Perfect Image Segmentation Using Pulse Coupled Neural Networks

G. Kuntimad and H. S. Ranganath

***Abstract*—This paper describes a method for segmenting digital images using pulse coupled neural networks (PCNN's). The pulse coupled neuron (PCN) model used in PCNN is a modification of Eckhorn's cortical neuron model. A single layered laterally connected PCNN is capable of perfectly segmenting digital images even when there is a considerable overlap in the intensity ranges of adjacent regions. Conditions for perfect image segmentation are derived. It is also shown that addition of an inhibition receptive field to the neuron model increases the possibility of perfect segmentation. The inhibition input reduces the overlap of intensity ranges of adjacent regions by effectively compressing the intensity range of each region.**

***Index Terms*— Image segmentation, inhibition signal, perfect segmentation, pulse coupled neural network, pulse coupled neuron.**

I. Introduction

ECKHORN'S neuron is a result of the research effort that focused on the development of artificial neuron models that are capable of emulating the behavior of cortical neurons observed in the visual cortices of cats [1]. Eckhorn's neural networks, through stimulus forced and stimulus induced synchronization, are able to bridge temporal gaps and minor magnitude variations in the input data and cause the neurons with similar inputs to pulse together. Therefore, if a digital image is applied as input data to a two-dimensional Eckhorn's neural network, the network will group image pixels based on spatial proximity and brightness similarity. During grouping, the network will bridge small spatial gaps and minor local intensity variations. This is an extremely desirable property for window-based image processing applications.

But, Eckhorn's neuron model has certain properties that diminish the neuron's utility in image processing applications. Therefore, we have modified Eckhorn's neuron model such that the resulting model becomes more suitable for image processing applications than the original model. We refer to the modified model as the *pulse coupled neuron* (PCN). In the remainder of the paper, when there is no ambiguity, a pulse coupled neuron is simply referred to as a *neuron*. Section II describes the major differences between Eckhorn's neuron model and the pulse coupled neuron model.

The image segmentation approach using *pulse coupled neural network* (PCNN) is described in Section III. We have shown that a PCNN is capable of perfectly segmenting an image even when the intensity ranges of adjacent regions overlap, if certain conditions are satisfied. These conditions are derived in Section IV. Note that when an image is perfectly segmented, each pixel is correctly assigned to the region it belongs to.

If an image does not satisfy the perfect segmentation conditions initially, it may be possible to achieve perfect or improved segmentation by smoothing the image prior to segmentation or by incorporating an inhibition receptive field in the PCN model. These enhancements are presented in Section V. Finally, conclusions and recommendations for future research are given in Section VI.

II. PCN and PCNN for Image Processing Applications

The study of Eckhorn's neuron model from the image processing perspective reveals that the model has some practical limitations. These limitations are listed below.

- *The mathematical analysis of the operation of Eckhorn's neural network is a difficult task.* Due to the nonlinear dendrite tree, unconstrained threshold signal and massive interconnection, it is difficult to predict the pulsing behavior of neurons in the network. The analysis and interpretation of the results are equally difficult.
- *The grouping of image pixels based on spatial proximity and brightness similarity is ambiguous.* If a static digital image is applied to the network, neurons with similar inputs that are close to one another are expected to pulse together identifying a cluster of similar pixels in the image. However, in Eckhorn's neural network, if the neurons are allowed to pulse freely, the pulsing pattern is chaotic. Each neuron pulses with a different group as time progresses. In image processing applications, the ambiguous grouping of pixels is undesirable.
- *The determination of appropriate values for the network parameters is difficult.* In Eckhorn's neuron model, each leaky integrator has three parameters—the amplification factor, decay time constant and weighting factor. The determination of values for all the parameters to effectively control the network operation is not a trivial task.

Therefore, the pulse coupled neuron model was developed to overcome the shortcomings of Eckhorn's neuron model for image processing applications [2]. The major differences between the two models are described below:

1) *Feeding receptive field:* The feeding receptive field of the PCN N_k receives an external input $F_k(t)$ but does not receive inputs from other neurons (Fig. 1). When the input to the PCNN is a static image the external input to a PCN is the intensity of the corresponding pixel. The inclusion of a leaky integrator in the path of a static

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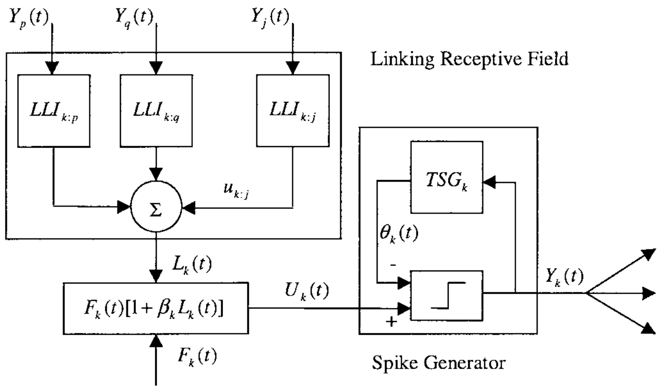


Fig. 1. Pulse coupled neuron.

external input offers no advantages. Therefore, the net feeding input to the neuron is the external input $F_k(t)$.

