Blood Cell Segmentation Based on Improved Pulse Coupled Neural Network and Fuzzy Entropy

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Abstract: *In the field of biomedical image processing, because of the low intensity and brightness of the cell image, and the complex structure of the cell image, the segmentation of cell images is very difficult. A large number of studies have shown that the Pulse Coupled Neural Networks (PCNN) is suitable for image segmentation. However, the traditional PCNN must set a large number of parameters in image segmentation, and the optimal number of iterations cannot be automatically determined. In this paper, a new improved PCNN model is proposed. The work of improved PCNN includes the acceptance portion of the PCNN model being simplified and the connection portion of PCNN being improved. In addition, the maximum fuzzy entropy is used as the criterion to determine the optimal number of iterations. Experimental results on blood cell image segmentation show that this proposed method can automatically determine the number of loop iterations and automatically select the best threshold. It also has the characteristics of fast convergence, high accuracy and good segmentation effect in blood cell image segmentation processing.*

Keywords: *Blood cell segmentation, Pulse Coupled Neural Network (PCNN), Fuzzy entropy.*

Introduction

In the biomedical field, especially in cell embryology, pathology research and wound healing, immunity, tumor cell metabolism and invasion mechanisms, cell structure and function relationship is a very important field of study. The quantitative analysis of the cell images is one premise of this research. Because of the low intensity of the cell image, the uneven brightness and the complex structure of the cell image, the segmentation and counting of the cells become very difficult. Edger proposed the improved image segmentation algorithm based on multiple resolution [6]. In fingerprint image segmentation algorithm based on contourlet transform technology is presented [15]. Berker et al. proposed a segmentation algorithm in plant cell morphology and cell image based on gradient information [1]. In addition to these segmentation methods, of pure mathematical principles, there are some cell segmentation methods, which combine the biochemical properties of the cell itself. James uses the characteristics of two kinds of light absorption spectra of plant cells, and proposed a method of plant cell segmentation based on morphological and spectral analysis [5].

In recent years, researchers have made extensive and deep research on the pulse coupled neural network, which shows a powerful processing ability in the field of image. In this paper, a new improved Pulse Coupled Neural Networks (PCNN) model is proposed. The work of improved PCNN includes that the acceptance portion of the PCNN model is simplified and the connection portion of PCNN is improved. In addition, the maximum fuzzy entropy is used as the criterion to determine the optimal number of iterations. Experiments on blood cell image segmentation is conducted, and the results show that this method can automatically determine the number of loop iterations and automatically select the best threshold. It also has the characteristics of fast convergence, high accuracy and good segmentation effect.

Materials and methods

The basic theory of PCNN model and the principle of image segmentation

In 1952, Hodgkin and Huxley began to study the electrochemical characteristics of neurons. In 1980, Gray and Eckhorn studied the visual cortex of a cat, and proposed a network model with pulse synchronization. In 1990, according to the cat's cerebral cortex synchronous pulse release phenomenon, Eckhorn put forward the demonstration of the phenomenon of pulse distribution link mode. Their experiments on the cerebral cortex of monkeys also were carried out with similar results. In 1994, Cootes published a paper describing the cycle fluctuation phenomenon of Pulse Coupled Neural Networks and the characters in image processing, such as rotation, scale, distortion, and strength invariance [3]. By the research of Johnson, Padgett and Rangannath, proposed the improved model of Eckhorn, and the PCNN model was established [4].

PCNN is based on the Eckhorn model, which is built on the activity of neurons in the visual cortex [9]. Further work has been done by Johnson and other researchers, which evolves into a single layer iterative neural network model. Therefore, it is more suitable for the natural biological visual characteristics. It makes full use of the special properties of the mammalian visual neural network (such as, linear addition, excitation and inhibition properties), and also takes into account the characteristics of the neuron specific nonlinear multiplicative modulation. It has no need for neural network training and parallel processing, and it also has the other advantages such as the parameters are not being determined in network operation and global optimum [10].

