Multi-object Segmentation

Based on Improved Pulse Coupled Neural Network

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Abstract

This paper introduces an approach for image segmentation by using pulse coupled neural network (PCNN), based on the phenomena of synchronous pulse bursts in the animal visual cortexes. The synchronous bursts of neurons with different input were generated in the proposed PCNN model to realize the multi-object segmentation. The criterion to automatically choose the dominant parameter (the linking strength β), which determines the synchronous-burst stimulus range, was described in order to stimulate its application in automatic image segmentation. Segmentations on several types of image are implemented with the proposed method and the experimental results demonstrate its validity.

Keywords: The Pulse-Coupled Neural Network (PCNN), Automatically Image Segmentation, Parameter Determination

1. Introduction

Pulse coupled neural networks (PCNN) were introduced as a simple model for the cortical neurons in the visual area of the cat's brain. Important research in the 80's and 90's led to the establishment of a general model for PCNN . Such models are proved to be highly applicable in the field of image processing, a series of optimal procedures being developed for contour detection and especially image segmentation. Taking PCNN abilities into consideration, we propose an extended PCNN using fast linking, and make some improvements to extend PCNN to work effectively. Finally, we apply this PCNN to actual images under various conditions of illuminations and demonstrate the effectiveness of this model through experiments.

In the second section of this paper, the PCNN's basic model and the fast-linking method are introduced. In the third section, the new approach for multi-object image segmentation based on fast linking is brought forward. In the fourth section, results of multi-object segmentation based on the proposed PCNN model are shown.

2. The pulse-coupled neural network

A simplied PCNN model

A simplified pulse coupled neuron(PCN) consists of three parts: the receptive field, the modulation field, and the pulse generator, see Figure 1. Compare with real neurons, this model contains some simplifications and approximations. Some factors, such as multiple ionic synaptic channels, active channels, cellular aging, temperature effects, are not considered. The two channels in the receptive field and the pulse generator are simplified too. Equations from Eq (1) to (5) describe this model.

$$F_j = S_j(n)$$

$$(1)$$

$$L_j(n) = \sum WY_j(n-1)$$

(2)

$$U_j(n) = F_j(n)(1 + \beta L_j(n))$$

(3)

$$Y_j(n) = \text{Step}(U_j(n) - \theta_j(n))$$

(4)

$$\theta_j(n) = \alpha^T \theta_j(n-1) + V^T Y_j(n)$$

(5)

The neuron receives input signals from other neurons and external sources by two channels in 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. Each neuron has two channels. One channel called F channel is the feeding input; the other called L channel is the linking input. In this paper, F channel receives signals from external sources, namely the intensity of the image pixel. In figure 1, feeding input is the intensity of the image pixel connected to neuron and received by channel F, see (1). L channel receives pulses emitted by neighboring neurons, see (2). In modulation field, see Figure 1, the linking input is added a constant positive bias firstly. Then it is multiplied by the feeding input and the bias is taken to be unity, see (3). β_j is the linking strength. The total internal activity U_j is the result of modulation and is inputted to the pulse generator. If U_j is greater than the threshold θ_j, the neuron output Y_j turns into 1 (namely the neuron fires), see (4). Then Y_j feedbacks to make θ_j rise over U_j immediately so that Y_j turns into 0. Therefore, when U_j is greater than θ_j, neuron j outputs a pulse. Next θ_j drops with time increasing. In Figure. 1 V_j^T and α_j^T are the amplitude gain and the time constant of the threshold adjuster, respectively.

Fast Linking Method

In order to process actual images under various conditions of illuminations, we apply PCNN with "fast linking", after the first signal is input, calculate all the output, and then refresh the linking territory. At last, the internal state is calculated, the output is decided. During the calculating process, if one of the neurons is changed, the linking territory is changed correspond. The calculation will continue until all the outputs are unchanged. Such cycle process is called one iterative. During this process, in order to keep the input unchanged, the linking territory will change constantly. The input wave transmit the data after one iteration is finished, while linking territory wave send information to all the elements of image during this iterative. This method is called Fastlinking. It can decrease the effect of timing quantification. The flashings in original model are all separated because the time delay of the linking field. While adopting the Fastlinking model, the neuron can be flashed in one terrirory, shown in Figure 2.

