Regular Paper

Brightness Information Processing Based on a Human Visual Model

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This paper describes brightness information processing within the framework of a human visual model. This model consists of two hierarchical stages, which are functional modules representing the retina and the brain, and provides mechanisms for lateral inhibition and for the filling-in process. Each module is constructed on the basis of neurophysiological and psychophysical findings. The receptive field of a retinal ganglion cell is described as the difference of two Gaussians (DOG), and spatial discontinuities of brightness can be detected by a mechanism that connects an on-center cell and an off-center cell to an AND gate. The model of the filling-in process, which was proposed to explain the phenomenon of "simultaneous contrast," is formulated as an iterative algorithm and implemented on a computer for image processing. Computer simulations of the proposed visual model of some brightness illusions, such as the Craik-O'Brien-Cornsweet effect, are presented. Simulation results indicate how the perception of these phenomena is affected by interactions among neighoring areas or spatially organized contrasts. As an application of this model to image processing, the extraction of objects from Chinese brush paintings is described, and the effectiveness of this model is verified.

1. Introduction

Humans can extract many types of useful information about their surroundings from measurements of the light provided by their visual processing faculties. Such information includes stereo disparity and depth, motion, shape contours, surface texture, shading, brightness, lightness, and color. Since the results of processing this information depend on the properties of human vision, it is very important to take full account of these properties when we try to understand how humans perceive their surroundings.

Physiological and anatomical studies have revealed the structure of the retina and visual cortex, the interconnections in the visual pathway, and so on in human or biological visual systems [1, 2, 3]. In the area of psychophysics, on the other hand, many experiments have been done to determine how humans perceive the brightness of objects that are not actually present, or how they perceive it depending on different bands of spatial frequency. The experimental results have shown several important features in human perception of brightness, such as Mach bands, subjective contours, simultaneous contrast, and spatial illusions [4, 5, 6]. It also has been definitely shown that the visual system consists of a hierarchy of functional modules that process specific information, and that these modules cooperate with each other [7].

In this paper, brightness information processing is considered mainly within the framework of a human visula model. For example, two gray-level patches appear different in brightness when they are viewed against different backgrounds, even if their brightness is actually, or physically, the same. This phenomenon, called "simultaneous contrast," is an example of the most familiar characteristic of brightness perception. This is a perceptual effect in which what we see is affected by spatial interactions among neighboring areas.

From the engineering or computational point of view, it is not necessary to imitate exactly the complete human visual process; it is sufficient to model the fundamental function of each processing module. The above-mentioned knowledge concerning biological visual systems guides and motivates the construction of a visual model.

Several models of brightness perception have been proposed [8, 9, 10, 11, 12], all of which follow the above approach. They are constructed on the assumption that the visual processing stages involved in brightness perception may be modeled by mathematical operations of differentiation and integration. The differentiation of the original function is analogous to the edge-detecting stage of visual processing, and integration is a model for the recovery of the shape of the luminance distribution.

Although these models can explain some brightness

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perception phenomena, the following problems remain [13]:

• Since the integration process transforms each abrupt luminance change into a brightness step, the difference in brightness between the first and last members of the chain consisting of a linear conjunction of more than two regions increases cumulatively.

• These models, based mainly on Horn's theory [10], cannot easily explain simultaneous brightness contrast. The reason for this is that, since simultaneous contrast contains no gradients, the thresholding stage has no gradient effects, and no nonlinearities are introduced. Consequently, equiluminant surfaces are predicted to appear equally bright.

As a new approach to these unresolved problems, this paper proposes a brightness perception model that uses a more physiologically oriented framework, introducing the dynamics of neural processing at various levels of the visual system. The proposed model actually attempts to reconstruct the exact neural architecture of the eye-brain system, and consists of a hierarchy of functional modules that provide the mechanisms of lateral inhibition, detection of brightness discontinuities, and the filling-in process. This model is formulated as an iterative algorithm based on existing knowledge of the human visual system, and can therefore be applied to image processing and/or simulations of the perception of brightness illusions.

This paper is organized as follows. Section 2 describes the two modules of the brightness perception model and their implementation on a computer through the use of existing findings in neurophysiologics and psychophysics. In Section 3, the application of this model to some computer simulations of visual illusions, such as simultaneous brightness contrast phenomena, is described. As an example of the application of this model to image processing, Section 4 presents the result of the extraction of objects from a Chinese brush-painting in ink by the perception model, comparing it with that of another method using an intensity histogram of an image. In Section 5 we make some concluding remarks and outline plans for future research in this area.