The traditional PCNN neuron model

By the study of pulse synchronous oscillation of a cat’s visual cortical neurons, Eckhorn proposed the pulse coupled neural model. This is the traditional PCNN model, which is shown in Fig. 1. The Eckhorn neural network is a feedback network that is composed of a number of neural networks [7]. The Eckhorn neural network is an integrated dynamic nonlinear system, which is composed of three parts: modulation field, receptive field and pulse generators. The Eckhorn neural network can reduce the input data interval and the small amplitude of the small difference between the synchronization and forced stimulation evoke stimulation. Thus, a similar input of neurons can be excited at the same time (also called ignition). Therefore, if a digital image is entered into the two-dimensional Eckhorn neural network, the image pixel classification is done by the network, which is based on the similarity between the similarity and the brightness.

The structure of traditional PCNN neuron is shown in Fig. 1, where j is the number of neurons. The receptive field of the neuron receives the output from other neurons $\{Y_1, ..., Y_k\}$ and the external excitation signal S_j. Respectively, the feed input signal F_j and the connected input signal L_j are formed by the leakage capacitance integral and weighted sum. In the modulation portion, the internal behavior U_j is obtained by the product of the signal F_j and signal L_j, and beta for the connection strength. The pulse generating portion is combined with the variable threshold comparator and a pulse generator, and the internal behavior U_j is compared with the dynamic threshold θ_j. If $\theta_j < U_j$, the pulse generator is turned on, and the neuron is fired to get the output of a pulse. When the output of Y_j is 1, the threshold value of θ_j is improved with feedback. When $\theta_j > U_j$, the pulse generator is turned off and pulse sending is stopped. Where the output of Y_j is 0, the closed value θ_j begins to rapidly decline, and the pulse generator is turned on again. When it falls down to less than U_j, it can be seen that the behavior of a single neuron is that the pulse sequence transmits the external stimulus at a certain frequency distribution of the pulse sequence under the action of external stimulation. This process is called the natural ignition of neurons.

$$F_j(n) = e^{-\alpha F \Delta t} F_j(n-1) + V_F \sum_k M_{kj} Y_k(n-1) + S_j \ , \tag{1}$$

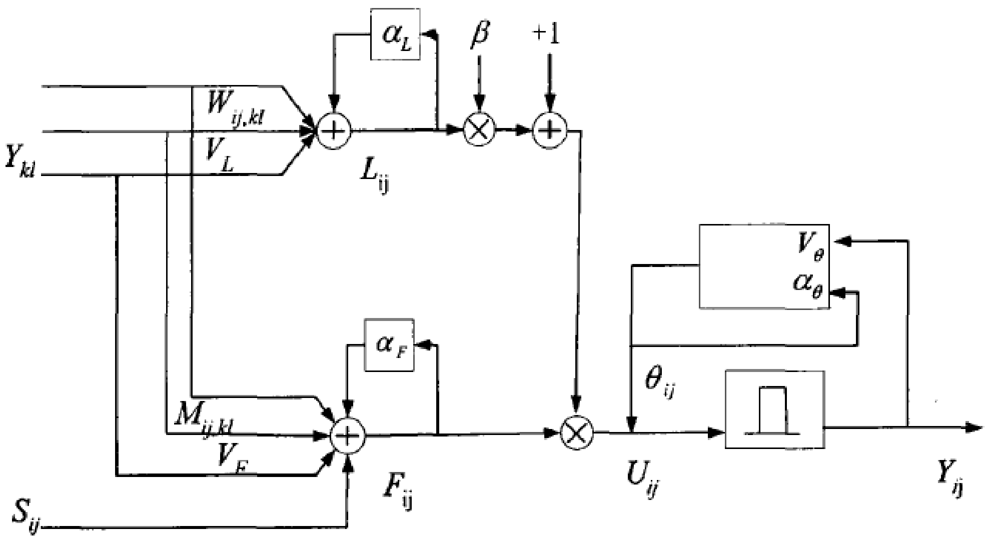
$$L_j(n) = e^{-\alpha F \Delta t} F_j(n-1) + V_F \sum_k W_{kj} Y_k(n-1) , \tag{2}$$

$$U_j(n) = F_j(n)(1+\beta L_j(n)) , \tag{3}$$

$$\theta_j(n) = e^{-\alpha F \Delta t} \theta_j(n-1) + V_\theta Y_j(n-1) , \tag{4}$$

$$Y_{ij}(n) \begin{cases} 1 & U_{ij}(n) > \theta_{ij}(n) \\ 0 & U_{ij}(n) \le \theta_{ij}(n) \end{cases} , \tag{5}$$

where L_j, F_j, U_j and Y_j are the connected inputs feeding inputs, and the internal active items and the output of the neuron j. W_{kj} and M_{kj} are the connected weight coefficients and feeding weight coefficients between the neurons.



