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Parallel Image Processing with Autowaves: Segmentation and Edge Extraction

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Abstract

Biologically inspired image processing algorithms like pulse-coupled neural network find many applications in image preprocessing such as segmentation and edge extraction. The two highly parallel methods of edge extraction from gray-scale images using pulse-coupled neural network are presented. The approach of both methods is based on phenomenon of autowaves, whose properties enable efficient parallel image processing.

Introduction

The term *autowave* was first introduced by R.V. Khorlov in [1] to indicate "autonomous waves." Autowaves represent a particular class of nonlinear waves, which propagates in an active media at the expense of the energy stored in the medium. They are often encountered in many biological processes, e.g., propagation in nerve fibers. Autowaves posses some typical properties that are different from those of classical waves in conservative systems. The shape and amplitude of autowaves remain constant during propagation, they do not reflect from inhomogeneities, there is no interference, two colliding autowaves annihilate each other. At the same time both autowaves and classical waves share the property of diffraction. These properties, especially annihilation and diffraction, make autowaves very useful for image analysis [2]. The purpose of this paper is to show how pulse-coupled neural network (PCNN) producing autowaves can be used for image preprocessing such as edge extraction.

Image Processing Using Pulse-Coupled Neural Network

The PCNN is a biologically inspired algorithm for image preprocessing [4,5]. It is to a very large extent based on the Eckhorn model of the cat visual cortex [3]. The typical neuron of the PCNN is shown in Fig. 1. The equations for a single iteration of the PCNN are

$$F_{ij}[n]=e^{-\alpha_F}F_{ij}[n-1]+S_{ij}+V_F\sum_{kl} m_{ijkl}Y_{kl}[n-1]$$

$$L_{ij}[n]=e^{-\alpha_L}L_{ij}[n-1]+V_L\sum_{kl} w_{ijkl}Y_{kl}[n-1]$$

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

$$Y_{ij}[n]=\begin{cases}1, & if\ U_{ij}[n]>\Theta_{ij}[n]\\ 0, & otherwise\end{cases}$$

$$\Theta_{ij}[n]=e^{-\alpha_\Theta}\Theta_{ij}[n-1]+V_\Theta Y_{ij}[n]$$

where S is the input signal, F is the feed, L is the link, U is the internal activity, Y is the pulse output, Θ is the dynamic threshold. The weight matrices M, and W are local interconnections, β is the linking constant. All neurons' values are 0 at $n<0$.

The basic simplified structure of the pulse-coupled neural network processor for a 2-D input image is shown in Fig. 2. An input gray-scale image is composed of KxN pixels. This image can be represented as an array of KxN normalized intensity values. Then the array is fed in at the KxN inputs of PCNN. Since initially all neurons are set to 0, it results in activation of all the neurons at a first iteration. The threshold of each neuron, Θ, significantly increases when the neuron fires, then the threshold value decays. When the threshold falls below the respective neuron's potential, U, the neuron fires again, which raises the threshold. The process continues creating binary pulses for each neuron. While this process goes on, neurons encourage their neighbors to fire simultaneously that is supported through interconnections. The firing neurons begin to communicate with their nearest neighbors, which in turn communicate with their neighbors. The result is an autowave that expands from active regions. Thus, if a group of neurons is close to firing, then one neuron can trigger the group. As a result of linking between neurons, invoked neurons pulsing activity leads to the synchronization between groups of neurons corresponding to sub-regions of the image with similar properties and produces a temporal series of binary images. These phenomena of synchronization and autowaves support image segmentation and edge extraction.

Edge Extraction

In one of conventional methods of extracting an edge of an object existing in an image, an input image is binarized using a certain threshold value and a binarizing borderline is extracted as an edge. In another methods, an edge is extracted using a differential operator without performing binarization. However, real images are noisy and it will not often lead to the detection of acceptable edges. An algorithm that implements preliminary smoothing based on similarities of properties of adjunct pixels can improve edge extraction. Adjustable smoothing that is controlled by β, and binding of pixels based on their properties, such as intensities, are the inherent characteristics of the PCNN.

The idea is as follows. The gray-scale image (Fig.3) is processed by PCNN algorithm to produce binary image containing segmentation result (Fig.4). Then, edge extraction (Fig.5) from the binary image can be done two ways using property of travelling linking wave, L, exhibiting autowaves properties.

