An Improved Non-coupled PCNN Model for Image Segmentation

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Abstract. Pulse-coupled neural network (PCNN) model is widely used in digital image processing, but it is always a difficult problem to set network parameters and determine the optimal segmentation. By analyzing the firing characteristics and network parameters setting for the non-coupled linking PCNN, we propose an improved non-coupled linking PCNN for image segmentation. The model introduce the coupling effect of neighboring neurons into the dynamic threshold subsystem, and using a combination of DNN network, manual adjusting on step length for setting the dynamic threshold initial value. When the dynamic threshold initial value is adjusted properly, the optimal segmentation for the image can be obtained. Using the proposed algorithm in image segmentation of Lena and mammographic images, the segmentation effect similar to that of the traditional model can be obtained by less iteration, and it shows faster speed and better robustness.

Keywords: Non-coupled PCNN model; Network parameters; Coupling effect of neighbor; DNN prediction.

1. Introduction

The pulse-coupled neural network (PCNN) model is a single-layer and no training of the third-generation artificial neural network. In 1990, Eckhorn. et al. [1] proposed a neural network model based on the neuron signal transduction of cats’ visual cortices. In 1999, Johnson et al. [2] modified it into a model adapted for image processing and named it the pulse coupled neural network (PCNN). Because neighboring pixels with the similar gray value for PCNN has the synchronization release pulse characteristic, the image segmentation, edge detection and other processing can be realized utilizing the characteristic. PCNN have both linking and non-linking mode, most applications for image processing in the coupled connection mode. It has been well applied in various kinds of image processing, but the setting of network parameters and the determination of the optimal iteration times are always difficult in application[3,4,5].

A large number of studies have shown that the characteristics of the coupled PCNN are greatly affected by the characteristics of non-linking network [6,7,8]. Since the non-linking PCNN has fewer network parameters, many researches have studied the application of the two modes of PCNN in image processing [9,10,11]. For example, Yanan Guo et al. detected micro-calcification clusters in mammographic images by coupling SPCNN model with only four parameters [12]. Changdong Wu et al. realized the automatic segmentation of catenary images by using the simplified PCNN model, and used the mean square deviation of pixel gray values in the range of connection weight matrix to adaptively set the connection coefficient, and used the cross entropy to realize the selection of optimal results, but other parameters were not discussed [13]; Zhihui Wang et al. proposed a novel multi-faceted adaptive image
fusion algorithm based on the pulse coupled neural network, and some parameters are set adaptively according to the image information, while others are set manually [14]; Guo Y put forward an improved PCNN model using significant eigenvalues as excitation, and that was used for segmentation of medical and other images [15]; Chen et al. presented a target recognition method in real scene using simplified PCNN model, and completed the adaptive setting of model parameters [16]; In summary, most of the existing studies focus on the application of PCNN in various image processing, and some studies focus on the adaptive setting of network parameters, but they all have their own limitations, especially on the determination of the optimal iteration times. Considering the difficulties in setting PCNN parameters and determining the optimal number of iterations, based on the non-coupled linking PCNN model with a fewer parameters, this paper brings the coupling effect of neighboring neurons into the dynamic threshold subsystem, and proposes an improved PCNN model that only needs to adjust one parameter and only needs one iteration to obtain the optimal segmentation.

2. Non-coupled Linking PCNN

Eqs. (1) - (3) show the mathematical model of the non-coupled linking PCNN. In the previous research, we gain the iteration time \( n_m \) and iteration period \( mT \) of the gray value \( S_{ij} \) in the network, and found the phenomenon of mathematical coupling effect for the network. Due to different network parameters, the impacts of the mathematical coupling is different for image segmentation. The setting of network parameters is always a difficult problem when it is used in actual image segmentation, and empirical parameters are used in most cases.

\[
U_{ij}(n) = F_{ij}(n) = S_{ij} \tag{1}
\]

\[
E_{ij}(n) = e^{\alpha E}F_{ij}(n-1) + V_E Y_{ij}(n-1) \tag{2}
\]

\[
Y_{ij}(n) = \varepsilon[U_{ij}(n) - E_{ij}(n)] \tag{3}
\]

Figure 1. Image segmentation process of non-coupled linking PCNN (H is entropy).

