Automated Color Image Edge Detection Using Improved PCNN Model

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Abstract: -Recent researches indicate that pulse coupled neural network can be used for image processing, such as image segmentation and edge detection effectively. However, up to now it has mainly been used for the processing of gray images or binary images, and the parameters of the network are always adjusted and confirmed manually for different images, which impede PCNN's application in image processing. To solve these problems, based on the model of Pulse Coupled Neural Network and the model of HIS, this paper bring forward an improved PCNN model in the color image segmentation with the parameters determined by images' spatial and gray characteristics automatically at the first, then use the above model to obtain the edge information. The experiment results show the good effect of the new PCNN model.

Key-Words: - pulse coupled neural network (PCNN), image processing, HIS, color image segmentation, parameter determination, image edge detection, spatial characteristics, gray characteristics

1 Introduction

Pulse Coupled Neural Network, PCNN [1] was brought forward by Eckhorn firstly. It is a model derived from a neural mammal model. PCNN models have biological background and are based on the experimental observations of synchronous pulse bursts in the cat and the monkey visual cortex. Johnson and his colleagues had modified the model of the initial PCNN, which was applicable to calculate in the computer more easily. The improved model of PCNN have the well feature of transmitting burst, which is used widely in the fields of image processing, pattern recognition and so on.

The existed algorithm of PCNN is often applied to the fields of segmentation of gray image[2], edge detection of gray image[3] or binary image[4] respectively, Bao qingfeng put forward a new algorithm based on PCNN firstly[5], in her paper, Bao used PCNN in the colorized image. However, Bao's algorithm is based on Xiao Dong Gu's [6], which is a simplified algorithm of image segmentation based on PCNN. In Bao's algorithm, the parameter of network should be adjusted manually firstly, and then it could be used to segment the image. At the same time, the author didn't use the model of PCNN to process edge detection of the image. So if she wanted to get the result of segmentation, she should adjust the parameters time after time, and switch the model of PCNN when edge detection began. This algorithm restricted the application of the PCNN in the fields of color image. In order to improve the model of PCNN, we put forward a new PCNN system, which can adjust the parameters of the network voluntarily based on the reference [5], and we can use it to process the segmentation and edge detection of colorized image. The experimental results show that we can get the approving results.

2 PCNN

PCNN is a neural network which is composed of lots of neurons. Every neuron is made up of dendritic tree, linking modulation, and pulse generator. Dendritic tree is divided into two small portions, which are applied to guide two different of input to the linking part of the neuron. One of them is applied to accept the outside input signal which we called it feed-in input, and the other one is used for receive other neuron's linking input. We can describe them as follows:

$$F_{ij}[n]=\exp(-\alpha_F)F_{ij}[n-1]+V_F\sum M_{ijkl}Y_{kl}(n-1)+I_{ij} \quad (1)$$

$$L_{ij}[n]=\exp(-\alpha_L)L_{ij}[n-1]+V_L\sum W_{ijkl}Y_{kl}[n-1] \quad (2)$$

$$U_{ij}[n]=F_{ij}[n](1+\beta L_{ij}[n]) \quad (3)$$

$$Y_{ij}[n]=\begin{cases}1\ , & U_{ij}[n]>T_{ij}[n]\\ 0\ , & otherwise\end{cases} \quad (4)$$

$$T_{ij}[n]=\exp(-\alpha_T)T_{ij}[n-1]+V_T Y_{ij}[n] \quad (5)$$

As the top formulas, I_{ij} , F_{ij} , L_{ij} , U_{ij} , Y_{ij} , T_{ij} mean separately neurons' outside stimulating input, feed-in input, linking input, inside activity, firing output, dynamic threshold. M and W are linking weight matrix (usually, $M=W$) , V_F , V_L , V_T mean separately inherent electricity in F_{ij} , L_{ij} , and T_{ij} , α_F , α_L , α_T mean separately attenuation time constants in F_{ij} , L_{ij} , T_{ij} , n is a loop constant, and Y_{ij} is a binary output.