2) *Internal activity:* The linking input modulates the feeding input in a nonlinear fashion to yield the internal activity of the neuron

$$U_k(t) = F_k(t)(1 + \beta_k L_k(t)) \tag{1}$$

where β_k, a positive constant, is referred to as the linking coefficient of the neuron N_k. The linking coefficient provides a simple and effective means of controlling the influence of the net linking input on the neuron's internal activity. The concept of linking coefficient is adopted from Johnson's work [3].

3) *Spike generator:* The spike generator consists of an impulse function generator and a threshold signal generator. The threshold signal generator, denoted by *TSG*$_k$, outputs the threshold signal $\theta_k(t)$. The major difference between Eckhorn's neuron and the pulse coupled neuron is in the operation of the threshold signal generator. Every time the pulse couple neuron pulses, its threshold signal generator is charged to a predetermined value V_k, *regardless of the value of the threshold signal just prior to pulsing of the neuron*. In other words, when N_k pulses $\theta_k(t)$ is not increased by V_k but set to V_k. It is assumed that the value of V_k is greater than any possible value for the internal activity of the neuron. If two successive firings of the neuron N_k are assumed to be at t_1 and t_2, the operation of the threshold signal generator is described by the following equation:

$$\theta_k(t) = \begin{cases} V_k, & t = t_1 \\ V_k \exp(-(t - t_1)/\tau_k), & t_1 < t < t_2 \\ V_k, & t = t_2 \end{cases} \tag{2}$$

where τ_k is the decay time constant of *TSG*$_k$.

A. Pulse Coupled Neural Network—PCNN

The pulse coupled neural network used for image processing applications is a single layer two-dimensional array of laterally linked pulse coupled neurons. The number of neurons in the network is equal to the number of pixels in the input image. There exists a one-to-one correspondence between the image pixels and network neurons (i.e., each pixel is associated with a unique neuron and vice versa). For example the neuron $N_{i,j}$ is associated with the pixel $P_{i,j}$. The key features of the PCNN are summarized below:

- The external input to $N_{i,j}$ is $X_{i,j}$, the intensity of the pixel $P_{i,j}$. Therefore, $F_{i,j}(t)$ is equal to $X_{i,j}$.
- All linking leaky integrators are identical to one another. The amplification factor and decay time constant of every linking leaky integrator in the network are V_l and τ_l, respectively.
- Each neuron receives linking inputs from its neighbors that are within a distance of r units from it. The distance between the neurons $N_{i,j}$ and $N_{p,q}$ is defined as the Euclidean distance between the corresponding pixels $P_{i,j}$ and $P_{p,q}$. The weighting factor for a linking input from a neuron that is at a distance of d units is $1/d^2$. Therefore, the weighting factor for the linking input from $N_{p,q}$ to $N_{i,j}$ is $u_{i,j:p,q} = 1/((i-p)^2 + (j-q)^2)$. The linking neighborhoods of $N_{i,j}$ for $r = 1.0$ and $r = 1.5$ are shown in Fig. 2. When $r = 1.0$, the neuron receives linking inputs from the four neighbors (Fig. 2(a)). Similarly, when $r = 1.5$, $N_{i,j}$ receives linking inputs from the eight neighbors, as shown in Fig. 2(b).
- The value of the linking coefficient is independent of the neuron (i.e., $\beta_{i,j} = \beta_{p,q} = \beta$, for all i, j and p, q).
- The threshold signal generators of all neurons in the PCNN are identical to one another. In other words, $V_{i,j} = V_{p,q} = V_\theta$ and $\tau_{i,j} = \tau_{p,q} = \tau_\theta$ for all i, j and p, q.

The terms *natural period* and *capture range* of a neuron are defined to better analyze and understand the behavior of the PCNN. These terms are described next.

Consider an unlinked neuron with constant feeding input C. A neuron that pulses due the influence of the feeding input alone is said to be pulsing naturally. It can be shown that a naturally pulsing neuron pulses periodically with time period $T(C)$ which is computed as $\tau_\theta \ln(V_\theta/C)$, where τ_θ and V_θ are the decay time constant and the TSG reset value of the neuron, respectively. The time period $T(C)$ is referred to as the *natural period* of the neuron (with constant feeding input C).

Now, consider two mutually linked neurons $N_{i,j}$ and $N_{p,q}$. Assume that $X_{i,j}$ is greater than $X_{p,q}$ and V_θ is greater than the maximum possible value of the internal activity of either of the two neurons. At $t = 0$, the neurons $N_{i,j}$ and $N_{p,q}$ are reset. When a neuron is reset its threshold value is forced to zero and the feeding input is applied, causing the neuron to pulse. Thus, both the neurons pulse together at $t = 0$. During the first pulsing event at $t = T(X_{i,j})$ the neuron $N_{i,j}$ pulses naturally and transmits the linking input to $N_{p,q}$. It is obvious that the neuron $N_{i,j}$ captures $N_{p,q}$ if

$$X_{p,q}(1 + \beta L_{p,q}(t)) \geq X_{i,j}. \tag{3}$$

The intensity range $(X_{i,j}/(1 + \beta L_{p,q}(t)), X_{i,j})$ is referred to as the *capture range* of $N_{p,q}$ with respect to $N_{i,j}$. If $X_{p,q}$ lies within the capture range, $N_{p,q}$ will be captured by $N_{i,j}$. Note that whether $N_{p,q}$ is captured by $N_{i,j}$ or not depends on the values of the intensity values, linking coefficient β, weighting factor $u_{p,q:i,j}$ and the time of arrival of the linking input.

