An Adaptive Binarization Method Based on Deblocking PCNN

Liejun Wang, Song Zhang* and Yanqing Qi

College of Information Science and Engineering, Xinjiang University,
Urumqi, P.R. China

Abstract

In recent years, the pulse coupled neural network (PCNN) is widely used in image segmentation, but the existing algorithm has an unsatisfactory performance with the definition of single threshold, especially in uneven illumination or low contrast image. In this paper, in order to eliminate the impact of the illumination and improve the adaptability, deblocking PCNN algorithm is utilized. It segments the image into several rectangles with the same size. Then PCNN algorithm is applied to segment each block and stopped by improved OSTU. The emulation experiment shows that this method is better than traditional image segmentation method in uneven illumination or low contrast image.

Key Words: PCNN, OSTU, Image Segmentation

1. Introduction

Image segmentation is one of the most critical technologies in image processing, such as image recognition, pattern recognition, computer vision, image retrieval. It is a technology to divide the image into a number of specific and unique areas and extract the target. The most valid and effective method is threshold segmentation based on gray-scale. How to select the suitable threshold in order to realize the correct segmentation is the key to image segmentation which makes a binary image neither to produce under-segmentation, nor over-segmentation.

PCNN is a self-organizing network that does not require training and the network was constructed by simulating the activities of the mammal’s visual cortex neurons and offers huge potential for image processing [1]. Up to now, the PCNN model is utilized in many image processing techniques especially in image segmentation [2]. The PCNN has numerous parameters that are not easily applied into real-world image segmentation. Thus, researchers focused on the simplified PCNN (SPCNN) and attended to automatically deal with SPCNN parameters for binary segmentation purpose [3–8].

Rava [9] presented a quantitative approach for the automatic and direct computation of the linking coefficient and primary firing threshold directly from the image histogram. Li [10] proposed a novel PCNN parameters automatic decision algorithm which transforms the parameters setting problem into parameters optimization based on immune algorithm. Bayes clustering method was incorporated with PCNN Gao [11] to extend the feasibility of the model for the extraction of targets with inhomogeneous brightness. It is a high performance iterative algorithm for automatic image segmentation by experiments on real-world infrared images. Zhou [12] presented a coarse-to-fine strategy for iterative segmentation. Simplified the original PCNN in terms of input and dynamic neural threshold in this strategy and also ensures that the parameters are adjusted properly and facilitates the automatic control of the result through iteration. Yoshihara [13] described the hardware implementation of the Inhibitory Connected Pulse Coupled Neural Network (IC-PCNN) in FPGA and the performance of the FPGA implemented IC-PCNN is enough for some applications in real time processing as showed in the study.

However, improving the performance still remains a
challenge and necessitates further research. In this paper, we present an adaptive binarization method based on deblocking PCNN. The number of iterations is the key of PCNN segmentation results which affect the quality. General PCNN algorithm could not stop iteration automatically. In this paper, the number of iteration is obtained from the improved OSTU which is taking into account the within-class variance and between-class variance. Improved OSTU makes the segmentation more precise. For uneven illumination or low contrast image, PCNN cannot segmentation correctly. The blocking mechanism makes it significantly improves segmentation performance which for these special cases have better results.

This letter is organized as follows. Section 2 briefly describes the tradition PCNN and OTSU, and details the proposed algorithm. Section 3 demonstrates the high performance of the proposed model through four standard gray images in MATLAB. Section 4 concludes our work and gives the prospects for further study.

2. Debloking PCNN

2.1 Original PCNN Model

In this section, we briefly describe the original PCNN model and its principle of segmentation. The original PCNN model was developed by Eckhorn [1], which is a two-dimensional neural network. Each neuron in a network corresponds to a pixel in an input image, as shown in Figure 1. Generally, a pulse-coupled neuron consists of three main parts: input field, modulation field, and pulse generator.

The input field contains a feeding input F and linking input L. Each input communicates with neighboring neurons through the weights matrices M and W with the constant $V_F$ and $V_L$, and retains their previous state through the exponential decay factors $\alpha_F$ and $\alpha_L$, respectively. Particularly, the input F receives the external stimulus S, which corresponds to the intensity of a pixel in an input image I of size $M \times N$.

The significant characteristics of PCNN include the synchronous dynamic activity of neurons and periodic threshold dynamics. The inputs L and F are combined in the modulation field through the linking coefficient $\beta$ to yield the internal activity U, which is compared to the previous state of the dynamic threshold E to produce the output Y in the pulse generator. If the neuron ij fires ($Y_{ij}$ is set to 1), the threshold value $V_E$ will significantly increase. Thereafter, the corresponding threshold would decay through the time decay factor $\alpha_E$ until the neuron fires again.