Fig.1 is the iterative output process of non-coupled PCNN when the network parameters are properly set, which shows that an optimal segmentation is obtained in the fourth iteration. Therefore, the non-coupled PCNN can be better used for image segmentation only when both appropriate network parameters are set and the optimal iteration number can be adaptively determined, and the solution of these two key problems has always been a difficult puzzle. At the same time, in the process of the network iteration, the change of dynamic threshold for each neuron is only affected by its own firing state except exponential attenuation, which does not reflect the coupling effect of neighborhood pixels.

3. Improved Non-coupled Linking PCNN

3.1. Simplification of the Non-coupled PCNN Model

From the previous analysis for the traditional non-coupled PCNN, the optimal segmentation result depends on the setting of network parameters when the PCNN is used for image segmentation, and even
for the appropriate setting of network parameters, the best segmentation effect is also related to the number of iterations for the network. Therefore, considering the difficulties in setting parameters of traditional PCNN and selecting the optimal segmentation iteration times, the coupling effect of neighborhood pixels is introduced into the dynamic threshold subsystem of PCNN, which is based on the traditional non-coupled PCNN model, and propose an improved non-coupled linking PCNN model with initial dynamic threshold $E_0$ for image segmentation. Only the dynamic threshold attenuation exponential $a_E$ and the linking weight matrix $W$ reflecting the coupling effect of the neighborhood are retained in this model, the optimal segmentation can be obtained only by one iteration when parameters are set properly, thus it has high-efficiency image segmentation performance. Its mathematical models are shown in Eq. (4) to Eq. (7).

$$F_y(n) = S_y$$  \hspace{1cm} (4)

$$C_y = \sum W S_{ij}$$  \hspace{1cm} (5)

$$E_y(n) = e^{-a_E} E_y(n-1) + C_y$$  \hspace{1cm} (6)

$$Y_y(n) = e[F_y(n) - E_y(n)]$$  \hspace{1cm} (7)

Where $S_y$ represents the input of the PCNN and is the normalized gray value of a pixel corresponding to a neuron. $W$ is the linking weight matrix, and that is generally the weak coupling mode, $W = [0.01 \ 0.01 \ 0.01; 0.01 \ 0 \ 0.01; 0.01 \ 0.01 \ 0.01]$, which reflects the pixel $(i, j)$ affected by the neighboring pixels. $C_y$ reflects the whole coupling effect of neighboring pixels on the center neuron.

### 3.2. Influence of $a_E$ on the Network Output

In the improved PCNN model, the changes of dynamic threshold mean value $\mu_E$ affect the iteration output of whole network when the initial dynamic threshold $E_0$ is determined. When the dynamic threshold $E_0 = 20$ and parameter $a_E$ is equal to 1.20 and 4.60 respectively, the variation of dynamic threshold mean value $\mu_E$ with the iteration times is shown in Fig.2

![Figure 2. Changes of dynamic threshold mean value ($E_0 = 20$).](image)

In Fig. 2, the blue line is the normalized mean value of the image, reflecting the average gray level of the whole image. Under the condition of the same initial dynamic threshold $E_0$, when $a_E = 1.20$, the dynamic threshold mean value $\mu_E$ changes slowly. After three iterations, $\mu_E$ is always greater than the normalized mean value of the image. From Eqs. (6) and (7), it can be seen that most neurons with gray values will be suppressed while a few will be fired. When $a_E = 4.60$, $\mu_E$ is smaller than the
normalized mean value of the image after the first iteration. Then in that output of the first iteration, most of the gray value neurons will be in the firing state. The changes of the dynamic threshold mean value $\mu_E$ and the output of network iteration are shown in Fig. 3.