In the model of PCNN, the linking coefficient β plays an important role. The larger β is, the further distance is transmitted. It can be obviously seen in the Fastlinking model. Figure 3 shows the segmentations of different β. It also can be seen from Figure3 (b) and (c) that, for the connected territory, the value of β influences the amount of neurons.

3. Multi-object segmentation using improved PCNN

Supplementary term

In Fastlinking model, the effect of β only is limited in the connected area that is, in the connected area, between the neurons pulsed with the highest grey value and those with the lowest the range of grey will enlarge because β increased. But this will not influence those unconnected neurons. This property can make the different results even they are in the same grey degree, the neurons connected to the higher grey degree will be fired, but those unconnected to the higher grey degree will not be fired. The segmented image can be seen in figure 4.

For those duties using PCNN separate the connected target territory from the background, Fastlinking model is more advanced. But to those which want to separate multiple targets from different background synchronously, the traditional Fastlinking has some limited, such as not making the firing synchronously.

We can describe this type segmentation as: to realize synchronous firing of the objects with different intensity as many as possible. To address this problem, we make an improvement to the model. We define a loop variable t in a step. An

iteration of variable t is defined as a sub routine. From the second sub routine, a correction term defined as Eq (6) was added into internal activity:

$$L_j^{add}(t) = \frac{F_j(t-1)}{F_{j\min}(t-1)} * E_j$$

(6)

Where $F_j(t-1) = \begin{cases} F_j(n) & j \in (\Phi_F(t-1) \setminus \Phi_Y(t)) \\ 0 & otherwise \end{cases}$

$$\Phi_F(t-1) = \{j \mid F_{\min}(t-1) < F_j(n) < F_{\max}(t-1)\}$$

$$\Phi_Y(t-1) = \{j \mid Y(t-1) = 1\}$$

Where, $F_{\min}(t-1)$ and $F_{\max}(t-1)$ are the highest and lowest intensity pulsed in t-1 sub-step respectively. E_j is the edge data of the image. Then, the internal activation of the neuron can be modeled as follow

$$U_j^{add}(t) = F_j(n)(1 + \beta L_j(t) + \gamma L_j^{add}(t))$$

(7)

where γ is the power index, the larger γ is, the stronger the correction is, and vice versa. The correction term is zero when $\gamma = 0$ and the model is the classic PCNN model with Fastlinking.

The internal activity of neurons on the edges of the object-regions with lower highest-grayscale are raised to the threshold to fire by inducing the edge data into the proposed model, and some neurons linking with them are captured. So the object-regions with lower highest-grayscale are segmented. In the model, it is β to mainly determine the range of the intensity of synchronous pulsed neurons and correction term to expand the space of the wave propagation to generate firing seeds in unlinking region. The regions created by seeds capturing the linking neurons, separated by the edges, are each marked in order to be convenient to be segmented.

Determination of β

The linking strength β should be satisfied: 1) To ensure that the points in target area will be captured, 2) To ensure that the points in background cannot be captured. If the condition 1) is satisfied, β must be large enough; while 2) is satisfied then β will be smaller. From the principle of firing, the neuron must satisfy:

$$U_j(n) \geq \theta_j(n)$$

(8)

Take the first firing as an example, let $\theta_{ij}(0) = f_{\max} = \max(S)$, choose the neuron P from the fired part freely, its input is f_P then according to Eq (3) and Eq (8): $f_P(n)(1 + \beta l_P(t)) \geq f_{\max}$ make small transformation:

$$\beta \geq \frac{\Delta f}{l_P(t) \times f_P(n)}$$

(9)

where, $\Delta f = f_{\max} - f_P(n)$ is the distance between input and the threshold value, which denotes the impulse range of

PCNN in one iterative. Let Y (t-1) be the output of t-1sub-iterative. Then there will be two uttermost conditions of

neighborhood of a neuron in the tth iterative linking area, all neurons are fired or the only neighbor neurons are fired, we

can describe by the matrix as follows:

$$Y_{ij}^{\max}(t-1) = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \text{or} \quad Y_{ij}^{\min}(t-1) = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The central neuron is (i, j). If we adapt 1/r kernel, and let $r=3$, then combine Eq (3) and Eq (9), the range of β is:

$$\beta \geq 1.0 \frac{\Delta f}{f_P(n)}$$

(10)

or

$$\beta \geq 11.1 \frac{\Delta f}{f_P(n)}$$

(11)