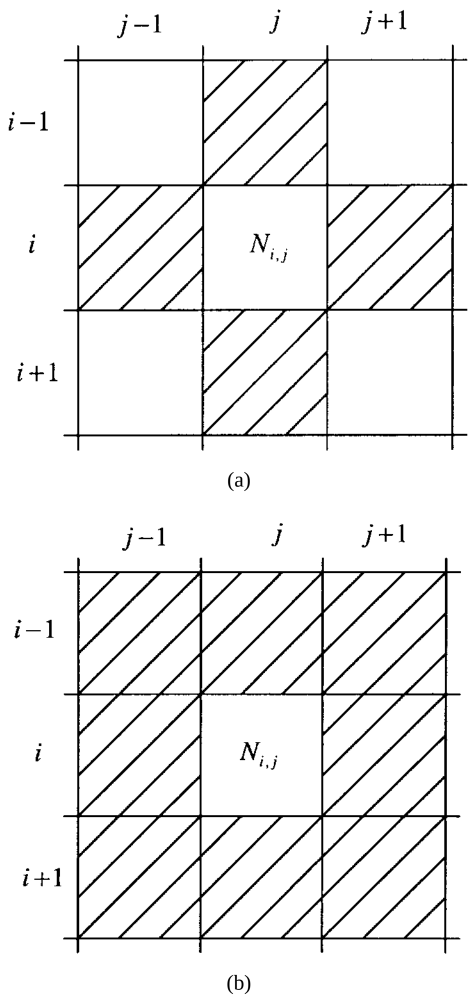


Fig. 2. Linking neighborhood of a pulse coupled neuron. (a) Linking radius $r = 1.0$. (b) Linking radius $r = 1.5$.

The concept of the capture range may be extended to a group of mutually connected neurons as follows. All the neurons pulse together at $t = 0$, due to reset. Assume that a set of neurons pulse naturally at time t_1. This set may capture other neurons which are linked to the set. Each neuron which receives a linking input that is high enough to increase the neuron's internal activity above the threshold signal is captured by the pulsing neurons. Therefore, the capture range of $N_{i,j}$ with respect to the group of pulsing neurons is $(\theta_{i,j}(t_1)/(1+\beta L_{i,j}(t_1)), \theta_{i,j}(t_1))$ where $L_{i,j}(t_1)$ is the total linking input from all the neurons pulsing at time t_1. If $X_{i,j}$ lies within the capture range, $N_{i,j}$ pulses at t_1 and sends linking inputs to all neurons that are linked to $N_{i,j}$. The pulsing of $N_{i,j}$ and the transmission of the linking inputs to other neurons are assumed to be instantaneous. Since the linking inputs decay fast, if a group of neurons that pulse at t_1 fail to capture $N_{i,j}$ at t_1, the group will not be able to capture $N_{i,j}$ at a later time due to the current pulsing.

1) Selection of V_θ: Let $X_{\min}$ and $X_{\max}$ be the minimum and maximum values of the feeding inputs (or intensities) to the network. All neurons in the network pulse at $t = 0$. Later, the neurons for which the feeding input is equal to $X_{\max}$ pulse naturally at $t = T(X_{\max})$. Those neurons whose feeding inputs lie within their respective capture ranges are also forced to pulse at $t = T(X_{\max})$. This process of natural pulsing and capture continues indefinitely. By the time $t = T(X_{\min})$, all neurons in the network pulse at least once. By the proper selection of the value of V_θ, each neuron can be restricted to pulse exactly once during the interval $[0, T(X_{\min})]$. If the network is reset (i.e., all threshold signals are forced to zero) at $t = T(X_{\min})$, the network will repeat the pulsing pattern of the interval $[0, T(X_{\min})]$ in the interval $[T(X_{\min}), 2T(X_{\min})]$. Thus, if the network is periodically reset at times $t = nT(X_{\min})$, where n is a positive integer, the network will produce periodic output. The time between two successive resettings of the network is referred to as a *pulsing cycle*. The determination of the minimum value for V_θ which guarantees that each neuron pulses exactly once during a pulsing cycle is given below.

Consider the sequence of events that takes place during the first pulsing cycle.

- All the neurons pulse at $t = 0$. The outputs of all the threshold signal generators are charged to V_θ and start to decay exponentially.
- The neurons corresponding to the highest intensity $(X_{\max})$ pixels pulse first naturally at $t = T(X_{\max})$ and capture all neurons whose feeding inputs are within their respective capture ranges.
- The neurons corresponding to the lowest intensity $(X_{\min})$ pixels which have not pulsed at an earlier time due to the capture phenomenon pulse naturally at $T(X_{\min})$.

