International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.5 (2014), pp.249-258
http://dx.doi.org/10.14257/ijsip.2014.7.5.22

Automatic Image Segmentation with PCNN Algorithm Based on Grayscale Correlation

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Abstract

In order to use pulse coupled neural networks (PCNN) for precise automatic image segmentation, we propose an improved PCNN model. We first establish a connection weight matrix based on the image local gray correlation and on the Euclid distance. We then used the minimum variance ratio criterion to automatically determine PCNN cycle times, and achieve automatic image segmentation. The simulation results show that this method can automatically determine the number of iterations PCNN, and that it is highly feasible and better segmentation effect.

Keywords: *Image segmentation, Pulse coupled neural net-work, Grayscale correlation, the minimum of variance ratio*

1. Introduction

Pulse coupled neural networks (PCNN) were proposed based on the sync pulse distribution phenomenon in the brain's visual cortex in various mammals, such as cats and monkeys [1]. PCNN has many advantages over traditional image processing. Since put forward, PCNN have been used extensively for image segmentation, image denoising, image enhancement, and image fusion [2-3]. Compared with the traditional neural network model, when we utilized PCNN model in digital image segmentation, the advantage of using a PCNN model in digital image segmentation is that it no sample preparation is needed. However, the threshold parameters, connection coefficient, decay time constant weighting factor, and other parameters, must be set in advance. This results in the segmentation quality being greatly influenced by the loop iterations. Currently, no methods have been designed to automatically set all the necessary PCNN model parameters to achieve accurate segmentation based on the digital image characteristics. The segmentation result also depends on the ignition cycles of the model. A variety of methods to improve model parameters and determined iteration times have been proposed in order to improve segmentation results. Ma Yide, *et al.*, proposed a PCNN model based on cross entropy, as well as a PCNN automatic segmentation algorithm based on genetic algorithms [4-5], Gu Xiaodon, *et al.*, put forward a PCNN algorithm based on the unit-linking portion of the genetic algorithm [6], and Stewart R D, Zhang Qing, *et al.*, applied the region growing to automatic segmentation of PCNN [7-8]. With these methods, and others, it is still difficult to achieve ideal segmentation results, as well as the least time was used in segmentation based on the existing algorithms. In this paper, we put forward an improved PCNN algorithm based on gray correlation and the minimum variance ratio that addresses problems associated with previous algorithms.

The between-cluster variance method (Ostu) is the most commonly used image segmentation technique. For simple single, or twin, peak images, Ostu produces good segmentation results. However, with complex multimodal images, the segmentation effect of

ISSN: 2005-4254 IJSIP

this algorithm is not ideal. One advantage of using the Ostu algorithm is that it is less time-consuming than many other algorithms [9]. The Ostu method only takes the background and the goal of the difference between the two classes of objects into account. Based on the Ostu algorithm, we put forward the minimum variance criterion that considers the differences between similar and non-similar objects in order to control the iteration times of the PCNN model.

Most of the existing image segmentation algorithms based on the PCNN model do not consider the local gray level image correlations, even though local gray scale changes are critical for image segmentation and edge detection. We propose a method to establish the local gray correlation function, according to the image gray scale characters, and a structured power connection matrix w of the PCNN model based on the gray correlation. Finally, in order to achieve digital image automatic segmentation by using PCNN model, we utilized the minimum variance method to control iteration times. Experimental results suggest that the segmentation results from this method are superior to those obtained from using traditional segmentation methods, and had more extensive applicability.

2. PCNN Model and the Theory of Image Segmentation

2.1 PCNN Model

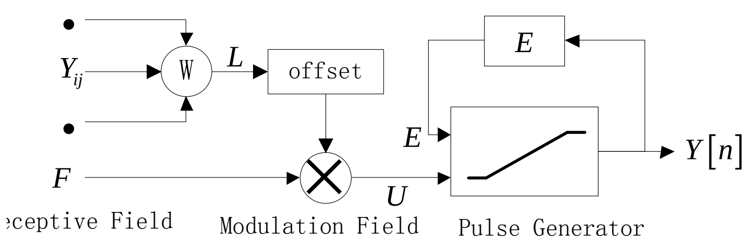

Figure 1. PCNNs Neuron Model

The pulse coupled neural network is a two-dimensional neural network composed of pulse-coupled neurons. The PCNN neuron model consists of three parts: the receptive fields, the modulation fields, and the pulse generator (Figure 1) [10].