But in practice, it is between two extremely condition. If all the neurons with higher grey value than f_P (including f_P) are expected to be fired, β defined by form Eq (11) must be chosen. Then the smallest input fired is:

$$f_{P\min}(n) = \frac{f_{\max}}{(1+11.1 \frac{\Delta f}{f_P(n)})}$$

(12)

If form Eq (10) is selected as a rule, then f_P must be the smallest pulse value, some neurons whose value are higher than f_P will not be fired. Considering the above two rules, we adapt form Eq (11) as the basic rule, f_P will be decided by the whole grey distribution. From the segmentation example, to the above duty, when we select the first trough(12) near the highest value as f_P, the result is better.

Improved PCNN algorithm

The parameters we selected ensure that we can get the result in one iterative. The last result is saved in Y. The detailed steps are as followed:

Step1: Initialization

Let the unitary image grayscale value as the impulse signal S_j;

Make differential to the image; get the verge value of image as the outside input;

 Initialize the parameter of the net;

Step2: Fastlinking processing: t is the iterative variable

a) Let $t_{\max}=20$; t=1;

b) The first iterative t=1, from Eq (1)~(5),calculate each PCNN internal and output part, then put the result in $Y_{ij}^{(t)}(1)$;

c) From t=2 iterative, internal activation defined by Eq.(3) will be replaced by Eq.(7), then calculate each PCNN internal and output part, then put the result in $Y_{ij}^{(t)}$;

d) t=t+1;

e) If t<$t_{\max}$ then move to step c); otherwise output Y_{ij}.

Figure 5 shows the segmentation of the improved PCNN algorithm on the image of figure 4(a) The maximum grey level of each fired region are 1.0 and 0.8 respectively.

4. Experiments

We test some image with multi-target in improved model. Figure 6 and Figure 7 show the examples of the proposed PCNN and Fastlinking model. Fig6 contains the images composed of the objects include long, thin lines and the background has large homogenous areas, such as the handwriting. Fig7 contains the images composed   of many grains of target objects, which are much smaller than the background such as the rice. The proposed PCNN is fit for such simple background image. Obviously, the improved PCNN model segment more target area than Fastlinking model. Figure 8 shows some segmentations for natural images. (a) is the original input image; (b) is the segment output, including the target area and non-target area. For this example, we adapt geometry characteristic method to segment the area. Firstly, the pixel number in this area must satisfy some extent. The other area is the non-target area. Then

approximate the target area, for example, the shape of plane is approximated by "T" shape or cross shape; the shape of face is approximated by oval. After such filtering, the area left is the target. Column (c) shows the extracted objects. The traditional PCNN model has better robustness to noise. The paper compared the improved PCNN model and the traditional Fastlinking model. Figure 9 is the compared results. The former figure is the rate of false negative; the latter figure is the rate of false positive. From them, it can be seen that, to lowly noised image, the rate of false negative in improved PCNN model is lower than traditional Fastlinking model. To highly noised image, the rates of false negative in improved PCNN model are different for the edge detectors. Canny operator is the lowest, Sobel is lower, Prewit operator and Sobel operator are near. When considering the rate of false positive, Prewit operator and Sobel operator are almost same and the lowest; traditional Fastlinking is higher; Canny operator is the highest. Considering the above analysis, Sobel operator is more suitable for this application.

5. Conclusion

This paper improved the traditional PCNN model and added verge data at the input target area. Neurons of different grey in the non-connected area are fired simultaneity, in order to realize segmentation of multi-target. The paper defined the important parameter β which is the key factoring firing processor. The experiment proved that in the multi-object identification the improved PCNN model is superior to the traditional Fastlinking model for the non-noise image. When existing noise in the image, decreasing the noise is affected by the verge detection operator. All in all, proposed PCNN model preserved the advantages of traditional Faslinking, and realized the simultaneous segmentation of multiple objects.