One is to take the obtained binary image (Fig.6), invert it (Fig.7) and present this inverted image to a PCNN. First output image from PCNN is an exact copy of the inverted image, and at the next iteration PCNN produces image (Fig.9) containing edges of the white blobs of the original binary image (Fig.6). These are edges we are looking for. The method is based on the property of linking wave propagation from currently active regions of the image to neighbors that were inactive before. As a result, pixels close to the active regions become activated producing the edges.

The other is to wait until a segmented region (Fig.6) has pulsed. Immediately after the pulse a linking wave is launched from the edge of the active region. In order to extract edge of the region, we have to perform logical "AND" of the front of linking wave (Fig. 8) and original image (Fig.6). The result of the operation is the edges of currently active regions (Fig.9). Referring to Fig. 10 and 11, details are shown highlighting the difference between the linking wave front and the correct edges. From their comparison the difference between the wave front and the edges of the active (white) regions is clearly visible. It is also obvious, that depending on our needs we can easily extract edges from the same wave front either for an active region or for its complement (black region). Another modification of this method of edge extraction is to check linking input value for each neuron of the region that has just pulsed. Comparison of this value against neuron's threshold, which depends on the interconnection weights, gives edge pixels since it will be always less than neuron's threshold for edge pixels.

Summary

We presented two methods how PCNN can be used to extract edges from images. In a coupled array of PCNN neurons linking travelling waves make possible edge detection by propagation through the image. All the methods are inherently parallel. Another opportunity for the use of PCNN travelling waves include detection of closed curves, e.g. holes, within extracted blobs and image thinning.

References

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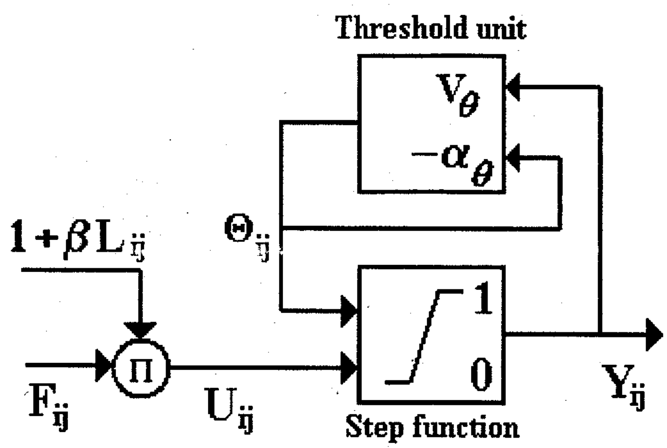

Fig.1. The basic PCNN neuron.

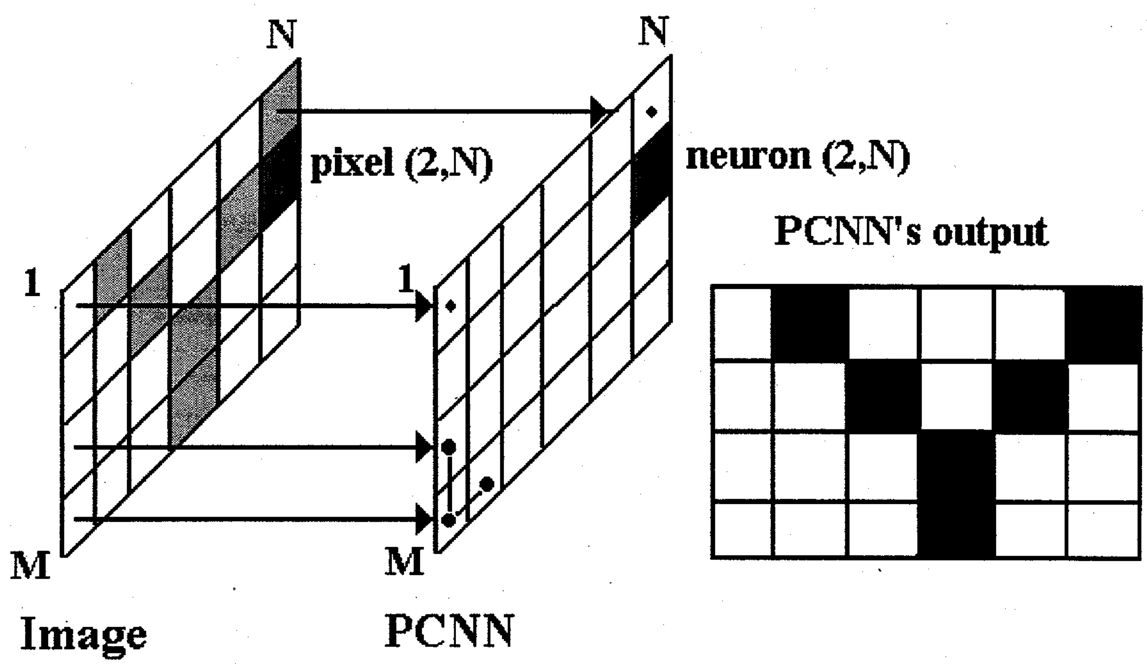

Fig. 2. Image processing using pulse-coupled neural network (PCNN).