The following equations describe the behavior of a single pulse-coupled neuron:

$$F_{ij}(n) = e^{-\alpha_F} F_{ij}(n-1) + V_F \sum_{k,l} M_{ij,k} Y_{kl}(n-1) + I_{ij}$$

$$L_{ij}(n) = e^{-\alpha_L} L_{ij}(n-1) + V_L \sum_{k,l} W_{ij,k} Y_{kl}(n-1)$$

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

$$Y_{ij}(n) = \begin{cases} U_{ij}(n) > \theta_{ij}(n-1) & \text{1} \\ \text{0 otherwise} & \text{others} \end{cases}$$

where $k,l$ denotes the neighborhood of neuron $ij$. $M_{ij,kl}$ and $W_{ij,kl}$ represent the synaptic weights from the position of neuron $kl$ to the position of neuron $ij$, respectively.

However, the determination of values for the PCNN parameters greatly increases the flexibility of this model in handling different images, and makes it hard to obtain the accuracy of the segmentation.

2.2 Simplified PCNN Model

To reduce the complexity of the network (PCNN) and to increase the computing speed, in this section, we will present a framework of SPCNN for image segmen-
The structure of simplify PCNN Model as shown in Figure 2, and two inputs $F$ and $L$ are simplified and can be rewritten as follows:

$$F_{ij}(n) = I_{ij}$$  \hspace{1cm} (6)  

$$L_{ij}(n) = \sum_{k,l} W_{ij,kl} Y_{kl}(n-1)$$  \hspace{1cm} (7)

where $W_{ij,kl}$ could be computed as follows:

$$W_{ij,kl} = \begin{bmatrix} 0 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}$$  \hspace{1cm} (8)

From Eq. (8), it is obvious that the synaptic strength is inversely proportional to the spatial distance, that is as follow:

$$w_{ij,kl} = \begin{bmatrix} 0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}$$  \hspace{1cm} (9)

In the proposed model, only the linking coefficient $\beta$ should be adjusted. This parameter represents the linking strength of neurons and plays a significant role in neural behavior. This value is often determined by trial and error in previous studies. Generally, a large $\beta$ value encourages low-brightness neurons to fire, whereas a small $\beta$ value decreases the ability to capture neighboring neurons and maintains high similarity in the fired region. This may greatly increase the complexity in assigning a proper value to this parameter.

### 2.3 Improved OTSU Method

The tradition PCNN model cannot stop iteration automatically at the optimal threshold. Therefore, the optimal threshold value is obtained by improved OTSU method in this paper. In 1979, Otsu proposed a commonly used adaptive threshold algorithm [14]. It is built on a gray scale image, according to criteria for a max class distance to determine the threshold. The proposed method takes the interclass class variance of the OTSU as the objective function, and determines the number of iterations $t$ adaptively by evaluating the fitness value. That is to say, the algorithm can adaptively converge to the optimal segmentation threshold by the improved OTSU method.

Let the pixels of a given image be represented in $L$ gray levels $[1, 2, ..., L]$. The number of pixels at level $i$ is $n_i$ and the total number of pixels is $N$, then $N$

$$N = \sum_{i=1}^{L} n_i$$  \hspace{1cm} (10)

Let threshold $t$ divide the image into $C_0$ and $C_1$ two regions, $C_0$ denotes pixels with levels $[1, ..., t]$, and $C_1$ denotes pixels with levels $[t+1, ..., L]$. The probability of $C_0$, $C_1$ are:

$$w_0 = \frac{1}{t} \sum_{i=1}^{t} p_i$$  \hspace{1cm} (11)

$$w_1 = \frac{1}{L-t} \sum_{i=t+1}^{L} p_i$$  \hspace{1cm} (12)

The mean of $C_0$, $C_1$ gray value are:

$$\mu_0 = \frac{1}{t} \sum_{i=1}^{t} iP_i / w_0$$  \hspace{1cm} (13)

$$\mu_1 = \frac{1}{L-t} \sum_{i=t+1}^{L} p_i / w_1$$  \hspace{1cm} (14)

The image total mean level of the original image is:

$$\mu_T = \omega_0 \mu_0 + \omega_1 \mu_1$$  \hspace{1cm} (15)

The class variances are given by

$$\sigma_0^2 = \frac{1}{t} \sum_{i=1}^{t} (i - \mu_0)^2 p_i / \omega_0$$  \hspace{1cm} (16)

$$\sigma_1^2 = \frac{1}{L-t} \sum_{i=t+1}^{L} (i - \mu_1)^2 p_i / \omega_1$$  \hspace{1cm} (17)

The between-class variance is

$$\sigma_b^2 = \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2$$  \hspace{1cm} (18)

General, the $\sigma_b^2$ can be used as the criterion of optimal
segmentation threshold, if value of t makes the maximum $\sigma^2_{\text{B}}$ is the optimal threshold value of the request. That is, the more distance of two mean $\mu_0$ and $\mu_1$, the larger value of $\sigma^2_{\text{B}}$.