Due to traditional PCNN model complexity, we adopted the standard improved PCNN model [10]. The discrete mathematics equation of the simplified PCNN model is described as:

$$F_{ij}(n) = I_{ij} \tag{1}$$

$$L_{ij}(n) = \sum w_{ijkl} Y_{ij}(n-1) \tag{2}$$

$$U_{ij}(n) = F_{ij}(n)\left(1+\beta L_{ij}(n)\right) \tag{3}$$

$$\theta_{ij}[n] = \exp(-\alpha_{\theta})\theta_{ij}[n-1] \tag{4}$$

$$Y_{ij}[n] = \begin{cases} 0, & U_{ij}[n] > \theta_{ij}[n] \\ 1, & \text{otherwise} \end{cases} \tag{5}$$

Where i, j describe the position of the neuron, n is the current iteration, I_{ij} is the input stimulation signal (when we do image processing, I_{ij} usually takes the gray pixel value that is located in line i and column j of the image), F_{ij}, L_{ij}, U_{ij}, θ_{ij} are the feeding inputs of the neurons, linking inputs of neurons, internal activity of neurons, and the dynamic threshold of the neurons, respectively. w is the power connection matrix, α_θ is the time constant decay factor of dynamic threshold value, β is the strength of the linking, and Y_{ij} is the binary output of the PCNN model.

2.2 The Theory of Image Segmentation Utilized PCNN Model

During image processing, the digital image, with a size of M*N and a grayscale value of L, can be regarded as a two-dimensional matrix with a range of values from 0 to L and the size is M*N. During image segmentation, the matrix elements and PCNN model neurons can be put into one-to-one correspondence, where the pixel value I_{ij} corresponds to the neurons' input S_{ij} on the corresponding position. The initial state of the neurons was set to 0. Following the first iteration, internal activity U_{ij} is equal to the neurons' input S_{ij}, all the neurons threshold began to attenuate from the initial value, when a neuron's threshold attenuated till smaller or equal to the correspond U, this neuron was fired(natural fired), and output a pulse $Y=1$, at the same time, the threshold θ of this neuron sharply increased, the pulse output stopped. Then θ began to attenuate, when θ attenuated till smaller or equal to correspond U again, pulse-generated again. When several cycles are ran, the neurons produce an output sequence $Y[n]$, which contains information describing the area, boundary, texture and other characteristics of the digital image [11-12].

3. The Establishment of Gray Correlation Weight Matrix

A majority of the existing image segmentation algorithms based on the PCNN model were established with the weight matrix w referring to the $Euclid$ distance between pixels. These algorithms did not take into account the influence of the gray correlation between pixels. In digital imaging, information about the mutation of the target area grey value and the background grey value is often the key to segmentation. The gray value of the target areas generally has many similarities allowing for accurate digital image segmentation. Here, we established a gray correlation function the following four conditions: (1) Big gray similarity between the target points, (2) small gray similarity between the target and the background, and (3) small gray similarity between the background points [13]. (4) The maximum gray correlation between two pixels is 1.

If the gray value of image pixels is set as $I_{ij}, 1 \le i, j \le M, N; M, N$ are the length and width of the digital image, and the degree of similarity between each pixel gray value is described as follows:

$$r_{ijkl} = e^{-c\left|I_{ij}-I_{kl}\right|}, \quad 1 \le i, j, k, l \le M, \mathrm{N} \tag{6}$$

where c was a constant, r_{ijkl} was the similarity degree of gray level between pixel (i, j) and pixel (k, l). This function satisfied the above-mentioned requirement of the gray correlation function. Based on the local correlation coefficient r_{ijkl} between pixel (i, j) and pixel (k,l), and the euclidean distance d_{ijkl}, where $d_{ijkl}=\sqrt{(i-l)^2+(j-k)^2}$, the correlation connection matrix based on grayscale is $w_{ijkl}=r_{ijkl}/d_{ijkl}$.

4. The Least Variable Ratio Principle

4.1 The Establishment of the Least Variable Ratio Principle

For the image with a grayscale of $S=(1,2,3,\cdots,i,\cdots j,\cdots;\mathrm{L})$, the image grayscale T is set as the segmentation threshold, and the image is segmented into two classes, C_1 and C_2, with grayscales defined as $S_1=(1,2,3,\cdots,\mathrm{T})$ and $S_2=(\mathrm{T}+1,\mathrm{T}+2,\mathrm{T}+3,\cdots,\mathrm{L})$, respectively ($C_1$ and C_2 were object region and background region respectively).