Fig. 3. The original gray-level image.

Fig. 4. PCNN output.

Fig. 5. Detected edges.

Fig.6. Segmented image.

Fig. 7. Inverted segmented image.

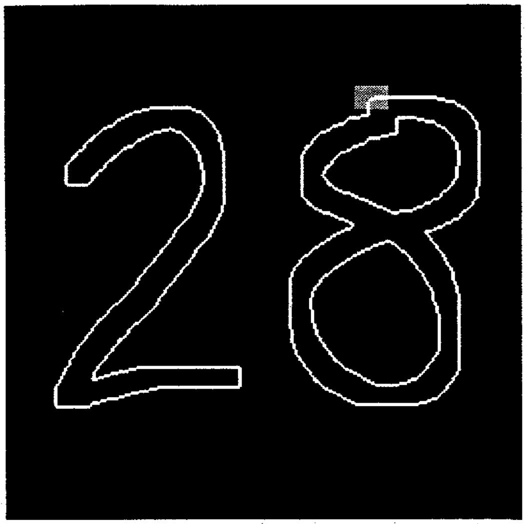

Fig. 8. Linking wave.

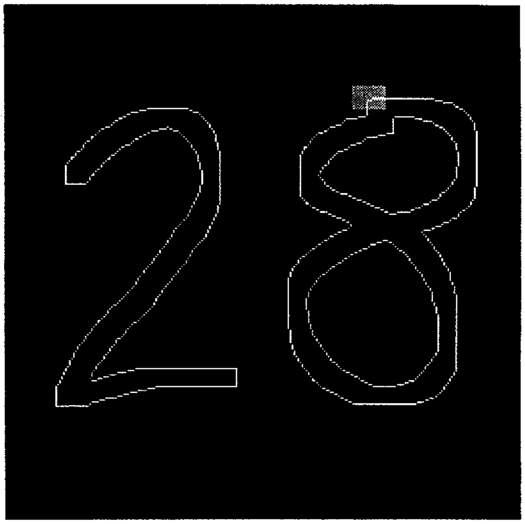

Fig. 9. Extracted edges.

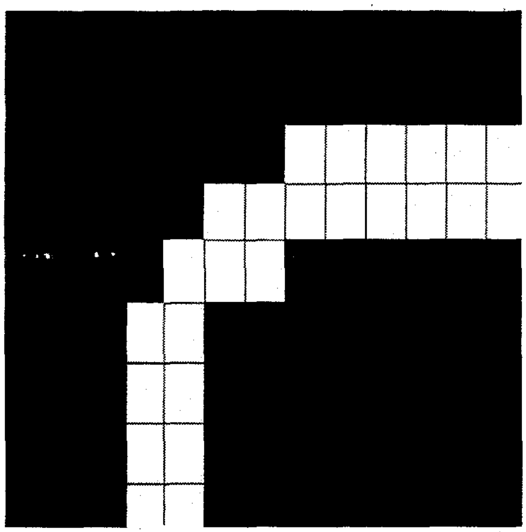

Fig. 10. Region, which is highlighted in Fig. 8.

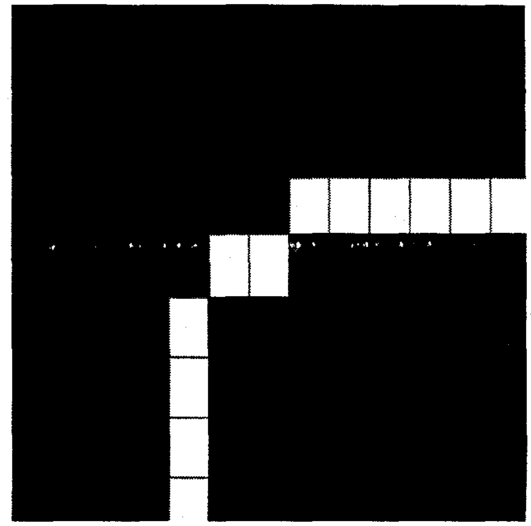

Fig. 11. Region, which is highlighted in Fig. 9.