As shown in figure 1, the neuron receives input signals from other neurons and from external sources through the receptive field. In general, the signals from other neurons are pulses; the signals from external sources are analog timing-varying signals, constants, or pulses. After inputting the receptive field, input signals are divided into two channels. One channel is feed-in input (F_{ij}); the other is linking input (L_{ij}). In general, the feeding connection has a slower characteristic response time constant than that of the linking connection. In modulation field, see Fig.1 and Equ. (3), at first, the linking input is added a constant positive bias. Then it is multiplied by the feed-in input. The bias is taken to be unity, β is the linking strength. The total inside activity U_{ij} is the result of modulation. Because the feed-in input has a slower characteristic response time constant than that of the linking input, U_{ij} is like a spikelike signal riding on an approximate constant. The pulse generator consists of a threshold adjuster, a threshold discriminator and a pulse creator. The threshold T_{ij} changes with the variation of the neuron's output pulse. When the neuron emits a pulse, it feeds back to increase the threshold. When T_{ij} arises more than U_{ij} , the pulse creator closes and stop emitting pulses. Then threshold value drops. When threshold T_{ij} drops less than U_{ij} , the pulse creator opens again and emits pulses, namely fires. If the neuron only emits a pulse when it fires, the threshold discriminator and the pulse former can be replaced by a step function. This model is shown in Fig.1. Meanwhile, Equ.(4) shows the neuron's output under single output pulse condition and Y_{ij} is the output. Connecting the neurons on another, then a PCNN model appears.

Unlike other neural network, there is no training involved for PCNN, and it is an extremely powerful algorithm that can be applied in a variety of ways to image processing. PCNN has the characteristics of grouping of pixels in term of 2D space similarity or gray similarity, reduces local gray difference of image, and makes up local tiny discontinuous points of image. Thus, the algorithm can remove noise, do segmentation, edge detection and object isolation, etc.

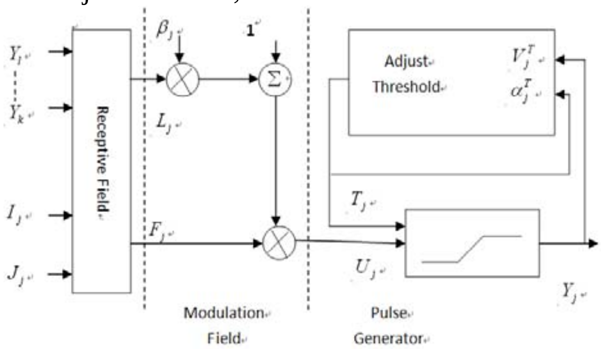


Fig.1 The model neuron of PCNN

When PCNN is used for the discrete image processing, it is a single layer 2D array of laterally linked neurons. Each neuron in the processing layer is directly tied to image pixel or set of neighboring image pixels, which means that the number of neurons is equal to that of pixels of input image, every neuron or pixel has its corresponding pixel or neuron, and every neuron is linked to its corresponding pixel and its neighboring neurons. Neuron iteratively processes signals from these nearby image pixels and linking from nearby neurons to produce a pulse train. Similarities in the input pixels cause the associated neurons to fire in synchrony indicating similar structure or texture. This synchrony of pulses is then used to segment similar structures or textures in the image.

3 . The description of the new model

Presently, there are two color models in common use now: RGB model and HIS model. When we use HIS model, it means hue, saturation, and intensity. HIS model has two advantages. Firstly, intensity has not relations with the color information of the image; secondly, hue and saturation have a close relation with the feeling of human. All of these features let HIS model fit for the image segmentation based on the human's vision system. In this paper, we use the HIS model. At the same time, we propose a new improved PCNN model which can ensure the parameters adaptively based on the traditional PCNN, and in this paper, we apply the same improved model to the color image segmentation and edge detection.

3.1 Confirming the parameters adaptively

Image segmentation and edge detection play important role in any image processing system. PCNN can be efficiently applied to image segmentation and edge detection. The performance of image segmentation and edge detection based on PCNN depends on the suitable PCNN parameters. However, the PCNN parameters which are suitable for segmenting a particular type of images may not be suitable for segmenting a different type of images. In this paper, we should describe how to get the suitable PCNN parameters to efficiently segment images and detect the edge of images.