2. Description of the Model

It is not easy to obtain precise models of the processing and transmission of visual information in the eye-brain system. In particular, visual information processing is so complex that no neural network model yet exists that can explain the brain function competely. From the computational point of view, however, it is sufficient to model the fundamental function of each processing module.

In this paper, information processing in the human visual system is considered as a two-stage hierarchy, illustrated in Fig. 1. One is the retinal stage, in which the spatio-temporal variation of the incoming light is

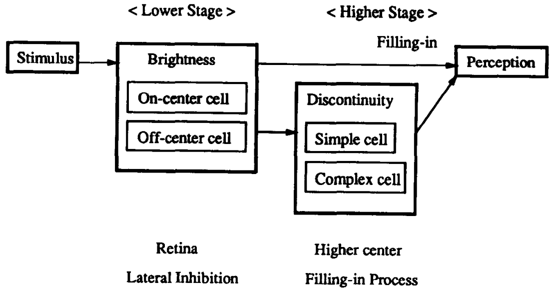

Fig. 1 Overview of the brightness perception model.

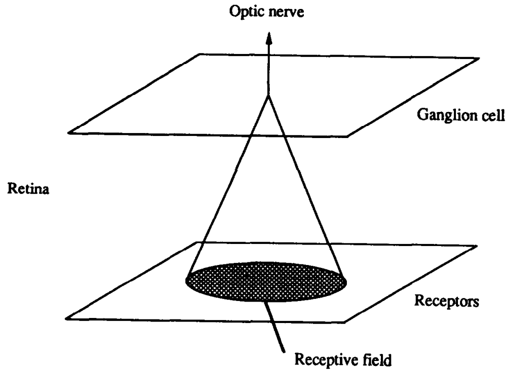

Fig. 2 Conceptual figure of the retinal model. This model consists of a two-layer hierarchy receptors and ganglion cells. A ganglion cell receives the convolution of the receptor signal with the receptive field function and transmits the signal to the LGN through the optic nerve.

measured. The other is the brain stage, in which a perception code or symbolic output is obtained by processing the data from the lower stage. We now give a detailed description of each processing module.

2.1 Lower Stage—Retinal Model

After the light striking the eye has been transformed into electric signals by a layer of rods and cones, it is transmitted to ganglion cells, which perform the last stage of the retina's precessing. The retinal model is based on existing knowledge of the ganglion cell.

The organization of the receptive field of an on-center cell is modeled as the result of superimposing a small central excitatory region on a large inhibitory "dome" that extends over the entire receptive field. These domes are described as Gaussians, and the receptive field is therefore described as a the difference of two Gaussians (DOG) [14, 15, 16]. Off-center cells have opposite properties.

The input signal to a ganglion cell is a convolution of outputs from receptor cells with the receptive field function, as shown in Fig. 2, and the corresponding output signal is transmitted to the optic nerve. The model of the ganglion cell can be considered as a neuron-like element. The state of an element is represented by a scalar x, called the potential. The dynamic behavior of the potential is generally described by the following differential equation [17]:

$$\tau \frac{\delta \chi(t)}{dt} = \sum_i w_i y_i(t) - x(t) - h, \qquad (1)$$

where $y_i(t)$ is the value of the ith input at time t, w_i is the synaptic weight of the ith input, and h is the threshold value of excitation. The output $z(t)$ of an element is determined as a function of the potential $x(t)$:

$$z(t) = f[x(t)], \qquad (2)$$

where f is an output function. When we consider the macroscopic behavior as a whole, the following equation is derived from equation (1):

$$x(t) = \sum_i w_i y_i(t) - h, \qquad (3)$$

on the assumption that small variations of the potential x can be ignored and that time t is considered as discrete [17].

For a more realistic and precise model, we assume that the threshold value of excitation h is not constant but increases in proportion to the output z. Moreover, when perceptive signals are dealt with, the linear behavior of the output function f is concerned [18], and thus the function f is given by

$$f[x] = \begin{cases} x, & x > 0, \\ 0, & x \leq 0. \end{cases} \qquad (4)$$

Suppose that receptor cells and ganglion cells are arranged on a two-dimensional grid and that the output of a receptor cell at location (i, j) is denoted as I_{ij}. The average membrane potential of an on-center cell, X_{ij}^{on}, is given by the following equation, which is derived from equation (3) by replacing the term of summation, $\Sigma_i w_i y_i(t)$, with DOG_{ij}:

$$Ax_{ij} = DOG_{ij} - h_{ij}, \qquad (5)$$

where A is constant. DOG_{ij} is a convolution of outputs from receptor cells with the receptive field function, and h_{ij} is the threshold value of excitation. These terms are obtained as follows:

$$DOG_{ij} = \sum_{(p,q)} B(G_{pqij}^{ex} - G_{pqij}^{in}) I_{pq}, \qquad (6)$$

$$G_{pqij}^{ex} = C \exp\{-[(i-p)^2 + (j-q)^2]/2\sigma_{ex}^2\}, \qquad (7)$$

$$G_{pqij}^{in} = D \exp\{-[(i-p)^2 + (j-q)^2]/2\sigma_{in}^2\}, \qquad (8)$$

$$h_{ij} = \sum_{(p,q)} (G_{pqij}^{ex} + G_{pqij}^{in}) I_{pq} x_{ij}, \qquad (9)$$

where B, C, D, σ_{ex}, and σ_{in} are constant. G_{pqij}^{ex} *and* G_{pqij}^{in} denote the excitatory and inhibitory regions of the receptive field, respectively.

By solving equations (5), (6), and (9), we get

$$x_{ij} = \frac{\Sigma_{(p,q)} B(G_{pqij}^{ex} - G_{pqij}^{in}) I_{pq}}{A + \Sigma_{(p,q)} (G_{pqij}^{ex} + G_{pqij}^{in}) I_{pq}}. \qquad (10)$$

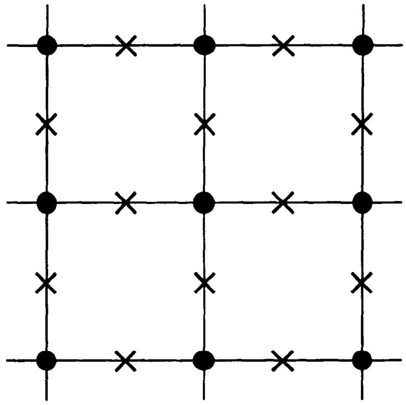

Fig. 3 Positional relationship between discontinuity elements and on/off-center cells. The symbols "×" and "●" denote discontinuity elements and on/off-center cells, respectively.

Moreover, from equation (4) for linearity, the output from an on-center ganglion cell at location (i, j) is the nonnegative part of x_{ij},

$$X_{ij}^{on} = \max(x_{ij}, 0). \qquad (11)$$

The output of an off-center cell, X_{ij}^{off}, is obtained in the same way.

2.2 Higher Stage—Brightness Perception

Visual information from the retina or the ganglion cells is transmitted to the lateral geniculate nucleus (LGN) and visual cortex, where some pattern features are extracted. After this, it is sent to the so-called "higher center" of vision, and brightness, color, texture, motion, and shape are perceived by complex processes.

The objective of this paper is to explain the perception of spatially organized brightness information. It is important to understand two functions in human perception of brightness; one is the detection of spatial discontinuities of intensity and the other is the filling-in process of brightness signals. This section describes the current physiological and psychophysical knowledge of these functions and the mechanisms of a perception model needed to realize them.

2.2.1 Mechanism for Detecting Brightness Discontinuities

Spatial discontinuities in brightness are detected by orientationally sensitive cells in the visual cortex to which visual information is transmitted from the LGN. There are two classes of orientationally sensitive cells: simple cells and complex cells. Simple cells are sensitive to orientation and to direction-of-contrast. Complex cells are also sensitive to orientation, but insensitive to direction-of-contrast in area 17 of monkeys and cats [19, 20, 21, 22].

First, simple cortical cells can be modeled as follows.

When an adjacent on-center and off-center cell of the LGN are both active, spatial discontinuities in brightness are detected between the two cells [7]. As illustrated in Fig. 3, these discontinuity elements may exist between cells that receive signals from the LGN; the discontinuities are denoted by the symbol " × " and the cells by the symbol " ● ". Thus, the output of each simple cell at the location (i, j) can be obtained by calculating the following four terms:

$$X^{on}_{ij}+X^{off}_{i+1,j},\ X^{on}_{ij}+X^{off}_{i,j+1},\ X^{off}_{ij}+X^{on}_{i+1,j},\ X^{off}_{ij}+X^{on}_{i,j+1}. \tag{12}$$

Next, the activities of complex cells, which are insensitive to contrast polarity, are obtained as the sum of the output signals from simple cells:

$$u_{ij}=(X^{on}_{ij}+X^{off}_{i+1,j})+(X^{off}_{ij}+X^{on}_{i+1,j}), \tag{13}$$

$$v_{ij}=(X^{on}_{ij}+X^{off}_{i,j+1})+(X^{off}_{ij}+X^{on}_{i,j+1}). \tag{14}$$

Finally, the output signals of complex cells are generated if the activities, u_{ij} and v_{ij}, exceed the threshold L:

$$U_{ij}=\begin{cases}1, & u_{ij}\geq L,\\ 0, & u_{ij}<L,\end{cases} \tag{15}$$

$$V_{ij}=\begin{cases}1, & v_{ij}\geq L,\\ 0, & v_{ij}<L.\end{cases} \tag{16}$$

2.2.2 Brightness Filling-in Mechanism

Gerrits and Vendrik proposed a theoretical model called a "filling-in process" to explain the phenomenon of "simultaneous contrast," which is the result of spatial interactions between neighboring areas. The basic idea of this theory is that the brightness of the interiors of homogeneous regions is determined by a process of lateral spread of neural activation initiated by units responding to abrupt changes of luminance [23].