(a) $a_E = 1.20$

(b) $a_E = 4.60$

**Figure 3.** Visualization of the dynamic threshold and the iterative output of the network. In order to intuitively reflect the changes of the dynamic threshold of neurons in the iteration process of network, the logarithmic enhancement processing is carried out on the dynamic threshold of neurons and displayed in image. Fig. 3 shows the dynamic threshold of neurons decreases continuously in the iterative process of the network, but different pixel positions have different dynamic threshold values, and the network shows a multi-threshold segmentation characteristic. With the increase of the number of network iterations, the mean value of the dynamic threshold becomes smaller and smaller, the corresponding image becomes darker and darker, and more and more neurons are fired. The iterative output of the network shows a transition from over-segmentation to under-segmentation. When the parameter $a_E$ is small, because the mean value of the dynamic threshold $\mu_E$ is still greater than the normalized mean value of the image after multiple iterations, the corresponding dynamic threshold image changes slowly from light to dark. Only after multiple iterations can the effect of image segmentation be shown. However, when the parameter $a_E$ is large, the image corresponding to the dynamic threshold is dark, and the under-segmentation effect will appear in the first iteration of the network.

### 3.3. Influence of $E_0$ on the Network Output

From the mathematical model of the improved PCNN, when the parameter $a_E$ is determined, the variation of the dynamic threshold mean value $\mu_E$ determines the iterative output of the whole network. When the parameter $a_E$ is 4.60 and the initial dynamic thresholds $E_0$ are 20 and 35, respectively, the
changes of the mean value of the dynamic threshold $\mu_E$ with the number of iterations are shown in Fig.4.

**Figure 4.** Changes of dynamic threshold mean value ($a_E = 4.60$).

In Fig.4, when $E_0 = 35$, $\mu_E$ is greater than the normalized average value of the image after the first iteration. According to Eqs. (6) and (7), most of the neurons will be suppressed, while a few will be fired. After the second iteration, the mean value of the dynamic threshold is less than the normalized mean value of the image, then most of the neurons will be in the firing state. When the initial dynamic threshold $E_0$ is 20, the mean value of the dynamic threshold $\mu_E$ is less than the normalized mean value of the image after the first iteration, then in the output of the first iteration, most neurons will be in the firing state. For the two initial dynamic thresholds $E_0$, the changes in the mean value of the dynamic threshold and the output of network iteration are shown in Fig.5.

**Figure 5.** Visualization of dynamic thresholds and the iteration outputs of the network ($a_E = 4.60$)
From Fig. 5, when the initial dynamic threshold $E_0$ is large, the visual image of the dynamic thresholds is bright and the corresponding segmentation result shows over-segmentation in the first iteration of the network. However, when $E_0$ is small, the corresponding visual image is dark after the dynamic threshold is attenuated once, and the output of the network shows under-segmentation.

4. Setting of Dynamic Threshold Initial Value $E_0$ Based on DNN Network

According to the analysis of the influence of parameters on the network output for improved PCNN above, we find that only one iteration for the improved PCNN could obtain the segmentation result. But whether the optimal segmentation results can be obtained depends on initial dynamic threshold $E_0$ and parameter $a_E$. According to the preliminary experiment, when the parameter $a_E$ is too small, the output image still needs to go through several iterations to get the segmentation result. Fig.2 shows that if the initial dynamic threshold $E_0$ is greater than or less than the gray mean of the image, over-segmentation and under-segmentation will occur respectively. Therefore, the value of the optimal dynamic threshold should be close to the normalized mean value of the image, so it can be seen that there is a certain relationship between the value of the initial dynamic threshold $a_E$ and the gray statistical characteristics of the image. However, considering that every input image has the different gray statistical characteristics, it is impossible to generalize the general rules for all cases by conventional methods. Therefore, the learning ability of the artificial neural network is a better solution to the mapping problem in this complex situation. We designed a DNN with three hidden layers. Where, the input layer is the gray statistical characteristics of the image, and the output layer is the initial dynamic threshold $E_0$ corresponding to the optimal segmentation by manual, which realizes the mapping relations between the image gray statistical characteristics and the Initial dynamic threshold $E_0$.

