

Spatial to Temporal Conversion of Images Using A Pulse-Coupled Neural Network

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Abstract A new electronic model of Pulse-Coupled Neural Network is proposed. This model exhibits very interesting features such as: segmentation, feature extraction, orientation independence and noise tolerance. Segmentation means that the output pattern depends strongly on the spatial location of the pixels in respect to one other. Feature extraction means that if the input image includes several patterns, then it is very likely the temporal output is a superposition of features in that image. The output temporal pattern is independent of the orientation of image or orientation of fragments of the image. With relatively low noise (less than 10%) the output pattern is virtually independent of the noise.

1. Introduction

The research in the area of Pulse-Coded Neural Networks and their abilities in the field of image manipulation inspire the proposed network. Some features of Pulse-Coded Neural Networks (PCNN) for optical image applications are image smoothing, segmentation, feature extraction and recognition [1]-[7]. Combining the Synchronization Effect with the pulse neuron introduces many new features into the area of neural network image techniques [4][9][10]. The addition of the Synchronization Effect introduces the idea of coupling the pulse-coded neurons to create a Pulse-Coupled Neural Network. The proposed network offers some powerful features: the ability to recognize an image or part of an image without regard to its orientation, inherent noise tolerance and a form of data compression [11][12]. The PCNN concept is also very simple and cost effective when considering its design and hardware requirements [13]-[16]. The purpose of this work is to use pulse behavior of neurons for image processing. The paper presents the ability of PCNNs to convert an image from its spatial representation to a temporal representation.

The most basic component of the human's nervous system is a neuron. In the human body, there exists on the order of 11 billion neurons. The method by which signals are propagated through the nervous system is via encoded pulse streams of small electrical currents. When the internal potential of the Axon Hillock exceeds the synaptic threshold, an electrical pulse is sent to the next neuron.

The time between pulses is called the *refractory period*. What can be considered the entry point of a neural impulse is the *dendrite*. Next, the body of the neuron feeds an electrical pulse from the *axon* through the *synaptic gap* and into another neuron.

In a biological neuron, axons may be long compared to the whole neuron. The axons are coated in a *myelin sheath*, which acts as an insulator for the neuron. There

exist open spots along the sheath where the sodium and the potassium ions may pass freely. These spots are referred to as the *nodes of Ranvier*, which allow small amounts of sodium and potassium ions to be exchanged.

The electronic model of a neuron [13]-[16] operating in pulse mode is shown in Fig. 1. The amount of energy generated in single pulse depends on the value of capacitance C_1 , while the refractory period is set by the $C_2 \cdot R_2$ time constant.

Input positive and negative currents are integrated on capacitance C_1 . The neuron generates a pulse once the input voltage on the capacitor exceeds the activation threshold. Various hardware models of the pulse-coded neuron were developed, and all have properties similar to the concept diagram shown in Fig. 1. A unique feature of the neuron in Fig. 1 is that the input and the output are on the same node.

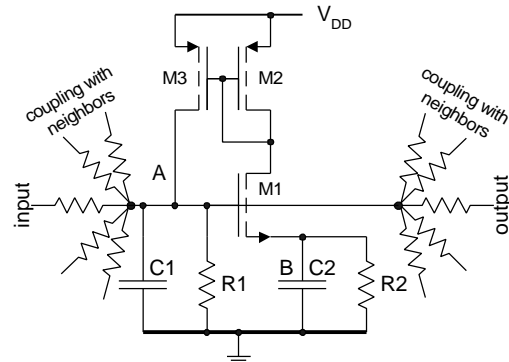


Fig. 1. Electronic Model of Neuron

The input-output node A integrates electrical current on C_1 , which eventually reaches the activation threshold. The threshold level is determined by the V_{TH} of transistor M_1 and transient voltage on capacitance C_2 (node B). Once the threshold is reached, all transistors M_1 , M_2 and M_3 conduct current charging both C_1 and C_2 . Once C_1 and C_2 are fully charged, V_{GS} of M_1 falls below the threshold level and transistors M_1 , M_2 and M_3 revert to the cutoff region again. The brief interval when the transistors are in their active modes of operation causes a pulse at the output. Next, C_1 and C_2 discharge at the rate of their respective time constants. During the refractory period, threshold values decrease with time starting with a very high value immediately following the pulse. This eventually decreases to a steady state value. The refractory period depends on time constant of C_2 . During the refractory period threshold is given by a formula:

$$V_{TH}(t) = V_{th1} + V_{C2}(t) - V_{C1}(t) \quad (1)$$

Pulse coupled neurons have several properties which distinguish them from more common neurons used in artificial neural networks such as frequency modulation and synchronization effect. When these neurons are used for image processing it leads to series interesting effects such as: effects of segmentation, feature extraction, orientation independence, and noise elimination.