According to the model, brightness information is perceived as follows. When a cortical on-center cell activates a highert-center brightness neuron, the generated brightness activity (B-activity) is not limited to the location of this one higher-center neuron but spreads around it. The same holds for the off-center cells and the generated dark activity (D-activity). However, the activity generated from a complex cell functions as a *barrier* to antagonistic spread activity. Thus the strong D-activity in the higher center always halts the further spread of B-activity.

In this section, a model of a filling-in mechanism is formulated and implemented as a local iterative operation. Initial inputs to the model are the signals from ganglion on-center cells of the retinal model, denoted for simplicity, as X_{ij} instead of X^{on}_{ij} (B-activity), and the discontinuity segments of brightness, U_{ij} and V_{ij} (barrier signals), as illustrated in Fig. 4. The filling-in procedure is given by the algorithm shown in Fig. 5.

The value of each pixel is replaced in such a way that the brightness level in the neighborhood illustrated in Fig. 4 becomes uniform. If any barrier signals are activated, corresponding pixels are excluded from the candidates for replacement. In algorithmical or computational terms, the following value determines whether any of the pixels is replaced:

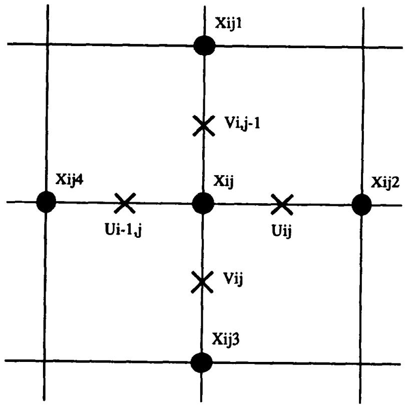

Fig. 4 Coordinate system of the filling-in mechanism model.

Algorithm:

```
procedure FILLING-IN
begin
    M = Number of pixels on a grid
    repeat
        l = 0
        replace = NO
        while (l < M)
        begin
            Select a point at local (i, j) on a grid arbitrarily but only once
            if (Need to be replaced) then
                Replace pixel value to be uniform within four-neighbors,
                    X_ijk(k = 1 ~ 4), in consideration of barrier signal
                replace = YES
            endif
            l = l + 1
        end
    until (replace = NO)
end
```

Fig. 5 Iterative procedure for the filling-in mechanism. For example, in Fig. 4, if $V_{ij}=1$ then X_{ij3} is excluded from the candidates for replacement.

$$\sum_{k=1}^{4}(1-BAR_k)(X_{ij}-X_{ijk})^2, \tag{17}$$

where $BAR_k=V_{i,j-1},\ U_{ij},\ V_{ij},\ U_{i-1,j}$ $(k=1, 2, 3, 4)$. In other words, if the change of X_{ij} or X_{ijk} increases the sum expressed by equation (17), the replacement is not performed.

The algorithm for the filling-in mechanism appears to have the same computational operation as that proposed by Geman and Geman [24], which is based on simulated annealing [25]. Although it is necessary for annealing-based approaches that images should be modeled as a limited class, that is, as a random Markov field, our approach requires no such limitation. Moreover, the filling-in algorithm is independent of external parameters, such as a temperature parameter for the simulated annealing.

3. Simulations of the Perception Model

In this section, we present computer simulations of illusory brightness phenomena, such as the Koffka-Benussi ring [5] and the Craik-O'Brien-Cornsweet effect [6], using the proposed model to illustrate the function of brightness perception.

In all the following simulations, the stimulus input data are on a two-dimensional grid of 40×40, and as a way to present two-dimensional signals or activity profiles we use three-dimensional graphs in which the x- and y-coordinates represent the spatial variables and the z-coordinates the strength of the signals or neural activity.

