid transfer-function. The nonlinearity is essential and it has a real-value output as shown in

$$Y_0[n] = f(U_0[n], E_0[n]) = \frac{1}{2} \left( 1 - \frac{1}{e^{y(U_0[n]-E_0[n])}} + 1 \right) \quad (6)$$

where $y$ is the parameter of sigmoid function. Fig. 1 shows the model of the neuron and the process of the spike generation.

Based on (5), spike generated by neuron $(i,j)$ whenever $U_0[n]$ reaches the threshold $E_0[n]$ from below at $t$.

$$U_0[n] = E_0[n] \quad \text{and} \quad \frac{d}{dt} U_0[n] > 0 \Rightarrow t = t_e \left( -\ln \left( \frac{U_0[n-1]}{V_0} e^{\tau_o/\tau} + S_0[n] \right) \frac{V_0}{V_0} \right) \times (1 + \sum W_{ijk} Y_0[n-1] + \text{GRAD}_0[n]) \right)$$

At the initial state, we assume that internal activity $U_0[n]$ equal to $S_0[n]$, the time $t^{(m)}$ when spike occurs is

$$t^{(m)} = t_e \ln(V_y/S_0) + m \tau_e \ln(1 + V_y/S_0) \quad m = 0, 1, 2, \ldots \quad (7)$$

2.2 Properties

In the model, if $X = 1$ that means the network works without linking connections and (2) can be rewritten as

$$U_0[n] = S_0 \left( e^{-\tau_o/\tau} + \frac{1 - e^{-\tau_o/\tau}}{1 - e^{-\tau_o/\tau}} \right) \quad (8)$$

Fig. 1. (A) The model of the spiking neuron used in this paper and (B) the mechanism of spikes occurring. Threshold $E$ decays exponentially and increases linearly to a tremendous value when the spike occurs. Presynaptic spikes arrive at the soma at different time and influence internal activity $U$. When the value of internal activity crosses threshold at $E^{(m)}$, the neuron generates a spike and internal activity $U$ decays exponentially by the time constant $\tau_e$.

Fig. 2 can be obtained from (4), (5) and (8) and it is the ideal representation of the internal activity, the dynamic threshold and the output of a neuron with connectionless. Here, neurons with similar stimuli are activated simultaneouly, and the more powerful stimulus, the easier produce impulse. Because the activation of neurons depends only on its stimulus, the output spikes can show the relationship of inputs of neurons but the space relation cannot be found. That means the model can capture neurons with similar feeding input but spikes are unstable and easy to be affected by noise because no neighbors information is considered. If the neuron is applied to image segmentation, it is hard to assign a homogeneous region.

If $S_0[n]$ is uniform for all indices $(i,j)$ and be set as zero, internal activity $U_0[n]$ is only controlled by linking input with neighbors when parameters are determined. Once one neuron generates spike, the spike triggers neighboring neurons to generate other spikes by communications, but other neurons have no chance. It should be noted that the inter-neuron communication only occurs when the neuron generates spike. The linking part of neurons consists of synaptic connections $\sum W_{ijk} Y_0[n-1]$ and the gradient field $\text{GRAD}_0[n]$, the synaptic connections are to smooth regions and the gradient field is to sharpen boundaries in image segmentation.
An activated neuron may result in the synchronous excitation of its neighbors with approximate intensity. For a digital image, the stimulus $S_{ij}$ of neuron are pixel intensities $I_{ij}$, each pixel corresponds to a neuron in network. Thresholds make up a curved-surface and the internal activity forms another surface. Because of the smoothness within region and enhancement at boundaries, the discontinuous of image could be detected. The output spike images after different iterations contain features of stimulus such as edge, texture and regional information and it is the source of the segmented image.

3. The region segmentation method

Image is a projection of a visual scene composed of objects which arrange with its manner, perspective, distortion and so on. In capture system, pixel intensity is produced by the intensity of reflected illumination from object surfaces with different properties. In the process of image formation, spatial transition in actuality scene could be regarded as discontinues of pixel intensity in image, in other words, the transition of object is represented as impulse of pixel intensity. As said in [7], "segmentation can be an extremely easy task if one has access to the production process that has created the discontinuities". The aim of segmentation used in SIC is detecting the impulses of image and describing relationships between regions in image and objects in scene.