2. Frequency modulation

The magnitude of the input current determines how soon or late the neuron will fire. This feature of mapping the input magnitude to a time domain pulse is similar to the relation between the eye of a human and the human visual cortex. Light acts as a stimulus to the neurons inside the eye, where the magnitude of the stimulus is dependent on the intensity of the light. The stimulus of the light regulates the frequency of the pulse stream that travels to the visual cortex in the brain. Fig 2 shows how a pulse neuron responds to the input stimulation of a sine wave.

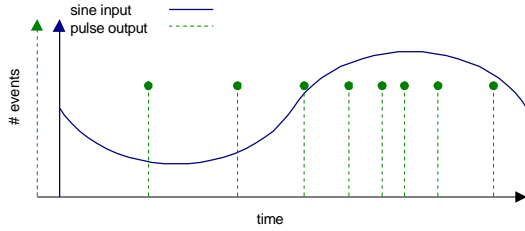


Fig. 2. Response of pulse neuron due to sine input stimulation.

3. Synchronization effect

When neighboring neurons are coupled together as shown in Fig. 3, the synchronization effect occurs. It means that firing neuron may trigger a similar action in neighboring neurons if their dc excitation is already close to a threshold. By adjusting the coupling strength, the radius of influence that each output has on its neighbors may be increased or decreased.

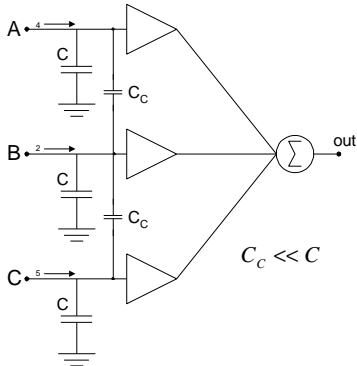


Fig. 3. Coupling between neighboring neurons

In image processing applications the light intensity of a given pixel stimulate the associated neuron. The time response is different depending on the coupling strength between neighboring neurons as shown in Fig. 4. Strong coupling neurons have a tendency to fire together for similar stimulus as shown in Fig. 4(b)

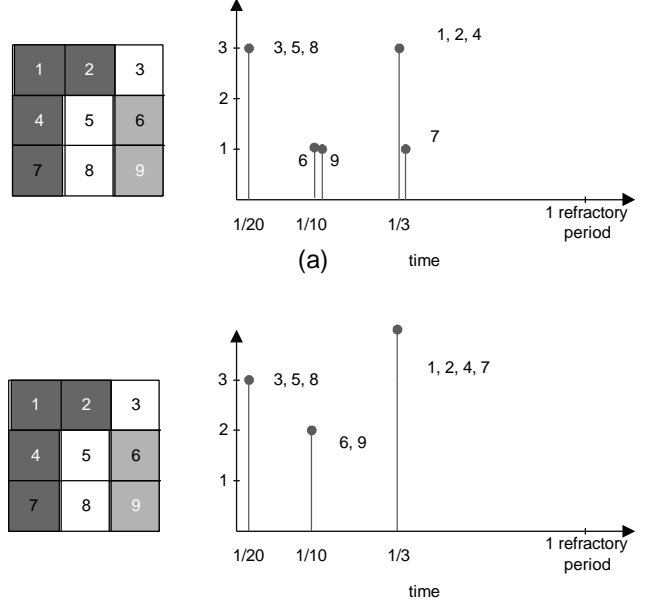


Fig. 4. Synchronization effect: (a) with weak coupling and (b) with strong coupling.

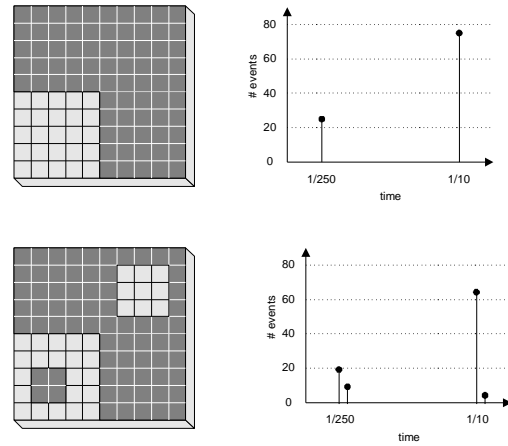


Fig. 5. Pulse responses for identical number of pixels with the same intensity but with different shapes.