Modulation field Receptive field Pulse generators

Fig. 1 The structure of traditional PCNN neuron

The simplified PCNN neuron model

In the previous section, the brief introduction of the traditional PCNN model reveals that the model has a more complex structure, feedback link, and too many parameters. So it is not easy to set parameters, and also brings great inconvenience to the application [8]. In order to make the PCNN model more suitable for image processing, further simplification and improvement to the traditional PCNN model is needed. In this section the simplified model of PCNN is introduced, and is shown in Fig. 2.

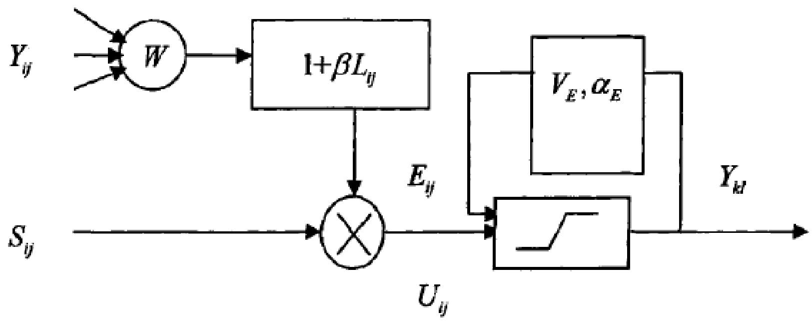


Fig. 2 Structure of the simplified PCNN neuron

The model can be expressed as a set of mathematical relations by the equations:

$$F_j(n) = S_{ij}, \tag{6}$$

$$L_{ij}(n) = \sum_{kl} W_{ijkl} Y_{kl}(n-1), \tag{7}$$

$$U_{ij}(n) = F_{ij}(n)(1+\beta L_{ij}(n)), \tag{8}$$

$$Y_{ij}(n) \begin{cases} 1 & U_{ij}(n) > E_{ij}(n-1) \\ 0 & \text{otherwise} \end{cases}, \tag{9}$$

$$E_{ij}(n) = e^{-\alpha_E} E_{ij}(n-1) + V_E Y_{ij}(n), \tag{10}$$

where PCNN model is used for image segmentation, the parameters of the segmentation results have a great impact. Up to now, the choice of models in the various parameters of the study by research scholars worldwide is still relatively limited.

However, in the simplified model above, only four parameters need to be artificially adjusted, which are W, β, α_E and V_E. The premise of the core features of the PCNN model is to facilitate the use of the model.

The principle of digital image processing by PCNN

When the PCNN is used for image processing, it is a single layer of two-dimensional local connection of the network, and the number of neurons is equal to the number of pixels in the input image. Each neuron is connected to the corresponding pixel, and is connected to the adjacent neurons. Each pixel's brightness input is relative to an input corresponding to the neurons. Furthermore, the output of each neuron and other adjacent neurons is connected by linear L and dynamic link item U_t. Each neuron's output has only two states; that is excitation (also known as ignition) or suppression (also known as no ignition). In most cases, the area of the image processing is 3×3.

The ignition frequency of PCNN f_{ij} is obtained according to the basic model of Eq. (3).

$$f_{ij}=\frac{\alpha_E}{\ln(1+\frac{V_E}{U_{ij}})}, \tag{11}$$

where V_E and α_E are the amplitude coefficient and time constant of the closed value, and U_{ij} is the internal active term which is composed of the nonlinear connection modulation.

It can be seen that the brightness of the corresponding pixel value is greater when the the firing frequency of the neuron is higher. At the same time, through the nonlinear multiplication modulation characteristics of the dynamic link U, the original non-fire neurons which meet certain conditions in the proximate area also transmit pulses, thus creating the pulse propagation in the network. This is the pulse propagation characteristics of PCNN, which can be effectively used for image processing such as image denoising, image segmentation, shadow removal, image edge extraction, etc. For different image processing problems in PCNN, the specific algorithm is different, but these algorithms are used in the pulse propagation characteristics of PCNN.