Interclass variance:

$$\delta_o^2=p_1\delta_1^2+p_2\delta_2^2= \\ p_1\sum_{i\in S_1}(i-\mu_1)^2 n_i+p_2\sum_{i\in S_2}(i-\mu_2)^2 n_i \tag{7}$$

Between-class variance:

$$\delta_{ob}^2=p_1(\mu_1-\mu)^2+p_2(\mu_2-\mu)^2 \tag{8}$$

N is the total number of the pixels in the digital image, δ_1^2 and δ_2^2 are the variance in the object region C_1 and background region C_2 respectively; p_1 and p_2 are the probabilities of occurrence, μ_1 and μ_2 are the pixel grayscale averages in C_1 and C_2, respectively, and $\mu=p_1\mu_1+p_2\mu_2$.

The minimum variance ratio was:

$$\phi=MIN\left(\delta_o^2/\delta_{ob}^2\right) \tag{9}$$

4.2. The Judgement of PCNN Iteration Times

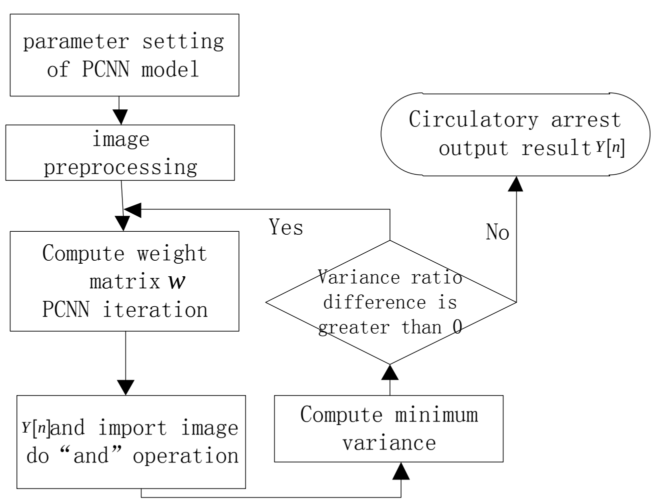

Figure 2. The Algorithm Flow Diagram of this Paper

We first enhanced the original image using the methods from [14], formulas (1) - (5) were utilized to cycle the image ignition. Each loop iteration step length was one, and we obtained the output pulse $Y[n]$. The image I was ended with the output pulse Y, which allowed us to obtain the image after one PCNN ignition. We then calculated the variance ratio of the image following ignition using formulas (7-9). The variance ratio difference of this iteration, and the variance ratio in last iteration, were calculated. If the difference was greater than zero, we continued to iterate the ignition. Otherwise, circulatory arrest, the binary image we obtained now was the best segmentation image.

5. Experimental Results and the Analysis of the Problems

We conducted multiple experiments to test the reliability and applicability of the proposed algorithm. Due to there was not enough space in this article, we chose the four most representative images to use in comparison of segmentation results. The algorithms compared were the classical Otsu method, the minimum cross entropy PCNN method, and the maximum information entropy PCNN method [15-17], the simulation tool used was Matlab7.8.0.

5.1 Experimental Results and Analysis

According to the simplified PCNN model, the parameters that needed to be set in the experiments were α_θ and β, both of which were set to 0.1. The connection weight matrix was w = [0.707 1 0.707; 1 0 1; 0.707, 1, 0.707] in both the minimum cross entropy PCNN method and the maximum information entropy PCNN method. In general, the digital information can be represented using shannon entropy, the greater shannon entropy of the image segmentation results, the more information were obtained from the original image, the details information contained in the result image was more abundant, thus the overall segmentation effect was even better. We utilized the shannon entropy of the final image to assess the quality of segmentation results, the definition and calculation method of shannon entropy was in reference [16]. The experimental results and the contrast effects are shown in Figures 3-6 and in Table 1.

The overall segmentation result is good in this paper (Table 1). The shannon entropy value obtained from the proposed PCNN algorithm, and the shannon entropy value obtained from the PCNN method based on maximum information, were similar. The segmentation results obtained from the Ostu algorithm and the minimum cross entropy PCNN model were unstable. The shannon entropy value obtained from different image segmentation results was rather changeable. For example, the maximum shannon entropy was 0.4866, based on the minimum cross entropy PCNN algorithm when segmented the pollen image, which was much lower than the shannon entropy from other several segmentation algorithms. Though the shannon entropy obtained from the PCNN model based on maximum entropy segmentation results were much bigger, but it could not do effective segmentation to some images, such as the image shown in Figure 5 (e).

