Pulse-Coupled Neurons for Image Filtering

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Abstract

A pulse-coupled neuron (PCN) circuit is proposed. This circuit uses a positive feedback circuit with two capacitors. One corresponds to the sodium ion potential and the other corresponds to the potassium ion potential and can be easily implemented in CMOS technology. The circuit behaves like a real neuron, generating a pulse train in which the frequency increases with an increase of input excitation. The circuit threshold increases after pulse generation and then gradually returns to the initial level. These electronic neuron models are used for image processing. Images with sharp corners and those with narrow pathways as features were generated and corrupted with noise. Performance of mean and median filters was compared to that of the new PCN networks with several strengths of coupling. These tests of the capabilities of the new circuit demonstrate successful restoration of interesting images and their features.

I. Introduction

Artificial neural networks have been used in many applications. They are able to easily solve some problems which would be difficult using traditional techniques. These artificial neural networks are based on weighted sums and soft threshold (sigmoidal) action of neurons. Pulse-coupled neurons (PCNs) are quite similar to biological neurons, and PCNs can perform the same function as sigmoidal type neurons. In addition, they exhibit unique synchronization features. These additional features are the focus of this study. Interesting results for image smoothing, image segmentation and feature extraction have been obtained using pulsed-coupled neural networks [1][2]. In all these results the Eckhorn [3][4] and Optican [5] neural models using signal multiplication are implemented. In this paper it is demonstrated that similar results can be obtained with a much simper neuron model without using signal multiplication. The electronic implementation of the model is also presented. Many different models of pulse-coupled neural networks have been proposed. Most of those electronic models are based on voltage or current controlled oscillators. Other models use spike generators which include a step function generator with negative feedback [6-12]. A good review of electronic models of pulse-coupled neural networks is given in [13,14]. Most of the developed electronic and mathematical models assume unidirectional signal flow from input to output. This is how neuron interaction in one layer was modeled by Hopfield [15], leading to neural networks with very interesting features. In case of the pulse type neuron presented here, it is sufficient to just introduce coupling between inputs. This is a unique feature of the electronic neuron model presented.

Use of artificial neural networks in pattern recognition applications is discussed by Padgett, Werbos and Kohonen [16] and covered in more detail in Rogers and Kabrisky [17]. Digital picture processing techniques have evolved from those in Rosenfeld and Kak [18] to incorporate a variety of neural networks based techniques. For the implementation of any neural application, processing of unlabeled data using an unsupervised neural network is recommended. Valuable knowledge of the system to be modeled or manipulated can be gained from such exploratory analysis. In terms of image processing, use of a PCNN can be very effective when smoothing, segmentation and/or feature extraction are of interest. The effective performance of the new, simplified model presented in this paper is demonstrated below.

II. Electronic Model of Pulse-Coupled Neuron

The conceptual diagram of the pulse type electronic neural cell is presented in Fig.1, and results from the SPICE simulations are shown in Fig. 2. The cell in Fig. 1 uses the concept of two capacitors with two different time constants [20]. Capacitor C1 is used to integrate incoming signals, and the C2 is responsible for the refractory period and threshold change after the pulse is generated. If the potential on C1 exceeds the potential on C2 by the threshold value of the transistor M1, then transistor M1 will activate transistors M2 and M3, leading to the rapid increase of the potentials on both capacitors. This positive feedback through transistors M1, M2 and M3 will be

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quickly terminated once capacitor C2 is fully charged and all transistors are turned off. During the recovery process, capacitor C2 is slowly discharged by resistor R2 and the neuron cell does not respond to incoming excitations. The pulse type action of the circuit is shown in Fig. 2.

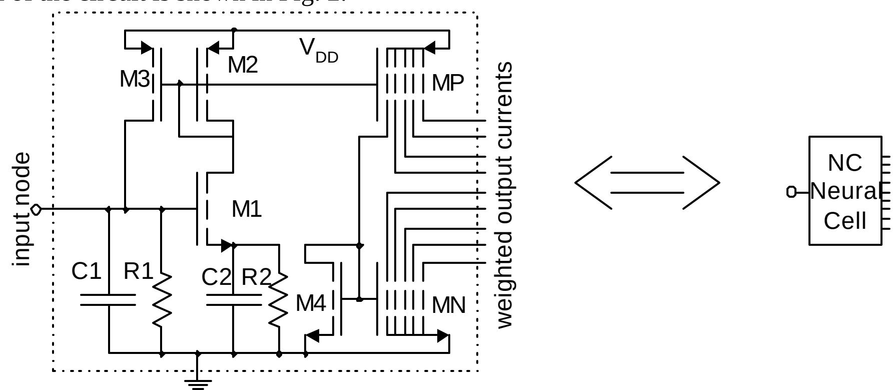


Figure 1. Circuit diagram of pulse-type neural cell: C1=C2=10pF; R1=50kΩ; R2=1MΩ; $W_1/L_1=3$; $W_2/L_2=3$; $W_3/L_3=3$; $V_{DD}=10V$; and input current in the range of 0.02 to 0.1mA.