At $t = T(X_{\min})$, the value of the threshold signal of a neuron $N_{i,j}$ which pulsed at $t = T(X_{\max})$ is

$$\theta_{i,j}(T(X_{\min})) = V_\theta \exp(-(T(X_{\min}) - T(X_{\max}))/\tau_\theta). \quad (4)$$

If V_θ is selected so that $\theta_{i,j}(T(X_{\min}))$ is greater than the maximum possible value of $U_{i,j}(T(X_{\min}))$ then each neuron is guaranteed to pulse exactly once during a pulsing cycle. Therefore,

$$V_\theta \exp(-(T(X_{\min}) - T(X_{\max}))/\tau_\theta) > U_{i,j}(T(X_{\min})). \quad (5)$$

Since $T(C) = \tau_\theta \ln(V_\theta/C)$, Inequality (5) reduces to

$$V_\theta(X_{\min}/X_{\max}) > X_{\max}(1 + \beta L_{i,j}(T(X_{\min}))). \quad (6)$$

The value of the linking input $L_{i,j}(T(X_{\min}))$ depends on the linking receptive field radius r and the number of neurons pulsing at $T(X_{\min})$ that are linked to $N_{i,j}$. For a given r, $L_{i,j}(T(X_{\min}))$ attains its maximum value $L_{\max}$ when all the neurons that are linked to $N_{i,j}$ pulse at $T(X_{\min})$. Therefore

$$V_\theta > \left(X_{\max}^2/X_{\min}\right)(1 + \beta L_{\max}). \quad (7)$$

It can be shown that the value of $L_{\max}$ for $r = 1.0$ and $r = 1.5$ are $4.0V_l$ and $6.0V_l$, respectively.

III. Image Segmentation Using PCNN

A reliable and robust image segmentation method is necessary for obtaining meaningful results from any image processing system. Horowitz *et al.* [4] have provided a good definition of image segmentation. They define image segmentation as the process of decomposing a given image, *IMG*, into disjoint nonempty regions or subimages $R_1, R_2, \cdots, R_K$ such that

1) $R_1 \cup R_2 \cup \cdots \cup R_K = IMG$;
2) R_i is connected for $i = 1, 2, \cdots, K$;
3) all pixels belonging to R_i are similar based on some meaningful similarity measure M;
4) pixels belonging to adjacent regions R_i and R_j are dissimilar based on M.

During the past two and a half decades image segmentation has been an active area of research. The effort has lead to the development of numerous deterministic, statistical, neural-network and knowledge-based approaches and algorithms. The recent review papers by Pal and Pal [5] and Haralick and Shapiro [6] summarize many of these techniques.

In spite of the extensive research, reliable image segmentation has proved to be an elusive goal. There are many factors which pose considerable challenge during image segmentation. Some of them are briefly described below. Discontinuities in the pixel intensities may be caused by illumination changes, differing surface reflectance properties, or orientations of the visible surfaces. Often there is not enough contrast between the background and object regions in the image. Each segmentation algorithm exploits certain characteristics of the image class to accomplish segmentation. An algorithm that is suitable for segmenting a particular type of images may not be suitable for segmenting a different type of images. It may be necessary to use different methods to segment different parts of a given image. Many of the existing techniques may not be suitable for real-time or near real-time implementation. Hung [7] has given a detailed description of the various factors that make image segmentation a challenging task.

The PCNN, by the virtue of the capture phenomenon, is capable of producing good segmentation results even when the input images are noisy and of poor contrast. It has been found that even when the intensity ranges of adjacent regions overlap, the PCNN can perfectly segment the regions if certain conditions are satisfied. Note that when an image is perfectly segmented, each pixel is correctly assigned to the region it belongs to. For images that violate the perfect segmentation conditions, it may be possible to achieve perfect or improved segmentation.

The general approach to segment images using PCNN is to adjust the parameters of the network so that the neurons corresponding to the pixels of a given region pulse together and the neurons corresponding to the pixels of adjacent regions do not pulse together.

Assume that the image to be segmented consists of K regions and is applied as an input to a PCNN. The network neurons pulse based on their feeding and linking inputs. Note that the feeding input to a neuron is equal to the intensity of its corresponding pixel. Due to the capture phenomenon the neurons associated with each group of spatially connected pixels with similar intensities tend to pulse together. Thus, each contiguous set of synchronously pulsing neurons identifies a segment of the image. A segment identified by the PCNN may be a region, part of a region or union of several regions and subregions of the image. Ideally, the goal is to choose the network parameters such that each segment exactly corresponds to a complete region in the image. If such parameters exist then perfect segmentation is possible. However, perfect segmentation of real images may not always be possible using the PCNN-based approach. In such cases, additional post processing is necessary to merge or split the segments.

IV. Conditions for Perfect Segmentation

In this section, conditions that lead to the perfect segmentation of a two region image are derived. Consider an image consisting of two regions—object and background. Spatially connected object pixels form R and background pixels form B. Let $(X_{R\min}, X_{R\max})$ and $(X_{B\min}, X_{B\max})$ be the intensity ranges of the object and the background pixels, respectively. Assume that $X_{R\max} > X_{B\max}$ and $X_{B\max} > X_{R\min}$. Since the intensity ranges of R and B overlap, thresholding techniques cannot produce perfect segmentation.

When the above image is applied as input to the PCNN, the following events occur in the given order during each pulsing cycle.