Firstly, we should transform a color image into the space of HIS, secondly, we set up a corresponding model of PCNN for the hue, saturation, intensity separately, and thirdly we should set image point: (i, j) to be unitary, at last, we get the final image: $f(i, j)$.

When we segment the image, we should set the right parameters based on the image's features of gray and space, and when we process edge detection, we use the same new PCNN model, and we just need to ensure the right area(gray value=1) of the binary image which has the corresponding neuron, and the corresponding neuron can fire the impulse alone the shape of the target and transform freely, then we control the dynamic threshold, we can get the whole edge of the target. So when we do the edge detection, we can predigest the parameters. The material methods as follows:

(1) Linking weights W_{ijkl} :

This parameter means how much the output impulse of the surrounding neuron has effect upon the current neuron. As for the current neuron's corresponding image point, more small the distance between it and its corresponding image point is, more close the differences between these image points are, then we can conclude that more strong the degree of effect is.

$$W_{ijkl}=\left(\frac{1/\left(\left|d_g(i+k,j+l)\times d_s(i+k,j+l)+1\right|\right)}{\sum_{k,l}\left(1/\left(\left|d_g(i+k,j+l)\times d_s(i+k,j+l)+1\right|\right)\right)}\right)^e \quad (6)$$

Let $d_g(i+k, j+l)$ means the distance of the gray value between two corresponding image points, and $d_s(i+k, j+l)$ means the distance of space between two corresponding image points.

$d_g(i+k,j+l)$ is defined : $f(i,j)-f(i+k,j+l)$

$d_g(i+k,j+l)$ is defined : $\sqrt{k^2+l^2}$;

When we do the image segmentation: let $e=1$; When we do the edge detection: we want to make the output impulse of neuron transform freely and quickly, let $e=0$ 。

(2) Adjusting the step of threshold value r :

Let $n_{\max}$ means the times of iterative in the image processing, we want to ensure the threshold value can be through all of the image points. The adjusting step of threshold value is: $r=1/n_{\max}$ (7)

When we do the edge detection: let $r=0$.

(3) inherent electricity V_T :

The inherent electricity V_T in the PCNN is used to judge whether the neuron is firing at a moment, if it is firing, then we should set V_T and let the corresponding threshold increase quickly. When $V_T>U_{ij}$, the impulse creator can stop firing. In this paper, we have the same V_T no matter what kinds of images, and let: $V_T=100$ (8)

(4) initial dynamic threshold T_{ij} : $T_{ij}=\alpha$ (9)

When we do the image segmentation: Let $\alpha=1$;

When we do the edge detection: Let $\alpha=0.15$.

(5) modulating parameters β :

$$\beta=\left(\sqrt{V_{ij}}/M_{ij}\right)^e \quad (10)$$

when we do the image segmentation: let $e=1$, then we can control the degree of increasing of F_{ij}, V_{ij} means that image point (i, j) which corresponding image points' gray value variance in the surrounding area, and M_{ij} means that image point (i, j) which corresponding image points' gray value mean in the surrounding area, when $M_{ij}=0$, let $\beta=0.2$. More small β and the distributing scope of gray value of image points are, more average the distributing is in the surrounding area, then we can find a little improving of gray value can make (i, j) with the neuron firing in the surrounding area at the same time, whereas, the distributing is not average, then we need a big improving of gray value can make (i, j) with the neuron firing in the surrounding area at the same time. In a certain extent, we can confirm the integrality of the area of segmentation.

When we do the edge detection, we will predigest β, and let $e = 0$.

3.2 The threshold segmentation of the image based on the Shannon entropy maximum rule

In the reference [7], the author defines the segmentation methods based on the Shannon entropy maximum rule as follows:

$$H(S) = -S_1 \ln S_1 - S_0 \ln S_0 \tag{11}$$

S_1 and S_0 mean the probability of the "1" and "0" in the output binary image separately. The formula (11) means that how much the information of statistical mean value of the image points ("1" or "0") include in a binary image after segmentation. Usually, the more Shannon entropy is, it means the image after segmentation get more information from the initial image, and then the image after segmentation has ample details, and well segmentation effect as a whole. In this paper, we will calculate the S_1 and S_0 from the output binary image Y by an iterative processing. When S_1 and S_0 make the H maximum, which means we get a best segmentation binary image: Y.