Table 1. DNN architecture.

| Layer type and network function | Parameters |
|--------------------------------|------------|
| Input                          | 256 nodes  |
| Hidden1                        | 17 nodes   |
| Hidden2                        | 20 nodes   |
| Hidden3                        | 25 nodes   |
| Output                         | 1 nodes    |
| Activation function of hidden  | Logsig     |
| Activation function of output  | Logsig     |
| Training function              | Trainlm    |
| Training samples               | 200        |
| Normalization of output        | [0,255] to [0,1] |

Table 1 shows the construction of the DNN. For the design of the training samples, the following schemes are adopted: (1) Select 80 images from MATLAB toolbox. (2) 20 mammographic images with calcification from MIAS. (3) Select 100 randomly photographed license plate images. After the initial dynamic threshold $E_0$ is obtained based on DNN network, the best value needs to be further adjusted manually. Through a lot of many experiments, we find that there is a positive or negative deviation named $\Delta E$ between the optimal value and the value predicted by the DNN network. When the segmentation result corresponding to the predicted value $E_0$ is over-segmentation, manually reduce $E_0$ in steps of $\Delta E$ until the optimal segmentation is obtained. When it is under-segmentation, manually increase $E_0$ in steps of $\Delta E$. Generally, setting $\Delta E(0)=10$ and manually adjusting the step size
according to the formula \( \Delta E(n) = \pm \Delta E(n-1) / 2 \), which can achieve the optimal segmentation of most images.

5. Experimental Simulation

Through the above analysis, the network only needs one iteration to obtain the optimal image segmentation in the condition of setting the appropriate parameters. As the label \( E_0 \) was found manually in the case of \( a_E = 4.60 \) in the training of the DNN network above, \( a_E = 4.60 \) should also be set when using the proposed algorithm. Figure 6 shows the segmentation result of Camera image.

**Figure 6.** Segmentation process of Camera image.

Fig.6 shows that the image corresponding to the predicted \( E_0(0) \) is over-segmentation, so it needs to be adjusted manually according to \( \Delta E(n) \). To further verify the proposed algorithm, four mammographic images with calcification from MIAS were randomly selected as test samples, on the basis of prediction and after manual adjustment, the segmentation results obtained by the proposed algorithm are shown in Fig.7.

**Figure 7.** Segmentation results of the mammographic images.
Figure 8. Comparison with other algorithms. (a) Original image; (b) Otsu; (c) Watershed algorithm; (d) Ref. [5]; (e) Result of the traditional PCNN; (f) The proposed algorithm.

Fig. 7 (a) shows that four mammographic images with calcification from MIAS. Fig. 7 (b) shows that the segmentation result of the proposed algorithm, Fig. 7(c) is the local magnification of the calcification area, and the range marked in red is the detected calcification cluster. Fig. 8 (b) and (c) are the segmentation results of two classical algorithms. (d) and (e) are the segmentation results of the traditional PCNN algorithm. It can be seen that the proposed algorithm is better than the others methods in details of image as well as the improved network has fewer parameters, so the segmentation efficiency is higher.

6. Conclusion

The setting of optimal parameters and the selection of the optimal number of iterations have always been a problem in various processing of images for the traditional PCNN. This paper analyzes the influence of parameters setting on the network characteristics for the non-coupled linking PCNN, and we find that the segmentation result of the image mainly depends on the change of the network thresholds. In this paper, we propose an improved non-coupled linking PCNN for image segmentation which bring the coupling effect of neighboring neurons into the dynamic threshold subsystem. When this model is used to image segmentation, the model only needs to set the single parameter through the combination of DNN prediction and manual adjustment, and the optimal segmentation result can be obtained in the first iteration for the proposed improved PCNN. Using it for the segmentation of Lena and medical images, it has achieved better results and higher efficiency than the traditional methods. The segmentation effect of the proposed algorithm only depends on the initial value setting of the dynamic threshold, however, the value of which cannot be fully set adaptively and accurately. Therefore, further studies would be needed to analysis the relationship between the initial value of the dynamic threshold, the gray statistical characteristics of the image and the network another parameter, and to improve the accuracy of the prediction. Also, the improved model uses a weakly coupled connection weight matrix, and how the network will behave under strong coupling is also the main research work in the next step.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (No. 61961037).

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