- The object neurons with the intensity $X_{R\max}$ pulse naturally at $t = T(X_{R\max})$.
- All object neurons that lie within their respective capture ranges are captured. For example, $N_{i,j}$ is captured by the pulsing neurons if the following inequality is true:

$$X_{i,j}(1 + \beta L_{i,j}(T(X_{R\max}))) \geq X_{R\max}. \tag{8}$$

- Every background neuron $N_{p,q}$, for which the following inequality is *not* true, is also captured by the pulsing neurons:

$$X_{p,q}(1 + \beta L_{p,q}(T(X_{R\max}))) < X_{R\max}. \tag{9}$$

- The object neurons that are not captured at $t = T(X_{R\max})$ pulse in several groups after $T(X_{R\max})$ and before $T(X_{B\min})$. The number of groups and the exact time at which each group pulses are determined by the intensity distribution of the image, β and other network parameters.
- At $t = T(X_{B\max})$, the neurons corresponding to the background pixels with the intensity $X_{B\max}$, not captured by object neurons so far, pulse naturally.
- Every neuron $N_{m,n}$, for which the following inequality is true, is captured by the pulsing neurons:

$$X_{m,n}(1 + \beta L_{m,n}(T(X_{B\max}))) \geq X_{B\max}. \tag{10}$$

- The remaining background neurons organize themselves into several groups and pulse after $t = T(X_{B\max})$ and before $T(X_{B\min})$.

If (8) is true for every object neuron and (9) and (10) are true for every background neuron, all the object neurons pulse together at $t = T(X_{R\max})$ and all the background neurons pulse together at $t = T(X_{B\max})$, thus segmenting the image perfectly.

For perfect segmentation to occur, the PCNN must ensure that

- the object neuron with $X_{R\min}$ as its feeding input pulses at $T(X_{R\max})$ even if it receives the minimum linking input $L_{R\min}$ from the pulsing object neurons;
- the background neuron with $X_{B\min}$ as its feeding input pulses at $T(X_{B\max})$ even if it receives the minimum linking input $L_{B\min}$ from the pulsing background neurons;
- the background neuron with $X_{B\max}$ as its feeding input does not pulse at $T(X_{R\max})$ even if it receives the maximum linking input $L_{R\max}$ from the pulsing object neurons.

Therefore

$$X_{R\min}(1+\beta L_{R\min}) \geq X_{R\max} \tag{11}$$
$$X_{B\min}(1+\beta L_{B\min}) \geq X_{B\max} \tag{12}$$

and

$$X_{B\max}(1+\beta L_{B\max}) < X_{R\max}. \tag{13}$$

Therefore, to ensure the capture of each region separately in its entirety, the value of the linking coefficient β should in the range $[\beta_{\min}, \beta_{\max}]$, where

$$\beta_{\max} = ((X_{R\max}/X_{B\max}) - 1)/L_{B\max}, \tag{14}$$

and

$$\beta_{\min} = \max[((X_{R\max}/X_{R\min}) - 1)/L_{R\min} \quad ((X_{B\max}/X_{B\min}) - 1)/L_{B\min}]. \tag{15}$$

If $\beta_{\min}$ happens to be less than $\beta_{\max}$ perfect segmentation is guaranteed. However, depending on the values of $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$, and the extent of the overlap of the intensity ranges, $\beta_{\min}$ may or may not be less than $\beta_{\max}$.

A. Effect of Object-Background Boundary Geometry

The values of $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ depend on the linking radius r and the object-background boundary geometry as illustrated in the following examples.

Example 1: Let R be a rectangular region as shown in Fig. 3. The locations of the occurrences of $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ for $r = 1.0$ and $r = 1.5$ are identified in Fig. 3(a) and (b), respectively. The neurons at the convex corners of R receive the minimum linking input from the pulsing neurons of R. Similarly, the neurons at the convex corners of B receive the minimum linking input from the pulsing neurons of B. The neurons of B that are along the boundary of R and B (excluding those at the corners) receive the maximum linking input from the pulsing neurons of R. It can be shown that, (a) for $r = 1$, $L_{R\min} = 2.0V_l$, $L_{B\min} = 2.0V_l$, and $L_{B\max} = 1.0V_l$, and (b) for $r = 1.5$, $L_{R\min} = 2.5V_l$, $L_{B\min} = 2.5V_l$, and $L_{B\max} = 2.0V_l$.

Example 2: Let R be an L-shaped region as shown in Fig. 4. The locations of the occurrences of $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ for $r = 1.0$ and $r = 1.5$ are identified in Fig. 4(a) and (b), respectively. It can be shown that, (a) for $r = 1$, $L_{R\min} = 2.0V_l$, $L_{B\min} = 2.0V_l$, and $L_{B\max} = 2.0V_l$, and (b) for $r = 1.5$, $L_{R\min} = 2.5V_l$, $L_{B\min} = 2.5V_l$, and $L_{B\max} = 3.5V_l$. In general, the values of $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ increase as the value of r increases, but at different rates. The rates of increase are determined by the object-background boundary geometry.