A gray image with size of $M \times N$ can be thought as a network with $M \times N$ neurons, each pixel corresponds to a neuron and the pixel intensity acts as the stimulus of neuron. The segmentation method takes the gradient-coupled spiking cortex model as an approach to image segmentation based on the firing rate encoding. The single output image contains incomplete information of edges and regions, such as discontinuous contours, unclosed regions, unwished small region caused by noise and so on, hence, a complementary work should be introduced. Connected components label is to optimize the continuous contours and similar pixels based on output images. Those will be detailed in following sections. Fig. 3 represents the segmentation process based on the model.

3.1. Segmentation algorithm

A digital image could be regarded as a three dimensional pattern and the pixel intensity acts as the third dimensional information. Set the pixels intensity as input stimulus of the model, the digital image can be partitioned into some non-overlapping regions as steps presented in Table 1.

Due to similar neighbors produce impulses synchronously, the model encodes image features by firing rate, and then estimates which region patches each pixel belong to. The nonlinear modulation between links and inputs could be considered as a fitting function, and its outputs of each node form a curved-surface. According to (2), the surface is smoothed within homogeneous regions by neighbors and enhanced at boundaries by gradient field. When an exponential decaying threshold is adopted, the curved-surface could be transected based on the sigmoid transfer function and the model outputs a series of binary images. Fig. 4

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Initialize the model</td>
</tr>
</tbody>
</table>
| Step 2 | Iteration  
For every neuron $(i, j)$  
Calculate its $U_{ij}[n]$ and $E_{ij}[n]$  
If $U_{ij}[n] > E_{ij}[n]$ then $Y_{ij}[n] = 1$  
Else change $E_{ij}[n]$  
End if |
| Step 3 | Choose the more suitable outputs $Y_{ij}[n]$ and complementary information each other, collect the most firing time information |
| Step 4 | Fusion based on fast connected components labeling |

![Fig. 3. The flow diagram of region segmentation.](image)

![Fig. 4. Segmentation example. (a) Curved surface of 'pepper' (b) Exponential decaying Threshold (c) Segmented image.](image)
(a) is a curved-surface of image "pepper" formed by the fitting function, (b) is exponential decaying threshold. The segmented image (c) can be obtained after CCL based on the output images.

3.2. Fast connected components labeling

In an output image, pixels numbered as "1" means those pixels belong to regions while pixels numbered as "0" refer to those pixels are at background. Usually the region is closed, but in a series of output spike images, the activated pixels (value is 1) may be disconnected despite those pixels are activated at the same time and have the similar intensity, in other words, they may not correspond to the same region in the original image. In addition, the intact regions or closed contours may not be detected according to one spike image, so it can be achieved with the help of information of other spike images. To search closed contours and similar pixels attributed to the same region, connected components labeling (CCL) is employed. CCL is to assign a number to each connected region to distinguish different regions. The number is the only one in the image and the maximum one is the number of regions in the output image in generally.

In generally, recursive algorithm and sequential algorithm are the most used methods for connected components labeling [25,26], but there are some weaknesses, for example recursive algorithm is inefficient and sequential algorithm is space expensive. This paper adopts a sequential connected components label method because the segmentation image from the segmentation model is binary.

![Fig. 5. Connected components label. (a) 4-Neighbor, (b) 8-Neighbor and (c) label at variance.](image)

![Fig. 6. Mapping between equivalence table and search table. (a) Equivalence table and (b) search table.](image)

Suppose the spike image is the output of the model after the N-th iteration, and the labeling number reaches to N0, all of pixels in a connected component can be labeled with the only and same number after the following two steps:

**Step 1:** the output spike image as Y is scanned from left to right, from top to down, if Y(i,j)=1, assign a value as V. The first value in this step is N0+1 and the other V is chosen as:

S1: if all the neighbors of Y(i,j) are zero, (i, j) is set as background and it is not a pixel of region.
S2: if there are only one non-zero element in the neighbors of (i, j), it is set using the only element.
S3: if all the labels of the neighbors are same, (i, j) is set as the same label.
S4: if all the labels of the neighbors are not same (shown as Fig. 5(c)), (i, j) is set as the any label. Here, the neighbors with different labels must be resolved by means of a new type of data structure named as equivalence table in next step.