Before making simulations, we give the parameters used in the model. On the basis of studies of the receptive fields of retinal ganglion cells [26], we use the following parameters: $A=1$, $B=90$, $C=17$, $D=0.33$, $\sigma_{ex}=0.5$, $\sigma_{in}=2.0$. These are the average values of the receptive field size and sensitivity for X cells. Since the actual receptive field size increases with retinal eccentricity, these parameters of the model, especially σ_{ex} and σ_{in} of the receptive field size, should be varied according to the retinal position. By introducing variable parameters, this model can be extended to include a capability for multi-resolution analysis, but this procedure is not implemented in our current model. Lastly, the threshold value for discontinuity detection, L, used in equations (15) and (16) is determined on the basis of perceptual experiments to find whether the adjacent areas can be distinguished. The criterion for such distinction is obtained from a characteristic of human behavior known as Weber's law [2]. All simulations in this paper use the value $L=15$.

3.1 The Koffka-Benussi Ring

The ring has an intermediate luminance level and is superimposed on a bipartite background, with one half having a high luminance level and the other half a low level, as shown in Fig. 6(a). The effect of such a stimulus is that the ring appears approximately uniform though gently inclined, as shown in Fig. 6(c). Figure 6(b) illustrates the barrier signal used in the process of the filling-in mechanism. The brightness signal diffuses freely within this single connected compartment, generating a region of averaged brightness.

The brightness perception is changed by the introduction of a black line dividing the ring into two halves.

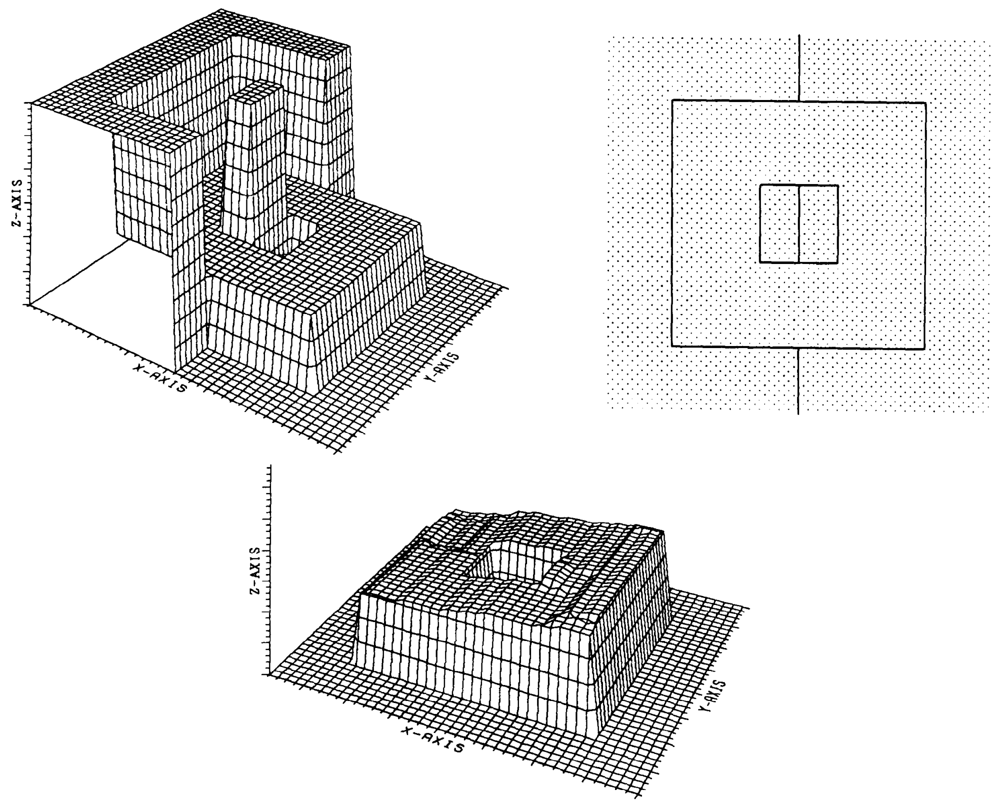

Fig. 6 Simulation of the Koffka-Benussi ring—undivided ring. (a) Two-dimensional stimulus distribution. (b) Output from complex cells, or barrier signal. (c) Output after filling-in operation, indicating the perceived brightness.

Figure 7(a) shows the strength of the stimulus. The brightness signal diffuses within the two compartmnents created by the barrier signals illustrated in Fig. 7(b). Thus, the ring is divided into two regions with homogeneous but different brightness levels, as shown in Fig. 7(c).

3.2 The Craik-O'Brien-Cornsweet Effect

The Craik-O'Brien-Cornsweet effect is a most attractive phenomenon [6]. When humans see two rectangles whose luminance is actually equal, except for an abrupt change of luminance overshoot on one side and an abrupt change undershoot on the other side of the midline, they perceive the former rectangle as brighter than the latter.