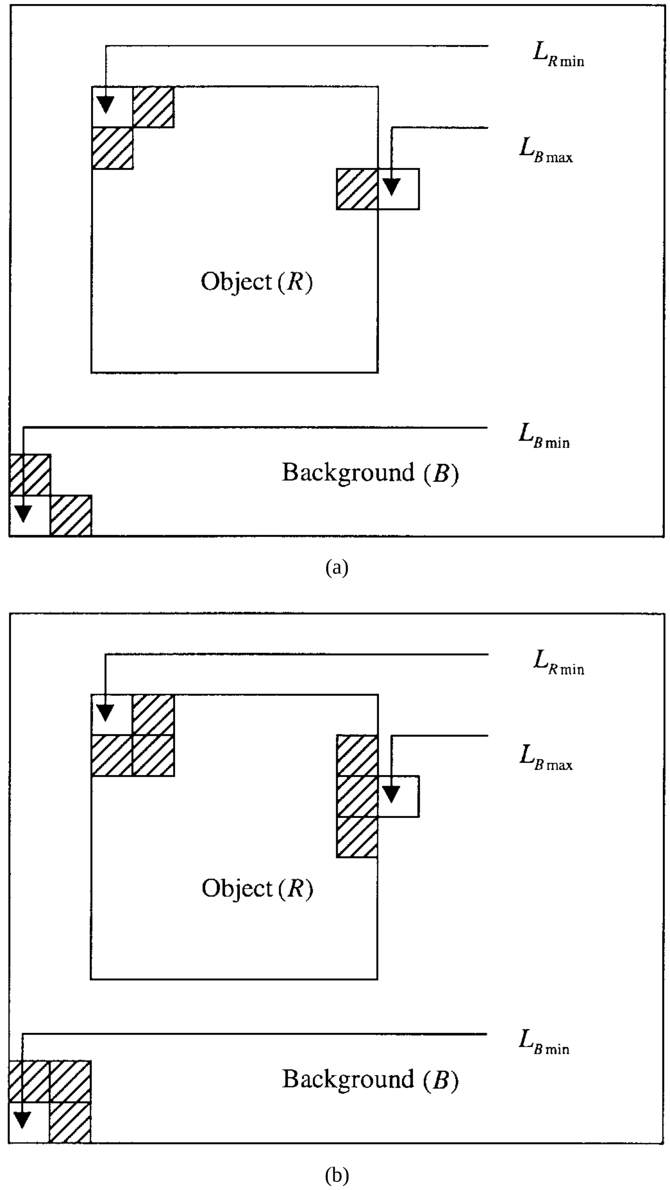
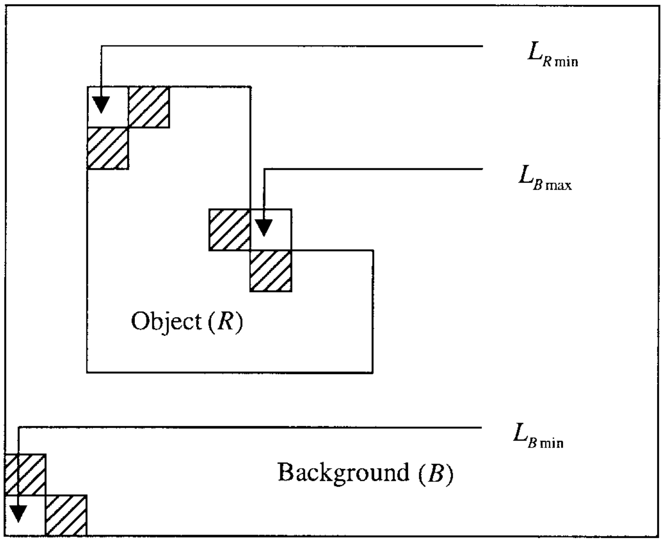


Fig. 3. $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ for a rectangular region. (a) $r = 1.0$. (b) $r = 1.5$.

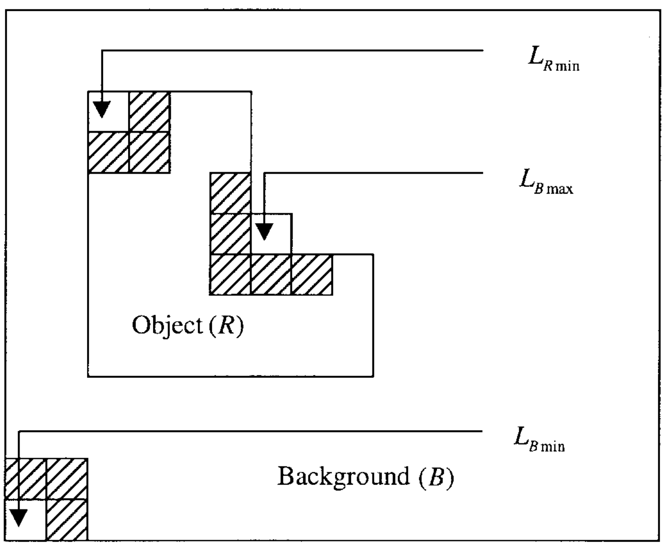
B. Effect of the Intensity Range and Overlap

The value of $\beta_{\min}$ increases with the increasing intensity ranges of the regions in the image. The value of $\beta_{\max}$ decreases as the extent of the overlap of the intensity ranges of adjacent regions increases. The perfect segmentation is guaranteed as long as $\beta_{\min}$ is less than $\beta_{\max}$. This is illustrated below.

Fig. 5(a) shows the image of Example 1 in which the intensity ranges of R and B are [150, 250] and [100, 175], respectively. For $r = 1.0$, it can be shown that $\beta_{\min} = 3/(8V_l)$ and $\beta_{\max} = 3/(7V_l)$. Since $\beta_{\max}$ is greater than $\beta_{\min}$, perfect segmentation of the image is guaranteed. When the image was segmented using the PCNN with $\beta = 0.4$, $r = 1.0$,



(a)

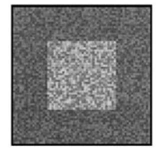


(b)

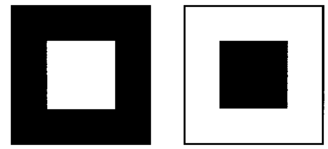
Fig. 4. $L_{R\min}$, $L_{B\min}$ and $L_{B\max}$ for an L-shaped region. (a) $r = 1.0$. (b) $r = 1.5$.