In a typical two peaks in the histogram, if there is a target and background at the same time, the histogram will be the presence of two peaks, so there must be an optimal threshold that can divide the most rational target and background. As shown in Figure 3, first obtain a histogram of the image cameraman, and then find the minimum gray value between two peaks is about 80. The OSTDU method obtains an approximate segmentation threshold that is 84. For the single peak or two peaks images the OSTDU method can obtain the optimal segmentation result, but for multi-peak images, OSTDU method is not good enough.

The between-class variance only reflects the difference between target and background two classes of image. In order to enhance the adaptability of the algorithm, another discriminate criterion measure of OSTDU is utilized as following:

$$\lambda = \frac{\sigma^2_{\text{B}}}{\sigma^2_{\text{W}}}$$  \hspace{1cm} (19)

where

$$\sigma^2_{\text{W}} = \omega_0 \sigma^2_{\text{T}} + \omega_1 \sigma^2_{\text{B}}$$ \hspace{1cm} (20)

Is the within-class variance, reflecting the difference between the pixels in the same class.

When the variance ratio $\lambda$ is maximum, indicating that the between-class variance reaches maximum and minimum within-class variance [15]. This means that the gray value difference between different classes of pixels is maximum and between similar pixel gray value is minimum, so the optimal segmentation threshold obtained when the ratio of $\lambda$ maximum. Segmentation results are more accurate.

Acquiring an image after ignition cycle using Equation (6)-(7)-(3)-(4)-(5), Then using (19) to calculate the variance ratio of the image. Comparing the variance ratio obtain with previous cycles. If a value greater than the former, the loop continues iteration, or stop iteration, then the number of iterations is the most optimal number of iterations and the threshold is the most optimal threshold.

### 2.4 Deblock PCNN

The global threshold method is to find a specific threshold to segment image into two regions which have similar grayscale. But it can fail when the background illumination is uneven or low contrast, and failing to reflect local distribution characteristics. Liu [16] introduced an OSTDU algorithm based on the idea of deblock, segmenting the image into several rectangles with the same size, and then applying OSTDU to select the optimal threshold for each block. This method achieved good segmentation results in the above case. We utilized deblock idea in simplified PCNN to compute optimal threshold in this paper [17].

The number of deblocks $\omega \times \omega$ have an effect on binarization performance and processing time. Large deblocks can represent more global information, and the result is more similar to global PCNN. However, it cannot reflect local distribution characteristics. Small sizes of deblocks can reflect local distribution characteristics ideally, but it may cause the fracture of image because of the arbitrary of the segmentation, and this may bring in more noise. In this paper we set $\omega = 2$ because it can not only obtain the image as much as possible information, but also reduce the inconsistent results may appear.

Boundary effects may appear at the edge areas between different blocks and affect the segmentation effect seriously. In order to obtain the change map, Zhong [18] used an overlap mechanism between the different blocks to overcome this problem, but it can’t eliminate boundary effects completely, gradient threshold mechanism is proposed and solve this problem prefect. In the paper, we use an overlap between the different blocks to overcome this problem the algorithm deals with a larger part of the image, then crops the central part and uses it as the result. The area inside the solid line is saved as the output result.

In Figure 4 the area inside the solid line is block to $2 \times 2$. The following steps are based on these blocks. As-
Assuming that the block size is $p \times q$, when dealing with the blocks by adopting the gradient threshold mechanism, the real processing part is $(p + m) \times (q + n)$ by proposed algorithm, then crops the central $(p - m) \times (q - n)$ area and uses it as the result, where $m$ and $n$ are boundary increment and greater than 0, here we choose $m = p/3$ and $n = q/3$. The following steps are based on these blocks. Assuming that the size of an image is $P \times Q$ and the block size is $p \times q$, when dealing with the blocks by adopting the deblocking mechanism, the real processing part is $(p + 2m) \times (q + 2n)$, where $m$ and $n$ are greater than 0. After this step, the original images at the different times, thus $t_1, t_2, t_3$ and $t_4$ represent the different thresholds of different blocks, from left to right and top to bottom respectively. Assuming $t_2$ greater than $t_1$, then the area $q \times 2m$ is buffer area deals with as follow:

$$T_{i,j} = T_{i+1,j} + (t_2 - t_1)/2m \quad \left\{ \begin{array}{l} i = p - m, p - m - 1, \ldots, p + m \\ i = 0, 1, \ldots, q \end{array} \right. \quad (21)$$

where $T_{i,j}$ indicates the pixel threshold of the image, $(i,j)$ indicates corresponding pixel coordinate. This method utilize the gradient threshold instead the mutation threshold as before, thereby eliminating the effects of the boundary.