The theory of maximum fuzzy entropy

Entropy is a basic and important concept in information theory, which describes the degree of uncertainty of a probable distribution. The concept of entropy is transplanted to the fuzzy set theory, and the concept of fuzzy entropy is obtained which describes the degree of uncertainty of a fuzzy set. Cheng et al. introduce the fuzzy theory into the threshold segmentation [11], and proposed a multi-threshold segmentation method based on the principle of fuzzy maximum entropy. The maximum fuzzy entropy criterion is used to search for a set of parameters in the gray space, so that the image of the image in this parameter is determined by the fuzzy partition to retain the original image with the maximum amount of information [14].

For a L gray level image X, the gray scale range is $\{r_0, r_1, ..., r_{L-1}\}$. The probability of each gray level P is set as follows. $P(r_k)=h_k,\ k=0,1,\ ...,\ L-1$. $U=\{A_1, A_2, ..., A_n\}$ is set as a finite fuzzy classification set, and Zadth proposed as a fuzzy entropy $H(U)$.

$$H(U)=\sum_{i=0}^{L-1}\mu_A(r_i)P(r_i)\log(P(r_i)). \tag{12}$$

When the principle of fuzzy maximum entropy is applied, it is often used to select the appropriate membership function. For the single threshold segmentation, a segmentation threshold θ is set according to the gray value of the pixels of the original image to be divided into two fuzzy sets, namely dark set and bright set. The dark fuzzy set contains a low gray value of pixels corresponding to the background of the image, and the bright fuzzy set contains a high gray value of pixels corresponding to the image of the target. The membership functions of these two fuzzy sets ($\mu_d(k)$ and $\mu_b(k)$) can be defined as follows:

$$\mu_d(k) = \begin{cases} 1, & k \le a \\ 1 - \dfrac{(k-a)^2}{(c-a)\times(b-a)}, & a < k \le b \\ \dfrac{(k-c)^2}{(c-a)\times(c-b)}, & b < k \le c \\ 0, & k > c \end{cases}, \tag{13}$$

$$\mu_b(k) = \begin{cases} 1, & k \le a \\ \dfrac{(k-a)^2}{(c-a)\times(b-a)}, & a < k \le b \\ 1 - \dfrac{(k-c)^2}{(c-a)\times(c-b)}, & b < k \le c \\ 0, & k > c \end{cases}. \tag{14}$$

Optimal threshold conditions is $\mu_d(k) = \mu_b(k) = 0.5$. At this time, the image's fuzzy entropy reaches the optimal threshold, then:

$$T_{opt} = b = \frac{a+c}{2}. \tag{15}$$

The improved PCNN image segmentation algorithm based on fuzzy entropy

Compared with the traditional neural network, the pulse coupled neural network does not need the training process to realize the image segmentation, but the key factor is used to select the reasonable segmentation parameters [2]. The traditional PCNN image segmentation algorithm generally uses the simplified PCNN neural network, because the parameters of the non-simplified PCNN network are too complex and the efficiency is very low, so it is not suitable for image segmentation. However, there are still many parameters that must be reasonably selected in the PCNN image segmentation algorithm, and these parameters can be used to obtain better segmentation results [12]. The traditional PCNN image segmentation algorithm uses the closed value attenuation function, because the image segmentation is characterized by the gray difference between the background and the target. That is to say, the difference in pixel brightness between them is great. So, there is no need to use the threshold value attenuation function index for image segmentation. It also increases the computation time and complexity of the algorithm.

In this paper, a new improved PCNN model is proposed. The work of improved PCNN includes that the acceptance portion of the PCNN model is simplified and the connection portion of PCNN is improved. In addition, the maximum information entropy is used as the criterion to determine the optimal number of iterations.