Equivalent table refers to the relationship of all the labels. The pixels, whose labels are contained in a same equivalence table, are assigned into the same region. For example, Eqlabel[4]=[4,7,14,17,23] as shown in Fig. 6, it means all the pixels labeled as 4, 7, 14, 17 and 23 are from the same region.

**Step 2:** The conflicting label must be labeled again with the help of equivalence table.

S1: resort each equivalence table by size.
S2: create one-dimensional search table. The position is the present label and the value is the new label.
S3: replace the conflicting label by the following relations:

\[
\text{SearchLabel}[\text{Eqlabel}[1][3]] = \text{Min} (\text{Eqlabel}[1][3])
\]

\[
\text{ImLabel}[3][3] = \text{SearchLabel}[\text{ImLabel}[1][3]][3]
\]

After the two steps, every pixel in the connected region takes the exclusive and same label value. It reduces the computational complexity of connected components label algorithm by an adding search table.

4. Experimental results

The segmentation method proposed in this paper is to be applied to region-oriented image compression, hence its performance is shown by a special way like the number of regions and contour pixels. In this section, we present experimental results of segmented images compared with other methods and relationships between compression ratio of SIC and segmented method. In addition, four quantitative criteria are rendered to evaluate the performance of the segmented method used in region-oriented image compression.

![Fig. 7. The segmented images. (a) The original image, (b) the segmented image with the proposed algorithm based on the output pulse image and the region connection method (99 regions, 4032 contour pixels), (c) image segmented with the BSS algorithm (99 regions, 4031 contour pixels), (d) image segmented with the algorithm based on [2](300 regions, 2678 contour pixels), (e) image segmented with the watershed algorithm (99 regions, 2659 contour pixels), and (f) image segmented with minimum cut.](image)
4.1. Results of the segmented method

The results of the segmented algorithm are shown in Fig. 7. Fig. 7(a) is the original "cameraman" image and (b) shows the segmented image using the proposed algorithm. Fig. 7(c), (d) and (e) show the results by the recursive shortest spanning tree (RSST) technique [27], the algorithm proposed in [2] and watershed algorithm. Pictures just show the edge information of segmented image to express the performance of the relationship between regions and contour pixels.

The proposed segmented algorithm extracts contours based on the output spike images of the model after different iterations. The proposed algorithm merges the small regions into its neighbors and completes some discontinuous contours based on the firing time information. It could be observed that the shape of the regions is clear and the proposed algorithm catches regions with lesser contour pixels compared with the other three methods.

For SIC, the number of contour pixels influences seriously compression ratio of coding algorithm. In most applications, it is expected as the number of the contour pixels is lesser and the number of regions is controlled. The number of contour pixels and regions is drawn compared with other algorithms to show the variation tendency of number of contour pixels per region. In Fig. 8, it could be observed that with certain parameters of the model, the coding method based on the model can get a balanced value of the number of contour pixels per region. It not only obtains higher compression ratio, but also holds the clear contour outline and output the higher quality reconstructed image.

The relation between compression ratio and the number of regions about "cameraman" is depicted in Fig. 9. It can be observed that compression ratio changes slowly with the increasing number of regions.

The algorithm is applied on 'peppers' and the results are compared with Canny, Sobel, Laplacian of Gaussian, Roberts, Freeman and Zemo-cross method shown in Fig. 10 with the help of histogram. It is observed that the proposed method could control the number of region and get lesser contour pixels.

4.2. Results based on quantitative evaluation criteria

In order to compare the algorithm accurately, four quantitative image evaluation criteria are introduced.