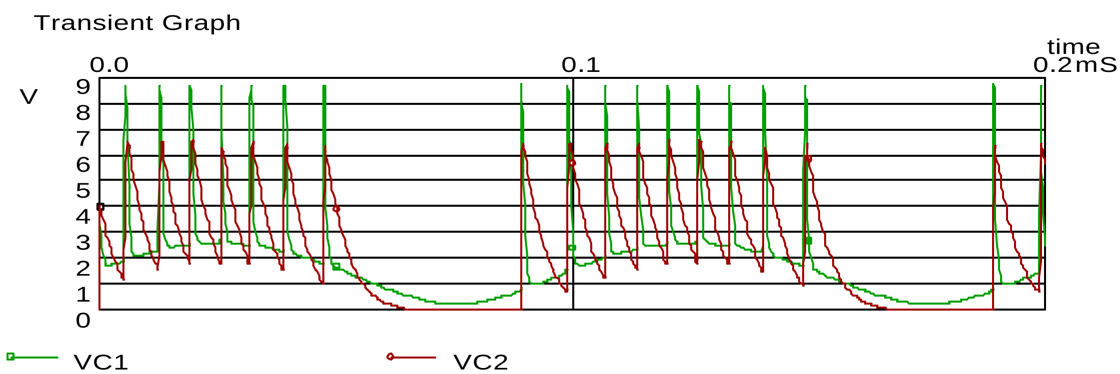


Fig. 2. Voltages on C1 and C2 of the circuit from Fig. 1. A current source with a shifted sinusoidal shape is connected to the input.

If neurons of this type are coupled together then firing time synchronization occurs. Fig. 3 shows that two coupled neurons with different input excitations X and Y often fire together. This synchronization effect, which is not observed in other artificial neuron models [19], can be used for image smoothing and filtering. For image processing each neuron input is coupled with the inputs of eight neighboring neurons.

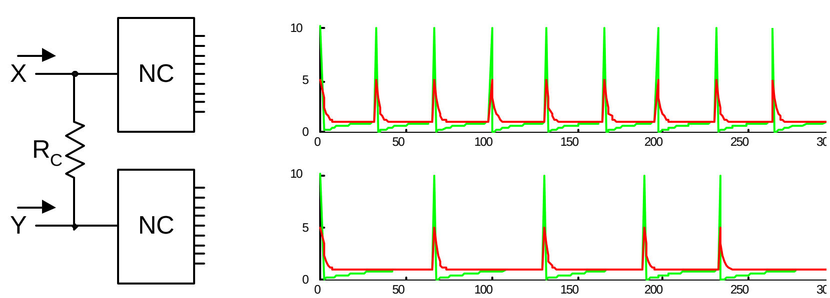
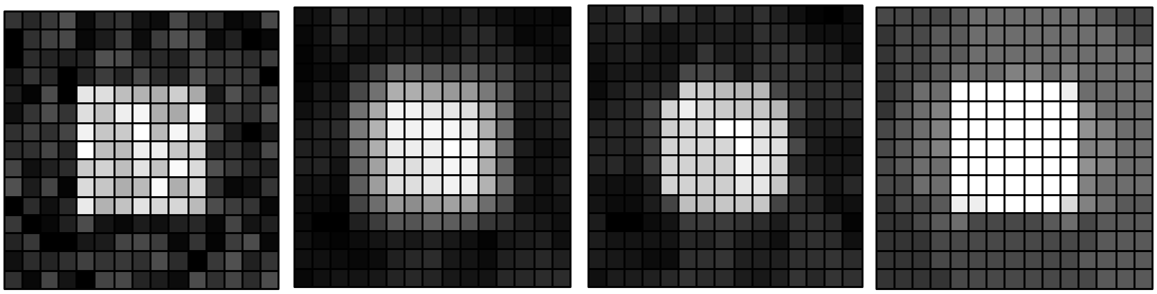


Fig. 3. Interaction of two neurons with coupled inputs: X=0.06mA; Y=0.05mA; R_C=5MΩ.