Figure 8(a) shows the two-dimensional stimulus distribution of this brightness phenomenon. Figure 8(b) shows the barrier signal and Fig. 8(c) the final perceived brighness level. It can be found that there is a difference in the perceived brightness level between the two regions across the midline.

3.3 Discussions

Computer simulated results of brightness perception can explain how brightness illusions are perceived, and therefore it can be considered that the proposed mechanism works in the same way as human vision. This is because the model does not merely attempt to perform image processing by means of neural techniques, but actually to construct the neural architecture used by the eye-brain system.

First, stimulus inputs are transmitted through the mechanism of lateral inhibition as initial inputs to a higher processing stage. These are data whose brightness level is enhanced in the same way as in human perception. By combining the data, then, spatial discontinuities in brightness are detected and used as barrier signals. Finally, the perceived brightness level is obtained by the filling-in process, in which is a lateral spread of iniial activations up to barrier signals. Lateral inhibition and the filling-in process do not work independently, but brightness perception is performed by the interaction between these modules.

4. Application to Image Processing

In order to verify the functioning of the proposed model, we demonstrate its application to achromatic

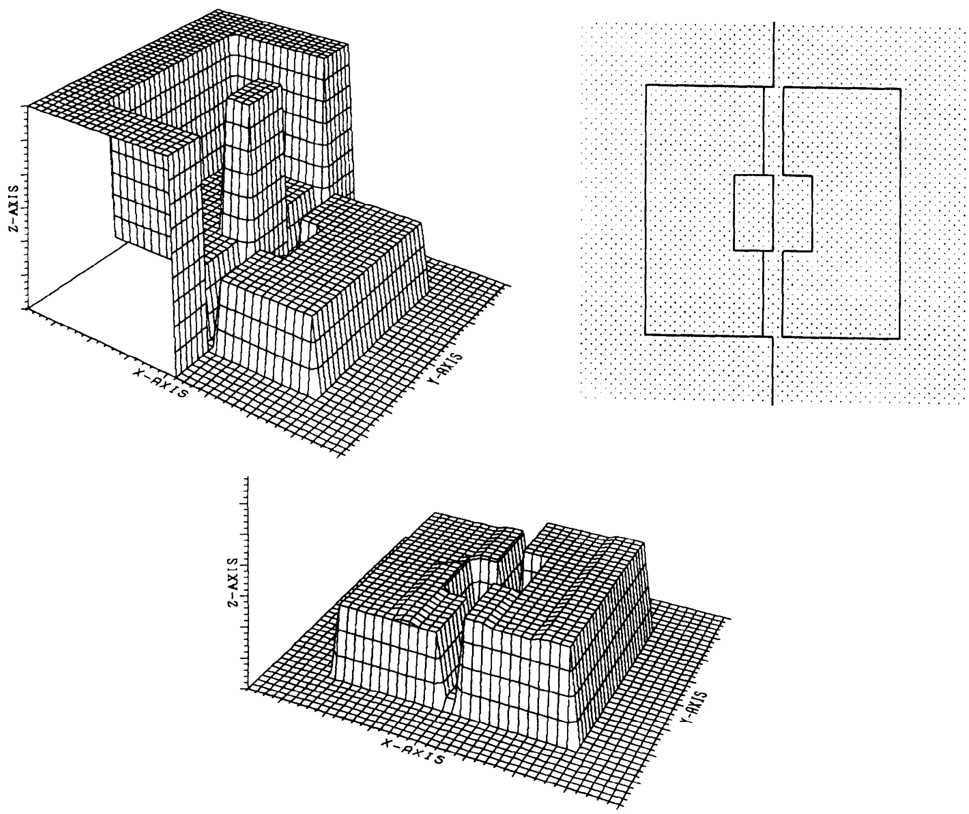

Fig. 7 Simulation of the Koffka-Benussi ring—divided ring. (a) Two-dimensional stimulus distribution. (b) Output from complex cells, or barrier signla. (c) Output after filling-in operation, indicating the perceived brightness.