![Graph showing the relation between compression ratio and the number of regions with image 'cameraman'.](image)

4.2.1. Effectivity measure (EM)

A new criterion, effectivity measure ratio between number of contour pixels and regions, is introduced to show the effectivity of the segmentation method used in region-oriented image coding. As shown in Section 4.1, to reduce the bits spending for contours and small regions, the segmented algorithm applied to image coding is interested in the performance on controlling the number of contour pixels and small regions. The effectivity measure is defined as

$$EM = \frac{\text{No. of contour pixels}}{\text{No. of regions}} \times \frac{\text{No. of pixels}}{\text{No. of contour pixels}}$$

(No. of contour pixels/no. of regions) shows the number of contour pixels per region and represents efficiency for presenting regions. (no. of contour pixels/no. of pixels) shows the proportion of the contour pixels number to all the pixels in the input image. A small value of EM means an effective representation of the image.

4.2.2. Uniformity measure (UM)

The aim of segmentation is partitioning the image into some non-overlapping regions with similar contribution which could reduce the bits spending for codes of region information based on linear combination of basis function, so the uniformity in every region is measured to describe the quality of segmented image. The uniformity measure is defined as

$$UM = 1 - \frac{1}{C_I} \sum_i \left( \sum_{(x,y) \in R_i} \left[ f(x,y) - \frac{1}{A_i} \sum_{(x,y) \in R_i} f(x,y) \right]^2 \right)$$

where \( f(x,y) \) is the initial image, \( R_i \) is the \( i \)-th region and \( A_i \) is its area, \( C_I \) is the constant. The more power of UM, the higher quality of segmented image.

4.2.3. Gray-level contrast (GC)

In the segmented image, it is homogeneous intra-region but large gray contrast inter-region. Suppose \( f_a \) and \( f_b \) represent the average gray intensity of a objective region and its neighboring regions, respectively. \( \nabla \) refers to the generalized gradient along the contour pixels of the objective region. The gray-level contrast is presented as

$$GC = \sum \frac{|f_a - f_b|}{f_a + f_b} \frac{\nabla}{\text{No. of contours}}$$

It looks forward to a smaller value of GC.
4.2.4. Shape measure (SM)

Another criterion for segmented method is based on the contour which expected as possible as smooth. The shape measure is a index to measure the smooth level of segmented image contours. It is defined as

\[
SM = \frac{1}{C_2} \sum_{(x,y)} |f(x,y) - \bar{f}(x,y)| \Delta (\text{Chain})
\]

where \(f(x,y)\) is the average gray intensity of the contour, \(\Delta (\text{Chain})\) is the difference between two next chain codes and \(C_2\) is the another constant. The greater value of \(SM\), contours are more smooth.

Table 2 shows results of some segmented methods based on the above quantitative evaluation criteria, here, four different type images are used as the test images. It is obvious that the proposed method well controls the number of contour pixels so it takes on a smaller \(EM\). Meanwhile, the proposed method can obtain preferable intra-region uniformity, inter-region gray level contrast and smooth contours. However, the other methods show its advantage on a certain respect, we cannot choose a best-fit segmentation method for region-oriented image compression only based on one evaluation criteria because different methods are exclusive and complementary. In order to meet Christopoulou's four factors for SIC, a composite index \(AVER\) is adopted and defined as \(AVER = (EM + UM + GC + SM)/4\). It is obvious that the proposed method is more suitable for segmented image compression based on the composite index \(AVER\).

In addition, time comparison of the different segmentation methods is presented. It shows OTSU and proposed method have
the optimal time consuming. But those data are only a reference for readers because segmentation methods are programmed by authors and time-consuming is just a simulation.

5. Conclusion

The segmentation method seriously determines the performance of region-oriented image compression. In order to obtain homogeneous regions and smooth contours, this paper proposed a new segmentation method based on a novel neural model. Inspired by firing rate encoding and threshold segmentation method, this model is based on the principle of similar neighboring neurons produce spikes synchronously because of smoothness by synapse linking within regions and sharpening with gradient field at boundaries. After the fast connected components label, homogeneous regions and smooth contours are obtained. Experiments show that the method can not only detect homogeneous regions, can also extract features and result in succinct effective contours, which is suitable for region-oriented image compression. Image coding based on the segmented algorithm can not only obtain a higher compression ratio, but also keep high reconstructed image with more details.

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