$V_\theta = 300$, $\tau_\theta = 15$, $V_l = 1$ and $\tau_l = 0.5$, all the neurons of R pulsed together as shown in Fig. 5(b). Later all the neurons of B pulsed together as shown in Fig. 5(c). The image was normalized by dividing each pixel value by 256 before it was applied as input to the PCNN.

If the intensity range of B is changed to [125, 200] [Fig. 6(a)], the extent of the overlap increases, the value of $\beta_{\min}$ decreases to $1/(3V_l)$ and the value of $\beta_{\max}$ decreases to $1/(4V_l)$. Since $\beta_{\max}$ is less than $\beta_{\min}$, there exists no value of β for which the perfect segmentation conditions are satisfied. Therefore, the perfect segmentation is not guaranteed. When β was set to $\beta_{\min}$ to capture each region entirely, many background neurons pulsed with object neurons as shown in Fig. 6(b). The remaining background neurons pulsed together at a later time as shown in Fig. 6(c). When the value of β was adjusted by trial and error to obtain the best possible segmentation of R, the region B fragmented into several



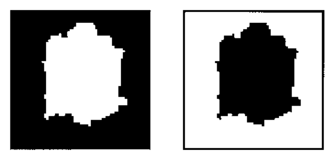
(a)



(b) (c)

Fig. 5. An example of perfect segmentation. (a) Input image. (b) Object segment. (c) Background segment. The object and background intensity ranges are [150, 250] and [100, 175], respectively. The image was segmented with $\beta = 0.4$ and $r = 1.0$.

(a)



(b) (c)

Fig. 6. An example of imperfect segmentation. (a) Input image. (b) Object segment. (c) Background segment. The object and background intensity ranges are [150, 250] and [125, 200], respectively. The image was segmented with $\beta = 0.33$ and $r = 1.0$.

segments as shown in Fig. 7. The value of the network parameters were $\beta = 0.16$, $r = 1.5$, $V_\theta = 300$, $\tau_\theta = 15$, $V_l = 1$, and $\tau_l = 0.5$.

Note that the perfect segmentation conditions are derived assuming the most adverse segmentation scenario. For example, the neurons that correspond to the darkest pixels of R are assumed to receive the minimum linking inputs from the pulsing neurons of R. The neurons corresponding to the brightest background pixels of B are assumed to receive the maximum linking inputs from the pulsing neurons of R. In reality, such extreme adverse conditions may not occur in the image. Therefore, it may be possible to segment the image perfectly even if the value of $\beta_{\min}$ exceeds the value of $\beta_{\max}$.

V. Techniques to Improve PCNN Performance

Almost always, intensity ranges of adjacent regions overlap considerably. The region boundaries may be complex with acute convex and concave corners and edges. It has been shown in Section IV that the intensity ranges of the regions in the image and the boundary geometries determine the level of performance of the PCNN. When the PCNN was not able to produce satisfactory results, an effort was made to improve the performance by modifying the input image and the PCNN

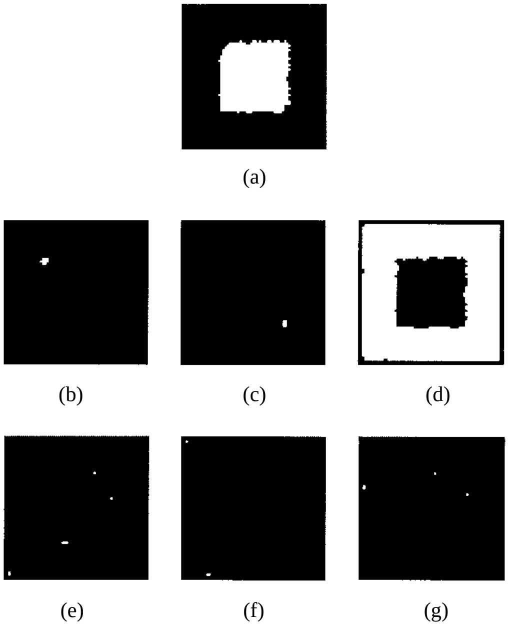


Fig. 7. An illustration of the region fragmentation problem. When the value of β and r were adjusted by trial and error to obtain the best possible segmentation of the object in Fig. 6(a), the background fragmented into six segments. (a) Object segment. (b)–(g) Background segments. The image was segmented with $\beta = 0.16$ and $r = 1.5$.

architecture. The techniques attempted and the results obtained are described below.

A. Image Smoothing

Smoothing an image compresses the intensity range of each region in the image. The extent of overlap of the intensity ranges of the regions in the image is also greatly reduced by the smoothing operation. Therefore, smoothing an image prior to its segmentation is expected to produce improved segmentation results.

The image in Fig. 6(a) was smoothed using the PCNN, as described in [8]. The PCNN was able to segment the smoothed image perfectly. The PCNN's that accomplish smoothing and segmentation are identical in architecture and topology. The fact that the same network can accomplish different tasks is a definite advantage. This feature is particularly beneficial when the PCNN is implemented in hardware because the programmable PCNN hardware reduces the complexity of the image processing system.