Other example is shown in Fig. 5 (a) and (b). The intensity of gray colors in both figures are identical and number of pixels with the same intensity are identical too. One may observe in Fig. 5 that very different pulse responses depend on the shape of images. The quantities of similar magnitude inputs that are grouped together and fire synchronously are represented along the y-axis as *events*. For instance, assume an input image that is one quarter light gray (input magnitude of 250), and three quarters

dark gray (input magnitude of 10). Very large circuits were simulated with SPICE programs where temporal patterns were recorded. Output signals were recorded only for 256 discrete times.

4. Effects of segmentation

Fig. 6. Shows three pictures of a globe. The first picture is undistorted, but the second and third are modified such that all the original pixels have been retained, but reorganized. The PCNN differs from a histogram in respect to the pulses and how they represent groupings within the input image. All patterns have the same histogram; the output of a PCNN is quite different.

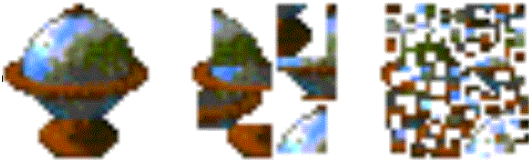


Fig. 6. Input image of globe

The PCNN outputs for the globes if Fig. 6 are shown in Fig. 7 through Fig. 9. The outputs are apparently very different. This is of course attributed to the rearrangement of the pixels within each image. Note significant difference in output patterns between original image and the distorted ones.

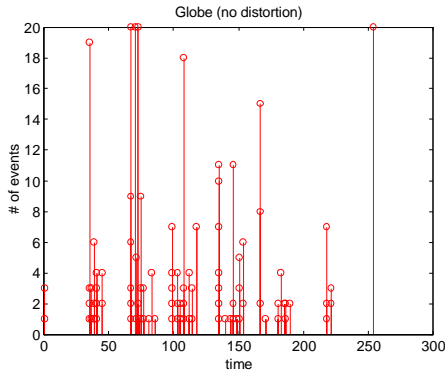


Fig. 7. PCNN output of globe with no segmentation

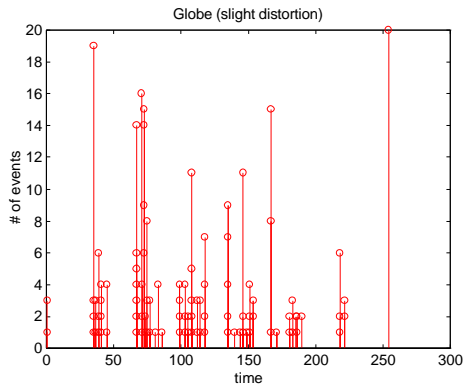


Fig. 8. PCNN output of globe with slight segmentation

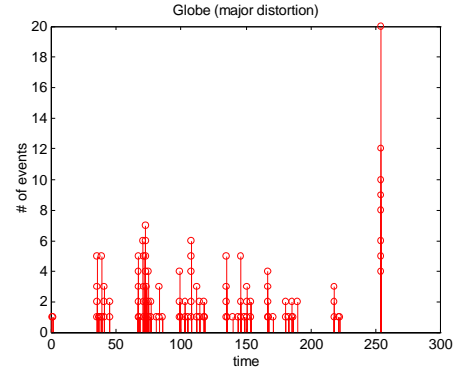


Fig. 9. PCNN output of globe with major segmentation

5. Orientation Independence

The ability to map spatial input to temporal output allows PCNNs to disregard the orientation of the applied input image. Fig. 10 shows image of butterfly with different orientations. It turns out that the output patterns are identical for all images shown in Fig. 10. Example of such output pattern is shown in Fig. 11. One may observe that even though the orientation of the butterfly changes, the input groups (i.e. the antennas or the wings) remain the same when considering relative positions.



Fig. 10. Butterfly images with different orientations

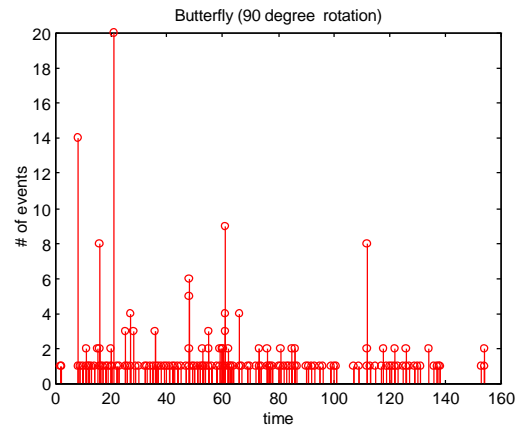


Fig. 11. Output pattern for butterfly image with 90 degree rotation. Patterns for 0 degrees, 180 degrees, and 270 degrees are identical!