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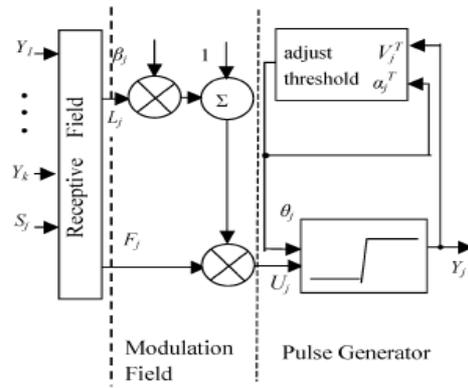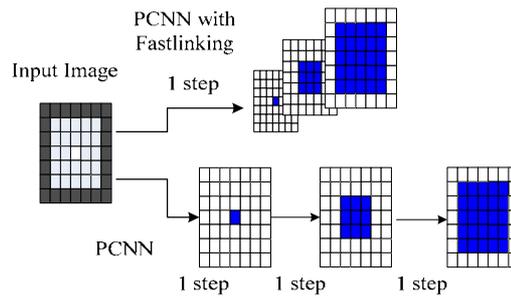
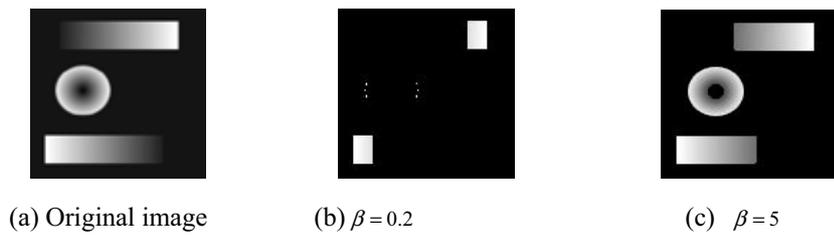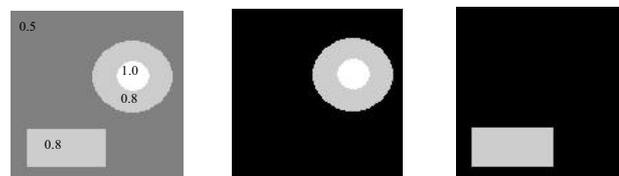Figure 1. Simplied   PCNN

Figure 2. Fastlinking model

(a) Original image   (b) $\beta = 0.2$ (c) $\beta = 5$

Figure 3. Segmentations with different β

(a) Original image   (b) results image

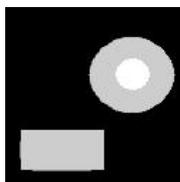Figure 4. Segmentation example of Fastlinking PCNN ($\beta = 1.0$)
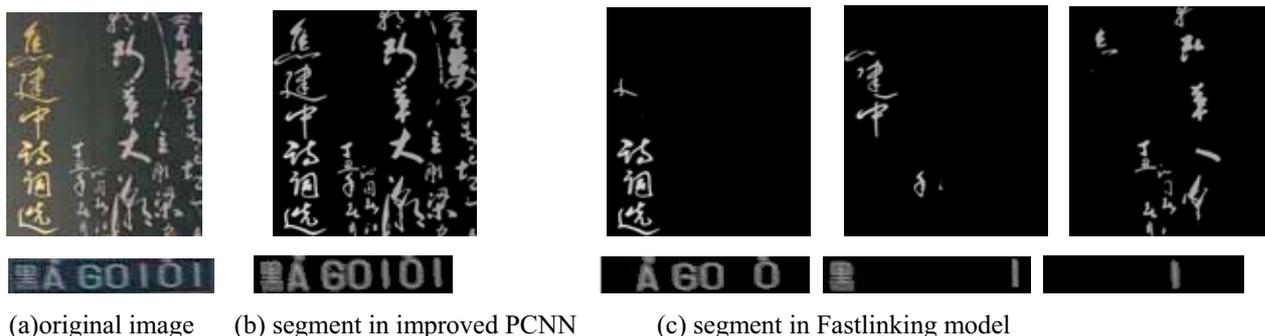
Figure 5. The segment result of improved PCNN

(a)original image   (b) segment in improved PCNN   (c) segment in Fastlinking model

Figure 6. The segment test between improved PCNN and Fastlinking model.

