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NEURAL NETWORK MODELS FOR ILLUSORY CONTOUR PERCEPTION

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Abstract

Image segmentation in unconstrained environments is a difficult process because frequently borders of objects are not well represented as intensity discontinuities. Illusory contours represent one such example. We examined two models of illusory contour perception by simulating neural network architectures that could be tested with gray level stimuli. The first model, based on the principles of a parameter transformation space, uses evidence collection schemes to signal the presence of contours only partially represented in the image data. The second is a simulation of a physiologically based model of neurons sensitive to illusory contours.

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1 Introduction

Segmentation depends on finding discontinuities in one or more image attributes, for example lightness, color, motion and depth. Computer vision algorithms frequently fail in segmentation of images from unconstrained environments because not all object boundaries are well represented as such discontinuities. And yet, human subjects are able to perceive contours and recognize objects (Fig. 1) despite impaired discontinuity data. The additional information appears to be somehow inferred from the available data.

Examples such as these suggest that comparatively little physical data is needed in order to create a percept; "making up" missing information seems to be a routine process. Evidence of

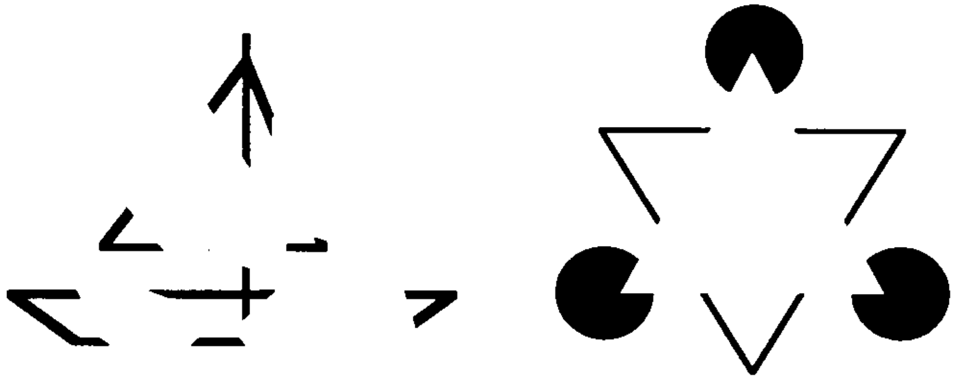


Figure 1: Perceptual completion in the absence of contour information. (a) An example of an object with partially occluded boundaries. (b) The borders of the illusory occluding triangle are perceptually salient despite lack of luminance contrast information.

similar processes are wide spread in vision. An example is the perceptual filling-in of retinal scotomas. Here, the path of the optic nerve prevents any retinal activity in a small area of the visual field; however, information from nearby areas is filled-in over this region to maintain consistency of perception [26]. A similar phenomenon is the ability of the human visual system to recognize objects despite missing information, such as might be lost due to occlusion (Fig. 1a). The missing information is inferred from partial segmentations generated from the image.

However, the neural mechanisms underlying such perceptual completion remain a matter of controversy. It is conceivable that the results at both the early and later stages of visual processing are not determined by the original image intensity alone; they seem to be "created" in order to maintain consistency with previously defined goals and expectations. Spatio-temporal sampling of the data space begins in the retina; loss of information due to scotomas or occlusions by retinal veins introduce discontinuities in the flow of visual information. Hence, the need for a mechanism to complete missing information, possibility in the interest of subjective goals.

This paper will examine two computational models of how perceptual completion could be produced by the visual system. We will focus on two common instances of completion, corresponding to occluded (Fig. 1a) and occluding (Fig. 1b) boundaries. We will present simulation results of neural network architectures designed to model both of these processes, and suggest a final framework based on a combination of bottom-up and recurrent processing strategies.

2 Illusory Contours

Illusory contours are boundaries of perceptually occluding surfaces which are not denoted by any physical luminance discontinuity. The psychological phenomenon is quite robust (see [22] for a review), arising in images where the coincidental alignment of incomplete inducing patterns is such that an occluding surface or boundary is perceived in front of the patterns. Boundaries of the surface are perceived as highly salient contours although there is no luminance discontinuity present in the region of the perceived contours. Normally associated with such illusory surfaces are two other effects, a perceptual brightening of the surface [12,18], and the impression of strong depth [3].