III. Image filtering

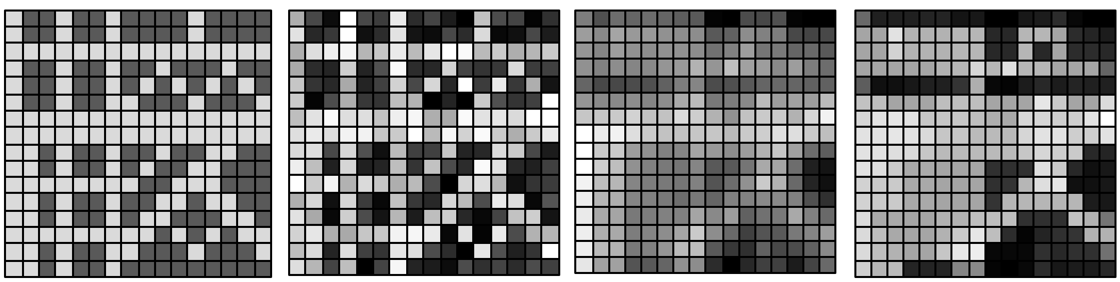
Image smoothing, image segmentation and feature extraction are known capabilities of pulse-coded neural networks. This paper presents some examples illustrating the successful performance of a simplified PCNN when presented with noisy images. First, a white square within a gray square is corrupted with uniform noise whose magnitude ranges within 50% of the difference of the two pattern intensities (Fig. 4(a)).



(a) (b) (c) (d)

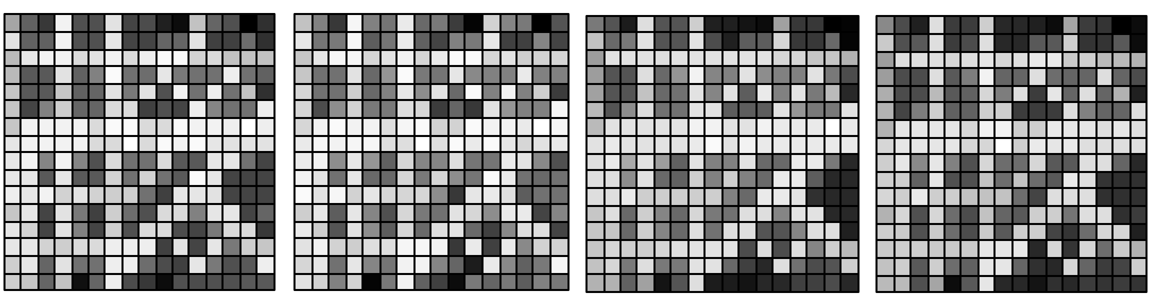
Fig. 4 Comparison of image smoothing for square pattern: (a) noisy image; (b) neighborhood averaging with one iteration; (c) median filtering with one iteration; (d) result of PCNN filtering with 5MΩ coupling.

Traditional mean filtering and median filtering are tested [18], and the predictably poor results are shown in Figs. 4(b) and 4(c). Results following processing with the new PCNN using coupling strengths of 5MΩ are illustrated in Figure 4(d). The restoration of segmentation in the squares image is very good. Special simulation software in MATLAB was developed for these experiments.



(a) (b) (c) (d)

Fig. 5. Filtering of a test pattern with detailed images using traditional smoothing techniques: (a) original image; (b) noisy image; (c) neighborhood averaging; (d) median filtering



(a) (b) (c) (d)

Fig. 6. Filtering of the test pattern of Figure 5 using PCNN filtering with (a) 15MΩ coupling; (b) 10MΩ coupling; (c) 7.5MΩ coupling; (d) 5MΩ coupling;

In order to further test the new PCNN on small pathways and curving features, another image was generated and corrupted with the same uniform noise as in the previous experiment. Mean and median filtering predictably performed poorly, but the new PCNN restored the features in the original image. Figures 5(a) and 5(b) illustrate the original and noisy image. The effects of mean and median filtering are shown in Fig. 5(c) and 5(d). The improved performance of the new PCNN is show in Fig. 6. Several coupling strengths are demonstrated.

IV. Conclusion

The new, biologically motivated pulse-coupled neuron circuit proposed in this paper can be easily implemented in CMOS technology. It uses a simple circuit and represents a significant reduction in complexity compared to other techniques discussed. The results indicate the satisfactory performance of the new PCNN on demanding images. Its performance on noisy images with sharp corners or narrow, winding patterns justifies further application of this concept.

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