Table 1. The Shannon Entropy Values of the Experimental Images

the maximum Shannon entropy	lena	cameraman	rice	pollen
the method in this paper	1.0000	0.9421	0.8784	0.9537
Ostu method	0.9807	0.8373	0.8213	0.9991
the minimum cross entropy PCNN	0.9981	0.9670	0.8149	0.4866
the maximum information entropy PCNN	0.9723	0.9662	0.8994	0.9760

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

Figure 3. Lena

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

Figure 4. Cameraman

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

Figure 5. Rice

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

Figure 6. Pollen

Figure 3(a), 4(a), 5(a) and 6(a) are the original images. Figure 3(b), 4(b), 5(b) and 6(b) are the segmentation results of algorithm in our paper. (c) Figure 3(c), 4(c), 5(c) and 6 (c) are the segmentation results from Ostu method. Figure 3(d), 4(d), 5(d) and 6(d) are the segmentation results of the minimum cross entropy PCNN. Figure 3(e), 4(e), 5(e) and 6(e) are the segmentation results of the maximum information entropy PCNN algorithm.

When the parameters are equal, the visual effect of the proposed algorithm higher than the segmentation effect based on the minimum cross entropy PCNN and the maximum information entropy PCNN (Figure 3-6). Although it is generally accepted that the Ostu algorithm was the optimal image segmentation algorithm, the visual effect of the segmentation results and the shannon entropy of the proposed algorithm were generally higher than that of the Ostu algorithm segmentation results. The segmentation results of the hat, hair and face facial details were particularly clear, while there was adhesion of the hat and the background in the Lena images of the other three algorithms (Figure 3). In Figure 4, the segmentation effects of the four algorithms were ideal. However, the proposed algorithm was could the most efficient at segmenting the edge details of the building. In the rice image, the segmentation effect of our algorithm was the most efficient. Our method completely segments the rice in the image, and the other three methods did not split the target image, especially the segmentation result by the maximum information entropy PCNN (Figure 5). In the pollen image, the PCNN segmentation method based on minimum cross entropy did not correctly recognize the target image. The overall segmentation effect obtained from the PCNN segmentation algorithm based on maximum information entropy was good, but it failed to fully reflect the details of the image (Figure 6). The other two algorithms gave ideal results.

5.2 The Analysis of the Exist Problems

The visual aspects and Shannon entropy values were the best in the proposed segmentation algorithm, but it still has two disadvantages. First, because it is necessary to calculate the connection weight matrix w, the time complexity degree of the algorithm was $O\left(N\log(\mathrm{N})\right)$. The time complexity degree of the algorithm based on the minimum cross entropy PCNN and the maximum information entropy PCNN were both $O\left(N\right)$. The time complexity degree of the traditional Ostu algorithm was $O\left(N^2\right)$. The proposed algorithm was slightly more time-consuming than the other algorithms. Second, due to the inherent defects of PCNN model, the image segmentation effects based on the PCNN algorithm is completely dependent on the digital image gray level information, and does not make full use of digital image space and texture information. This results in some images incorrectly identifying the target segmentation and the background information. These problems will be addressed in future studies.

6. Conclusion

In this paper, we proposed the establishment method of the local gray correlation function based on the digital image grayscale characteristics and a structured power connection matrix of PCNN model, according to the gray correlation. We then proposed a new improved PCNN algorithm based on the gray correlation algorithm by combining the improved PCNN algorithm and the Ostu method. When utilized, this new algorithm enhanced the original image by the improved PCNN model, and then PCNN loop iteration further enhanced the image. When iterating the right connections matrix was constructed according to gray correlation. In order to obtain satisfactory separation results, we introduced the theory of minimum variance ratio to determine the number of iterations. Finally, we utilized maximum shannon entropy criterion for validation. Many experiments were conducted to show that the improved PCNN model effectively segments images and can automatically determine the number of iterations. The improved PCNN algorithm must to calculate weight matrix, the running time is much longer than other methods. This will be addressed in future research.

Acknowledgements

This research was supported by the Fundamental Research Founds for National University, China University of Geosciences (Wuhan) and High-resolution integrated transport of

Remote Sensing Applications demonstration system advance research (07-Y30A05-9001-12/13).

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