6. Feature extraction

Another capability of the PCNN is feature extraction, or pattern subset recognition. Feature extraction allows the output spectrum of an image to be recognized as a subset of another image.



Fig. 12. Fire (left) and flame only (right) input Images

The two images shown in Fig. 12 have apparent similarities and the output patterns shown in Fig. 13 and 14 reflect this. There is a significant overlap of Fig. 14 in Fig. 13 this is what makes feature extraction possible.

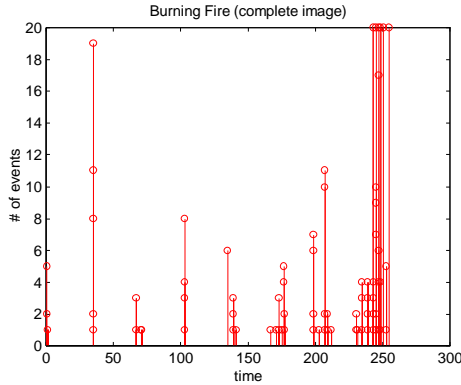


Fig. 13. PCNN output of complete image of fire

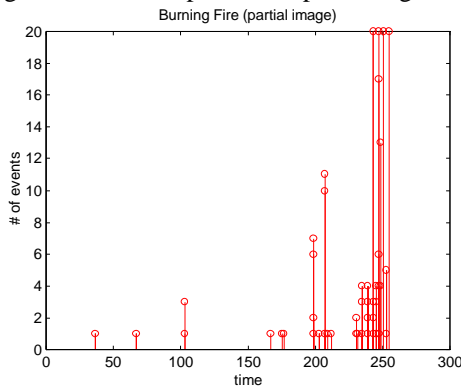


Fig. 14. PCNN output of flame only

By applying multiple PCNNs to one image, multiple images may be recognized within one input image. This occurs since image recognition for a PCNN is not only rotation independent, but also independent of physical location at the input

What may be difficult for a PCNN to recognize properly is a feature that is surrounded by similar inputs. An example of this may be when trying to identify a green

chameleon on a green leaf. If the edges of the feature synchronize with the surroundings, then feature extraction is much more difficult.

7. Noise elimination

Images shown in Fig. 15 are without noise and with 10% of noise. The output patterns for these two cases are shown in Fig. 16 and Fig. 17 respectively.



Fig. 15. Flower without noise and with noise.

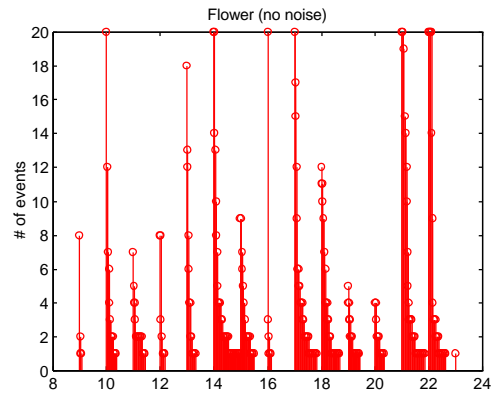


Fig. 16. Output pattern for the flower without noise

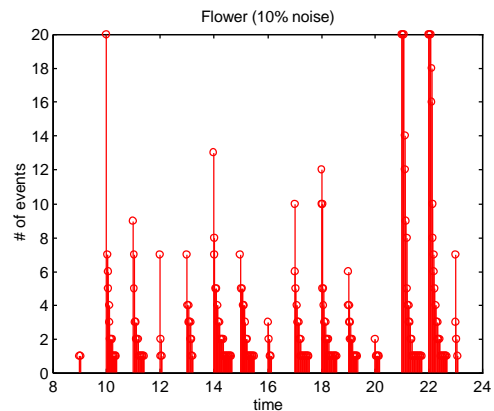


Fig. 17. Output pattern for the flower with noise

8. Conclusion

The proposed method of image recognition works extremely well in all of its simplicity. The PCNN has many features that resemble the human visual system. This thesis explores an area of pulse coded neural network that is original in its approach. The resemblance to the

human eye is quite spectacular, and all the features that exhibited by implementing the synchronization are quite impressive.

Image recognition using a pulse coupled neural network involves translating a spatial domain input to a time domain output. The input is applied as a magnitude scaled input, like a visual input to a human eye. The output is a series of pulses that represent the magnitude of the input as well as the size of the grouping of like-magnitude inputs. A pulse-coded neuron represents a biological neuron in the manner in which it reacts to stimulation. By coupling pulse-coded neurons, small amounts of current may cause a neuron that is near to firing to synchronize with its coupled firing neighbor. Features other than image recognition include orientation independence at the input, image data reduction, noise tolerance and scaled, and sub-image feature recognition.

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