Firstly, the original image is divided into image $2 \times 2$ by deblock mechanism, then for each piece by SPCNN algorithms iteration. The output obtained after each iteration calculate the image variance ratio using the formula (19), compared the variance ratio obtained with previous iteration. If the value is greater than the previous, the loop iterations continue, if the value less than or equal to the previous, then stop the iteration loop, the iteration number at this time is the best of iterations. The results of the four small blocks were combined to obtain a final result. Algorithm flow chart is shown in Figure 5.

![Figure 4. Deblocking mechanism.](image)

![Figure 5. Algorithm flow chart.](image)
3. Experiments and Analysis

In this section, we compared the proposed algorithm with OTSU method [14]. Improved PCNN model based on cross-entropy method [19] and adaptive threshold method [16], and those algorithms named as algorithm 1 to 3 respectively. Four standard gray images in MATLAB are used as experimental images. After experimenting time after time, the parameters of PCNN were selected as following: $\beta = 0.1; \alpha_0 = 0.1; W = [0.7 \ 0.7; 1 \ 0; 0.7 \ 0.7]$. All experiments were finished on the platform of MATLAB R2008a in a PC with Intel(R) Core (TM) I3-4150 CPU and 4.0 GB memories.

3.1 Subjective Analysis

The proposed adaptive binarization method process and the comparison results are shown in Figure 6. Images in the first row are the original gray images. The

![Figure 6](image.png)

**Figure 6.** Comparison of experiment results. Images in the row (1) are the original natural gray images. Row (2) are results of the deblock PCNN method proposed; Row (3) are algorithm 1 stand for OTSU method; Row (4) are algorithm 2 stand for Improved PCNN Model Based on Cross-entropy method; Row (5) are algorithm 3 stand for Adaptive Threshold method. Colum (a)(b)(c)(d) correspond to picture lena, mandi, rice and cameraman respectively.
second row are the output images of adaptive binarization method proposed. And from the third to the fifth row are stand for the results of algorithm from 1 to 3.

From the column (a) we can see the new method can detect more detailed information of the Lena image, such as the edge of the hat, the nose on its face. The results of algorithm 1 are similar to algorithm 2. Algorithm 3 get more detailed information at the edge of the hat but produced serious boundary effects.

As we see in the column (b), algorithm 1 and algorithm 2 get the error segment result and almost impossible to distinguish the characters of the woman since there are highlighted area in the background. Algorithm 3 get a better result than before due to the use of deblock idea, however there are obvious fructures in the middle of image. The algorithm proposed excels and more natural than others obviously, and we can easily distinguish the details of people’s faces and clothes.

Image rice is an uneven illumination in column (c), the brightness upper half is higher than the bottom half. Experimental results show that algorithm 1 and algorithm 2 cannot correct segment bottom rice in the picture. The segmentation image of algorithm 3 is better however a handful of rice the edge is unclear. The proposed algorithm segmentation results close to perfect where only one rice shadow still remains in the lower left corner.

In the last picture cameraman, the best image segmentation result is algorithm 1 that is OSTU method. The algorithm 2 and 3 has lost background details. The result of new algorithm proposed is not.

3.2 Objective Analysis

For most images, the Shannon entropy represents the information of the images. The more the Shannon entropy of the segmented image, the information obtained from the original image is greater, and the details of the segmentation image are also more abundant, and the overall segmentation effect is better.

Shannon entropy is

\[ H = -P_0 \log(P_0) - P_1 \log(P_1) \quad (22) \]

where \( P_0 \) and \( P_1 \) denote the output Y of segmented image is 0 and 1 probability. Only when \( P_0 \) and \( P_1 \) equal 1/2, the maximum value for the Shannon entropy is 1.

From Table 1 we can see the Shannon entropy of new algorithm proposed is better than other algorithm in most of the time, only with picture mandi is lower than algorithm 2.

The computing time is also the important performance evaluation of the algorithm. As we can see the running time of new algorithm proposed is not fine from Table 2. It is slower than other algorithms in most cases, and a few cases were slightly faster than algorithm 1.

4. Conclusions

This paper presents a new Adaptive Binarization Method Based on deblocking PCNN and Improved OTSU. The algorithm can automatically discover the best iteration times by applying the improved OTSU, and get the best segmentation results. Then deblock idea makes the algorithm adapt different image especially in uneven illumination or low contrast image. Meanwhile the algorithm of eliminating boundary effects is proposed to perfect the purpose of binarization optimization. Finally this new approach is compared with a classic binarization method and the experimental result shows that the new method is better in keeping with the original edge feature and available to more application. However the proposed algorithm achieves more satisfactory segmentation effect, the proposed algorithm is difficult to meet the real-time needs. Therefore in the next research, attempting to use intelligent optimization algorithm to improve the efficiency of segmentation, will be the most important research target.

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