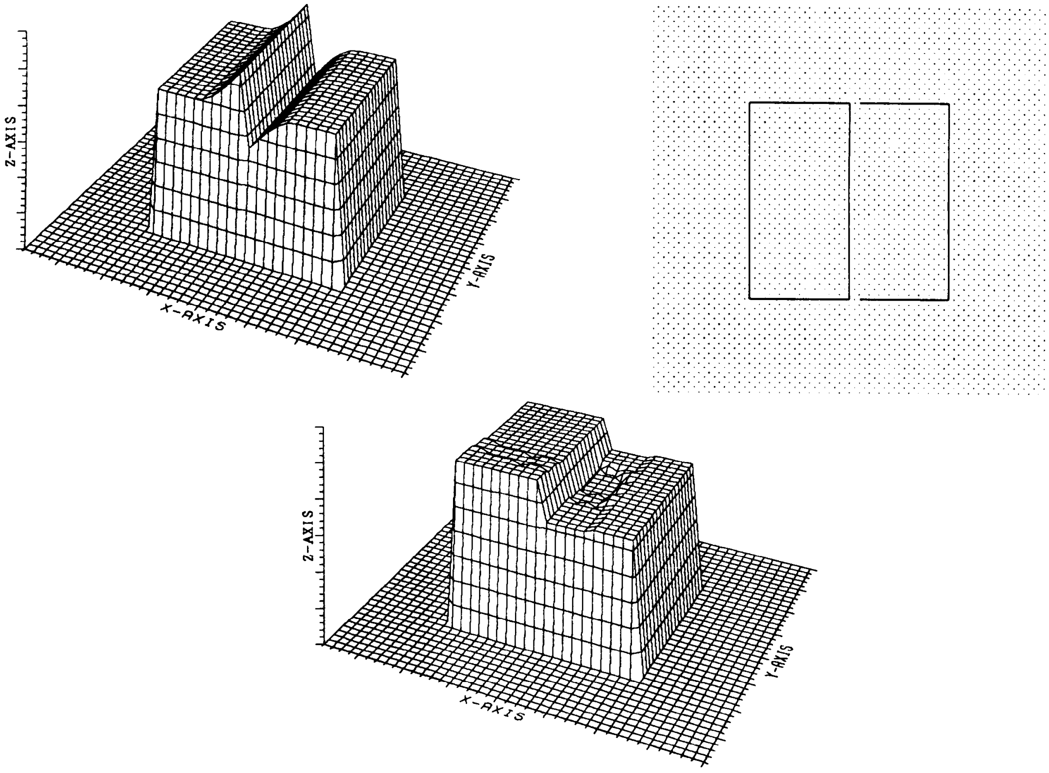

Fig. 8 Simulation of the Craik-O'Brien-Cornsweet effect. (a) Two-dimensional stimulus distribution. (b) Output from complex cells, or barrier signal. (c) Output after filling-in operation, indicating the perceived brightness.

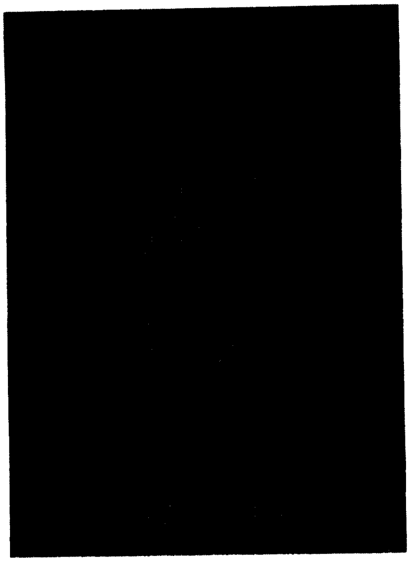

Fig. 9 Example of an original image with a signal magnitude range of 256 gray levels.

Fig. 10 Objects extracted from the original image by using its gray-level histogram are represented by black regions.

image processing. Chinese brush-paintings in ink are adopted as images to be processed by the model. Satisfactory results are not obtained by applying conventional processing methods to such paintings. This is because, in visual art, the effect of brightness enhancement induced by visual properties has been used for the illusory production of bright and dark areas by means of faint differences beyond contours [27].

Application of this perception model to extracting objects from Chinese paintings is a significant way of analyzing and interpreting the paintings in terms of their layout structure [28, 29].

In general, objects are extracted in such a way as to segment the image into two classes, the object and the background, by converting an original image into a binary image with a threshold value selected from a histogram of the original image. Since there is a difference between the actual gray level and the perceived level, extracted objects in the binary image do not always correspond to those that humans perceive as objects. Thus, such images should be processed at the perceived level of image intensity, which is computed as the output of the brightness perception model.

The example of an original image shown in Fig. 9 was taken with a CCD array camera and digitized to 8 bits/pixel, or 256 gray levels. Figure 10 is the associated binary array for the original image after a thresholding operation with a threshold value selected from a