(a) original image   (b) segment in improved PCNN   (c) segment in Fastlinking model
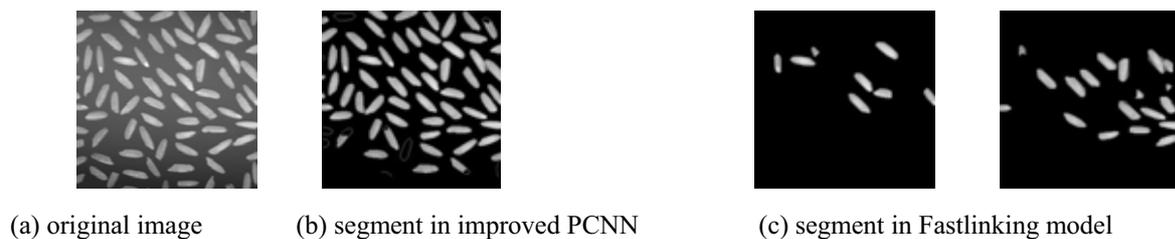
Figure 7. The segment test between improved PCNN and Fastlinking model.

(a) original image   (b) segment in improved PCNN   (c) abstract target area
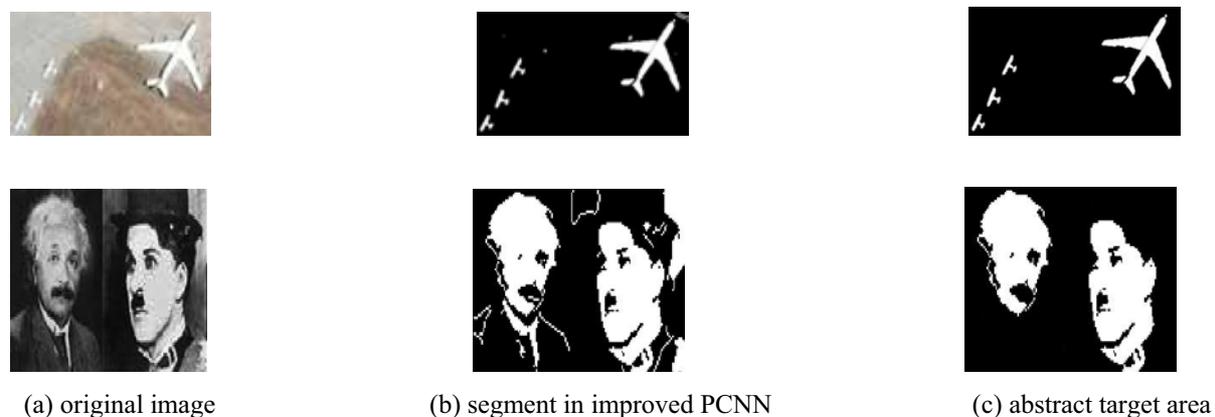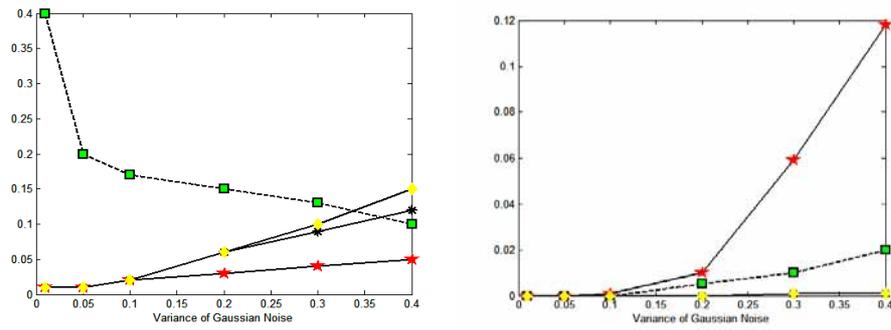
Figure 8. The segment test of improved PCNN

Figure 9. The segment compare between improved PCNN and Fastlinking model. Dash line is the traditional Fastlinking model; -◆-,-*-and -★-are the Prewit operator, Sobel operator and canny operator. The left figure is the rate of false negative; the right figure is the rate of false positive.