3.3 The new model of color image segmentation

At the first, we should transform the initial color image into HIS space, and then we can get the hue image, saturation image, and intensity image.

We should calculate them by improved PCNN model respectively, the improved PCNN model as follows:

$$F_{ij}(n) = I_{ij} \tag{12}$$

$$L_{ij}(n) = \sum_{p \in K} W_p{}^e Y_p(n-1) \tag{13}$$

K is a 3*3 matrix, and it means a area which is surrounding the image point (i, j)

$$U_{ij}(n) = F_{ij}(n)(1 + \beta_{ij}{}^e L_{ij}(n)) \tag{14}$$

$$T_{ij}(n) = T_{ij}(n) - r + V_T Y(n) \tag{15}$$

$$Y_{ij}(n) = step(U_{ij}(n) - T_{ij}(n)) = \begin{cases} 1, & if\ U_{ij} > T_{ij} \\ 0, & else \end{cases} \tag{16}$$

Secondly, we use the PCNN model to calculate the hue image, saturation image, and intensity image separately as follows:

(1) We should transform the gray value of image point I_{ij} into be unitary, and the initial status of the neurons should be set as follows:

$L = U = \mathrm{Re}s = Y = 0$, $n_{\max} \in [10,50]$

K is a 3*3 matrix, and all of its value are 1, $\mathrm{Re}s$ is a matrix which saves the result, Y is a matrix which means the firing status, and n is the times of iteration, the rest are calculated by the top formulas automatically.

(2) $L_{ij} = \sum_{p \in K} W_p{}^e Y_p$; $U_{ij} = F_{ij}(1 + \beta_{ij}{}^e L_{ij})$;

$Y_{ij} = step(U_{ij} - T_{ij})$;

(3) $T = \alpha$;

(4) $L_{ij} = \sum_{p \in K} W_p{}^e Y_p$;

(5) $Tem = Y(i, j)$; $U_{ij} = F_{ij}(1 + \beta_{ij}{}^e L_{ij})$;

$Y_{ij} = step(U_{ij} - T_{ij})$; Tem is a temporary matrix ;

(6) If $Y(i, j) = Tem$ go to (7);

Else $L_{ij} = \sum_{p \in K} W_p{}^e Y_p$ go to (5);

(7)If $Y(i, j) = 1$ $\mathrm{Re}s(i, j) = 1$,

$Y(i, j)$ 、 $\mathrm{Re}s(i, j)$ are the corresponding elements of Y 、 $\mathrm{Re}s$;

(8) $T(i, j) = \alpha - r + V_T * Y$

(9)To calculate Shannon entropy of the corresponding image, if we find the maximum H when the times of iterative is n , and the corresponding $Y(n)$ is the last binary image.

(10) $n = n - 1$; If $n \neq 0$, go to (4); Else END ;

(11)To integrate the three binary images, then we can get the result, which is the segmentation image: Bin.

3.4 The new model of color image edge detection

Edges are very important to any vision system. An edge may be regarded as a boundary between two dissimilar regions in an image. These may be different surfaces of the object, or perhaps a boundary between light and shadow falling on a single surface. In this paper, as to the binary image: Bin, the edge detection algorithm can be obtained by the same PCNN model.

Firstly, we should let the corresponding image points of the bright area fire impulse, and the corresponding image points of the dark area do not fire impulse in this image, secondly, the bright area will transmit as the same width as an image point, then the edge between the dark area and bright area would be fired. If we control the transmitting distance, we can control the width of result of image edge detection expediently. For example, if the impulse of bright area transmits distance which is as the same width as 5 image points, and then we can get a result of image, which width is 5 image points. The model is as follows:

(1) To set a matrix: E, which can save the result of edge detection.