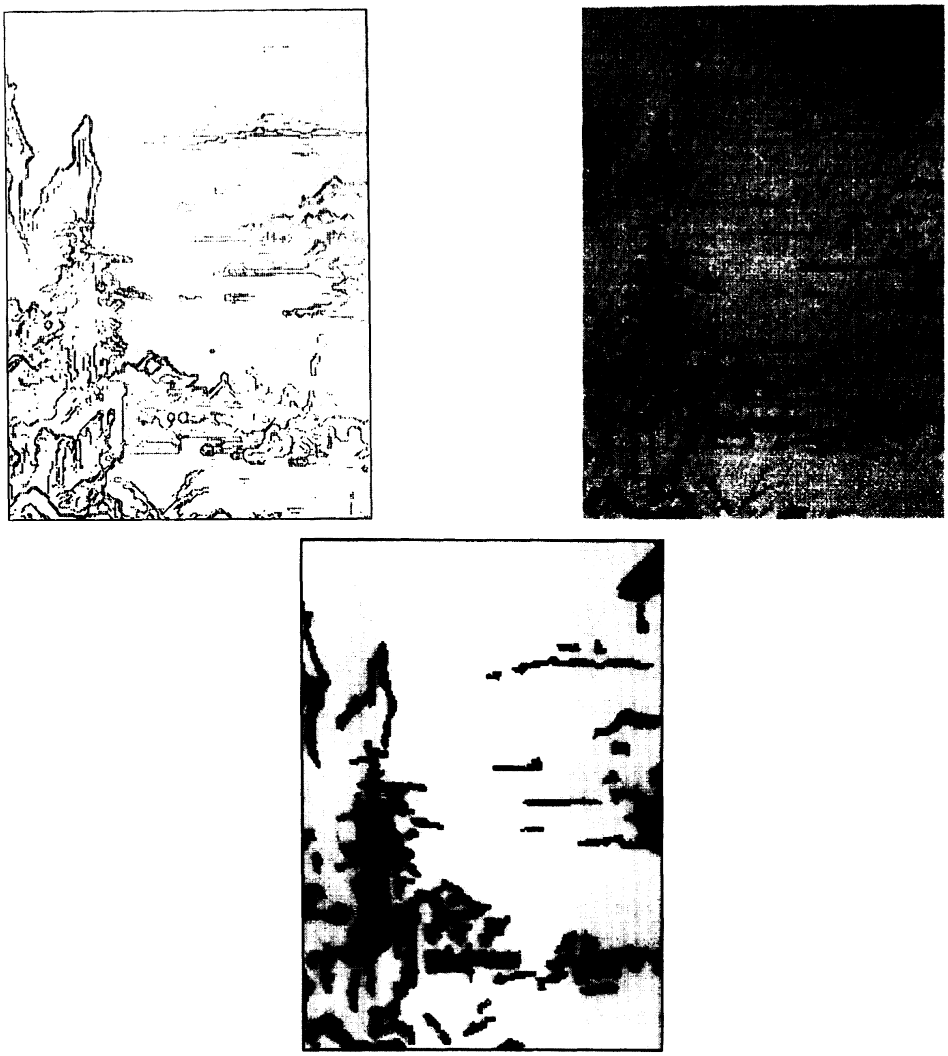

Fig. 11 Experimental results of object extraction using the proposed model. (a) Barrier signal. (b) Output after filling-in operation. (c) Objects extracted from the image (b).

histogram of the original image [30], in which extracted objects are denoted as black regions. The results show that some regions on the right side of the painting were extracted incorrectly and that details of the structure of objects were lost.

We now present the results obtained by using the perception model. Figure 11(a) shows the barrier signals, which are detected as brightness discontinuities in the image. As a result of the filling-in process, the associated perceived brightness is computed as shown in Fig. 11(b). A threshold value is selected from a histogram of the output of the model, namely the perceived brightnes level. Figure 11(c) shows the resulting thresholded image, in which objects are also represented as black regions.

The experimental results presented in this section indicate that objects can be extracted more easily than in conventional methods by introducing the properties of a biological visual system into the scheme of digital image processing.

5. Concluding Remarks

This paper has described a visual model of brightness perception that deals with two-dimensional properties of brightness. This model is based on existing knowledge of neurophysiology and psychophysics and is constructed as a hierarchy of two functional modules, one a mechanism for detecting spatial variation and discontinuity in brightness and the other a mechanism for diffusing brightness signals, in other words, the filling-in process. The receptive field is modeled a a DOG filter and the filling-in mechanism is formulated as an iterative operation.

Computer simulations of brightness enhancement phenomena induced by human visual properties are carried out and the adequacy of the model is demonstrated. The simulation results indicate how these phenomena are perceived as a result of the interaction among surroundings or spatially organized contrasts. Moreover, as an example, the model is applied to extracting objects from Chinese brush-paintings in ink and the results are much better than those obtained by a conventional method.

Our approach still poses interesting and important problems. Since the model described in this paper deals only with achromatic brightness effects, extensions, for example, to chromatic and multi-scale processing have to be considered. From the computational point of view, this algorithm should be implemented on parallel computer architectures, because it is highly parallel and can operate in real time on such architecture.

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