The improved PCNN model

There are many problems in the traditional PCNN model, such as the relevant parameters, the various threshold parameters, the decay time constant, the weighted factor and the connection strength, etc. [13]. In order to obtain good segmentation results, reasonable selection of the parameters is needed. The iteration number is determined by the choice of the method of human interaction, and threshold attenuation function changes exponentially with time. The law of this kind of change accords with the nonlinear character of the human eye to the brightness intensity response. It does not meet the requirement of image processing, which means the gray distribution has not been reflected.

In view of the above problems, the traditional PCNN model is improved based on the reservation of the PCNN coupling modulation mechanism and the pulse generation mechanism in this paper.

1) The receptive field F_{ij} only accepts the external stimuli; that is the gray value of pixels.

$$F_{ij} = I_{ij}. \tag{16}$$

2) In order to reflect the nature of the pixel region, the average of the adjacent area of pixels is introduced to the connection portion L_{ij}, and the smoothness of the processing is improved. Y_{ij} ($Y_{ij} = \frac{1}{N}\sum_{N(i)} d_{ij} Y_{ij}$) is set as the mean value of the output of adjacent pixels in a 3×3 pixels' area of neuron. Here d_{ij} is the distance between pixels and the adjacent points, where d_{ij} is measured by using Euclidean distance, and D is a constant and it equals 2 in the equation:

$$L_{ij} = \begin{cases} 1, & \overline{Y_{ij}} \geq 1 \\ \left|\overline{Y_{ij}} - D\right|, & 0 < \overline{Y_{ij}} < 1. \\ 0, & \overline{Y_{ij}} = 0 \end{cases} \tag{17}$$

3) The connection strength β of the internal activities U_{ij} determines the refractory period width meter capture period width of PCNN neurons. In a group of PCNN parameters, the greater the β is, the greater the U_{ij} is, and the larger the synchronous pulse bursts area is. Thus, the accuracy of image segmentation can be affected. In this paper, the method proposed in the literature [5] is used to define it as discrete coefficients CV (Variation of Coefficient):

$$\beta = \frac{sqrt(V_{ij})}{M_{ij}}. \tag{18}$$

4) The value function θ_{ij} uses an acceleration model to achieve decay. When a neuron is activated, the corresponding dynamic threshold becomes infinite, so that the neuron cannot be activated again in the next step.

$$\theta_{ij}(n)=\begin{cases}\theta_0, & n=0 \text{ and } Y(0)=0\\ g(n)\theta_{ij}(n-1), & Y_{ij}(n-1)=0\\ +\infty, & Y_{ij}(n-1)=1\end{cases}, \tag{19}$$

where $g(n)$ is a monotonic decreasing function.

The PCNN process is as follows. Firstly, a threshold is initialized large enough as θ, and the neurons can be globally suppressed when they are initialized ($Y_{ij}=0$). Subsequently, due to the $g(n)$ stimulation, the threshold is slowly reduced so that the neuron can be ignited ($Y_{ij}=1$). Once the ignition of neurons ($\theta_{ij}(n)=+\infty$), the neuron will not be ignited. Here the monotone function $g(n)$ is used as follows:

$$g(n)=1-\exp\left(\frac{-\alpha}{n}\right), \tag{20}$$

where n is expressed as the number of cycles of the PCNN network, and it is set to approximately 10-20 generally.

The improvement of θ_{ij} makes each neuron ignite only once, so the neurons output of ignition equals 1, and the neurons output of non-ignition equals 0.

5) In order to determine the optimal partition number of PCNN, the aforementioned fuzzy entropy is adopted, and Eq. (1) can reach the maximum. In this paper, the target and the background region of the image are selected as the fuzzy sets of the image, which are expressed as μ_A and μ_B respectively. The total fuzzy entropy of the image is a function of three parameters, and they are *a*, *b* and *c*. In the iterative process of PCNN, the fuzzy entropy of the original image is calculated according to the threshold value T_i at different times. The exhaustive method is used, which means the image intensity range (0-255) for a group of *a*, *b*, *c* values is searched in the range of the image (0-255), so as to satisfy the criterion of maximum fuzzy entropy. If the threshold at this time is the optimal threshold, the iteration ends, or the next iteration continues.

Implementation steps of the improved algorithm

The step of implementation of the image segmentation algorithm based on the improved PCNN and fuzzy entropy consists of three parts, which are as follows:

1) The initial value of the PCNN parameter is set so that each pixel is in a state of extinction.