B. Inclusion of Inhibition Receptive Field

The approach is to compress the effective intensity ranges of R and B, and the extent of their overlap by delaying the pulsing of the neurons that pulse naturally. If the pulsing of the neurons that initiate the capture event is delayed, then it is likely that the low intensity neurons in the region will lie within their capture ranges, thereby leading to good or even perfect segmentation. This is accomplished by modifying the pulse coupled neuron by adding an inhibition receptive field similar to its linking receptive field. Every neuron that has not yet pulsed in the inhibition neighborhood of $N_{i,j}$ transmits an

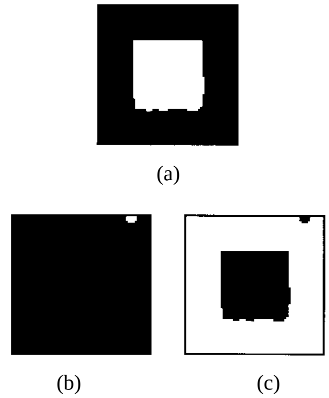


Fig. 8. Effect of inhibition input on segmentation. The image in Fig. 6(a) was segmented with $\beta = 0.16$, $r = 1.5$ and $\gamma = 0.05$. The resulting (a) Object segment and (b) and (c) Background segments.

inhibition input to $N_{i,j}$. Usually, the inhibition neighborhood and the linking neighborhood of a neuron are one and the same.

Let the inhibition input from $N_{k,l}$ to $N_{i,j}$ be $H_{i,j:k,l}$. Any one of the following methods can be used to generate $H_{i,j:k,l}$.

- The value of $H_{i,j:k,l}$ may be taken as a positive constant if $X_{i,j}$ is greater than $X_{k,l}$. Otherwise, its value may be taken as zero.
- The value of $H_{i,j:k,l}$ (positive) may be taken as proportional to the difference between $X_{i,j}$ and $X_{k,l}$ if $X_{i,j}$ is greater than $X_{k,l}$. Otherwise, its value may be taken as zero.

The net inhibition input $H_{i,j}$ is the sum of all the inhibition inputs received from the neurons in the inhibition neighborhood. The internal activity of $N_{i,j}$ is computed as

$$U_{i,j}(t) = X_{i,j}(1 + \beta L_{i,j}(t))(1 - \gamma H_{i,j}) \qquad (16)$$

where, γ is a positive inhibition coefficient.

When the inhibition input is absent the neurons of R with the highest intensity would pulse first at $t = T(X_{R\max})$ and initiate the capture event. Let $N_{i,j}$ be a neuron whose feeding input is $X_{R\max}$. Then, the presence of the inhibition input delays the natural pulsing time of $N_{i,j}$ from $T(X_{R\max})$ to $T(X_{R\max}(1 - \gamma H_{i,j}))$. Other neurons also experience similar delays. The inhibition signal received by a neuron corresponding to a pixel surrounded by brighter pixels is zero. On the other hand a neuron corresponding to a pixel surrounded by darker pixels receives a high inhibition input. As a result, the effective intensity ranges of R and B are compressed. Since $X_{B\max}$ is expected to decrease more than $X_{R\min}$, the extent of the overlap of the intensity ranges of R and B also decreases.

The image in Fig. 6(a) was segmented using the PCNN with inhibition inputs. The values of PCNN parameters were $\beta = 0.16$, $r = 1.5$, $V_\theta = 300$, $\tau_\theta = 15$, $V_l = 1$, and $\tau_l = 0.5$. The inhibition factor γ was set to 0.05. The results obtained with inhibition inputs, shown in Fig. 8, were significantly better than the result obtained without inhibition inputs. The edges are sharper and the regions are less fragmented in Fig. 8 than in Fig. 7.

VI. Conclusions and Recommendations

The modifications to Eckhorn's neuron do not fully agree with the known facts about biological neurons. However, the resulting pulse coupled neuron has retained the salient features of the cortical neurons. The pulse coupled neuron has proven to be a good processing element for image processing applications. The elimination of feeding leaky integrators, the assumption that all linking leaky integrators are identical, the proper selection of the maximum value for the threshold signal and the use of the linking coefficient has greatly simplified the analysis and control of the PCNN.

The derivation of conditions that guarantee perfect segmentation for an image even when the intensity ranges of adjacent regions overlap is a significant result. The perfect segmentation conditions have not been established for any other image segmentation method. The inclusion of inhibition receptive field in the neuron model has significantly improved the segmentation capabilities of the PCNN by compressing the intensity ranges of the individual regions in the image and by reducing the extent of overlap of the intensity ranges of adjacent regions.

The PCNN, being a new area of technology, presents many interesting and challenging problems.

1) The determination of appropriate values of the linking radius and the linking coefficient is not addressed in this paper. The future research should focus on the determination of the optimal values for r and β based on the intensity probability density function of the image and the boundary geometries of the objects in the image.
2) It appears that the implementation of PCNN could be greatly simplified if the linking and threshold signals are allowed to decay linearly rather than exponentially. Therefore, it is recommended that the image smoothing and segmentation capability of such networks be studied.
3) Since the PCNN's are expected to function in real-time systems, the technology for implementing them in digital and optical hardware must be developed.
4) In future, multilayer PCNN's and PCNN's for processing multispectral and time varying images need to be developed.

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