We should transform the Bin into be unitary which are 0.1(corresponding to the dark area of Bin), and 1(corresponding to the bright area of Bin), $F = Bin$, $L=U=Y=E=0$, $n_{\max} = N+1$, N is the width of the edge image, and the others are calculated by the top formulas automatically;

(2) $L = \sum_{p\in K} W_p{}^e Y_p$;

$U = F(1+\beta^e L)$; $Y = step(U-T)$;

(3) If $Y_{ij}=1$, $T_{ij} = T_{ij} + V_T Y_{ij}$, it means:
A neuron is inspired to fire, we should increase this neuron's threshold to stop it fire.

(4)if $n = N+1, n = n-1$,go back to (2) ; else $n = n-1$

(5)if $Y_{ij}=1, E_{ij}=1$。

(6)if $n=0$,we get the output: E , it is the edge image. Else go back to (2).

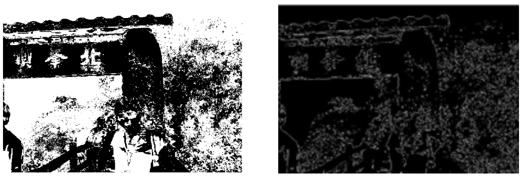
4 Experimental Results

We use the new model to process two different kinds of images: figure2 (a) and (b). We can find if we adopt the Bao's PCNN model, the results are figure 3(a) and (c) which create noises, some bright areas are short of segmentation, and the details are not good. When Bao detect image edge, the results are figure3 (b) and (d). They are not clear, and have lots of disconnected points, so we try to use the traditional method of Laplacian of Gaussian method to get the edges in figure4 (a) and (b). We find that edges are affected by noise present in an image clearly, and the processing results are lack of continuity, too. However, we apply the new PCNN model into the same images, and we get the segmentation results which are figure 5(a) and (c), we can find the details of the image keep integrality; and the shape of the image is intact. The results after edge detection are figure 5(b) and (d), we apply the same PCNN model into the image, our results have detected the whole targets' edge smoothly, and we can also change the width of the last results of images according to the necessary to make these images more clearly.

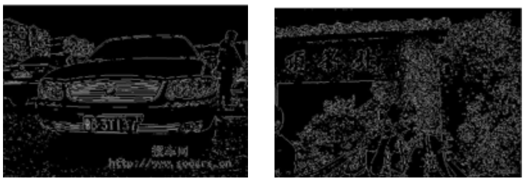
(a) The initial car's image (b)The initial person's image

Fig.2 Original image

(a) After segmentation (b) after edge detection

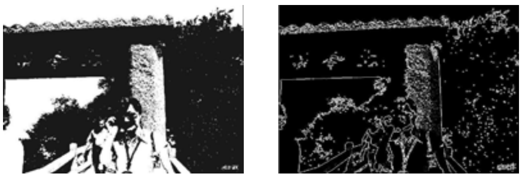


(c) After segmentation (d) after edge detection
Fig.3 Process results of model in references [5]



(a) After edge detection (b) after edge detection
Fig.4 Process results of Laplacian of Gaussian Method

(a) After segmentation (b) after edge detection



(c) After segmentation (d) after edge detection
Fig.5 Process results of new model

5 Conclusions

In this paper, we create an improved PCNN model, which can choose the right network parameters adaptively, and we apply it into different kinds of color images in the image segmentation and edge detection. At the different processing stage, the new PCNN model can adjust the network parameters automatically. After the experiment, we can get a robust and intact result no matter how complexity our processing image is in images and it would be interesting to see that no matter how small or large an object is in images, the achieved result is satisfactory according to this new PCNN model. However, this new PCNN model also has a lot of disadvantages and limitations. Firstly, the new PCNN model should waste more time to process images, which will restrict the application of this model to the environment of real time processing. Secondly, the parameter n_{max} is the times of iteration, which is a pivotal factor in the image segmentation, but we choose it based on the experience and ensure it based on entropy maximum rule, so how to get it more reasonably is a problem, too. As an open issue, how to improve the PCNN model, predigest the model, and increase its efficiency, we need to research more.

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