2) For each iteration, the steps below are implemented:

- In the 3×3 adjacent area, the signal of each neuron F_{ij} and L_{ij} is computed according to Eqs. (16) and (17), and to the threshold θ_{ij} is calculated by Eq. (19).
- The internal modulation signal of each neuron U_{ij} and β is calculated according to Eqs. (8) and (18).

- U_{ij} is compared with and threshold θ_{ij} and neurons are recorded as ignition or non-ignition.
- The fuzzy entropy of the image is determined to reach the maximum according to the previous description of the method.

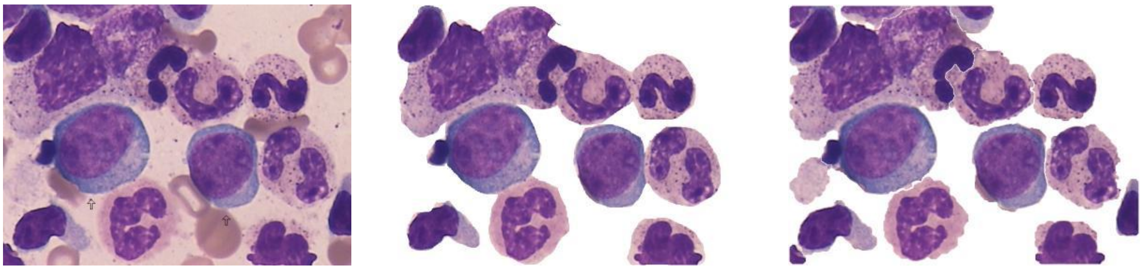
3) The maximum value of the fuzzy entropy is used as the final segmentation result.

Results and discussion

According to the proposed method, the comparative experiments are conducted on white blood cells image segmentation are conducted. Experimental data are collected blood cell images.

The experimental environment is Windows 7, MATLAB 9, 4GB memory, and 2 GHz CPU. The jitter of the fixation point in the experiment is three pixels, and the range is limited to ten pixels around the initial fixation point. In the test run time, the configuration of software for the Windows 7 system, C++ Visual environment programming.

The simplified PCCN was chosen to compare with the method proposed in this paper. Fig. 3 shows the results of blood cell images using different methods.



a) b) c)

Fig. 3 Blood cell images

In Fig. 3, we can see three different images, the first image is the original blood cell image, the second is the result using the simplified PCNN, and the last one is the result of the same image using the proposed method. The results show that the proposed method can obtain more useful blood cell images in the process of image segmentation.

The results in Table 1 show the accuracy and running time between these two different methods. In this table, two items are chosen including the nuclear region and the cytoplasmic region, and two different accuracies are obtained of these two regions. The results show that the method proposed in this paper has much more accurate image segmentation in both the nuclear region and cytoplasmic regions. I further shows that it is more difficult to realize the blood cell image segmentation in the cytoplasmic region than the nuclear region. The index of running time also reveals that the proposed method is faster than the simplified PCNN in blood cell image segmentation processing.

Table 1. Comparison between simplified PCNN and the proposed method

	Accuracy, (%) (nuclear region)	Accuracy, (%) (cytoplasmic region)	Running time, (s)
Simplified PCNN	92.45	87.51	8.2
Proposed method	94.72	90.65	3.2

Conclusion

In this paper, the traditional PCNN network model is improved, the PCNN network structure is simplified and the number of parameters of the network is reduced, so as to reduce the difficulty of setting artificial parameters. The network has a faster speed of convergence after simplifying the network. The method of dynamic threshold adjustment is adopted to overcome the difficulty in dividing the time period. According to the fuzzy characteristic of the image, the maximum fuzzy entropy criterion is proposed to judge the number of iterations to determine the final segmentation result. The experimental results show that the algorithm has a fast convergence rate and high segmentation accuracy, and it has a good effect on the complex blood cell image segmentation.

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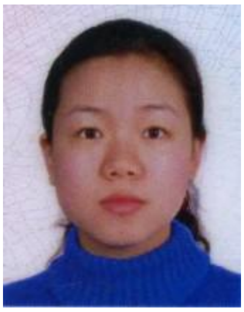

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