Explanations for the phenomenon of illusory contour perception range over a spectrum from early vison to higher, "cognitive" processes [28]. However, compelling physiological evidence indicates that some aspect of illusory contours are detected at relatively early layers of visual processing [27,33]. In these examples, cells in monkey visual area 18 and cat LGN which respond to moving, oriented luminance discontinuities respond equally well to moving, oriented perceptual illusory contours. Various psychophysical results demonstrate the interaction of illusory contours with primitive visual cues [17,23,24], and thus seem to confirm their generation in early visual processing.

Results such as these indicate that illusory contours may be a fundamental perceptual primitive used by biological systems in image segmentation. This provides a strong motivation for attempting to incorporate them into artificial vision systems. The neural network models presented in here are in this spirit; an attempt to incorporate the detection of illusory contours into image analysis systems to provide more robust segmentation techniques.

3 Methods

Simulations presented in this paper were performed using the UCLA-SFINX network simulator [16]. UCLA-SFINX allows the construction and simulation of large scale fixed or variable connection networks, with graphics based methods for presenting input image patterns to the network and displaying results. Input images were 128x128 pixel gray level (256 gray levels), representing an area of 16 square visual degrees. Network sizes ranged up to 800,000 units (typically organized into 128x128 unit layers), and in upwards of 30,000,000 connections.

4 Enhanced Hough Transform Model

In complex scenes with multiple occlusions where borders of an object are not fully represented as a luminance discontinuities, full boundaries must be inferred from the available contour information. The Hough transform provides a noise and occlusion insensitive technique for the detection of arbitrary analytic or non-analytic contour curves in an image [10,5,2]. Image feature points "vote" for curves passing through them using a transformation into a parameter space, which is then searched for evidence of the curves being detected. Thus, instead of fitting curves to data, we have a more tractable problem of detecting high density points in a parameter space. For example, a simple straight line parametrization is in terms of ρ, the perpendicular distance of the line from the origin, and θ, the angle of the normal to the line (see Fig. 2). Euclidean (x, y) coordinates are

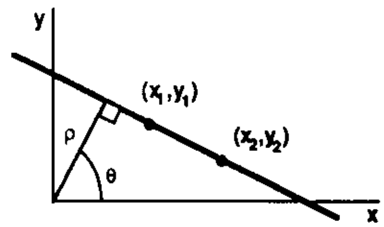


Figure 2: The geometry of the (ρ, θ) transformation.

transformed into (ρ, θ) space by $\rho = x cos\theta + y sin\theta$.

Thresholded edge pixels are used as feature points; each increments a counter representing the (ρ, θ) parameters of all lines passing through the it. Thus, collinear edge points increment the same (ρ, θ) counter. Counters are stored in a multi-dimensional accumulator array, which is thresholded to yield parameter combinations of high density, corresponding to lines present in the image.

4.1 Enhanced Model

Several modifications were made to the standard Hough transform model described above. First is the use of oriented edge information [2]; this has the effect of uniquely constraining the set of lines passing through a feature point (θ becomes fixed). Further, edges are detected at a variety of spatial scales to ensure capturing all relevant edge information.

A well known problem of the Hough transform is its inability to localize detected curves (see [11]); detected lines span the entire image. To solve this problem, we allow edge points to vote for finite length lines spanning a local neighborhood centered at the edge position. This line length is fixed across all spatial scales, and is typically in the range of 20 pixels in the simulations presented here. For implementation simplicity, direct parameter representation is removed. Instead, accumulator array counters correspond to pixel coordinates, and collect evidence for oriented lines passing through their specific spatial position.

However, this finite length voting process still results in slightly impaired line localization. To address this problem, we introduce a filtering process which ensures that completed line segments have support on both sides of a gap. This provides a mechanism for removing small spurious lines as well as trimming existing line segments, allowing robust filling-in to be done without sacrificing line end localization.

The final enhanced Hough transform model contains four steps: *1) Edge Detection*: at a full spectrum of orientations and spatial scales. *2) Transformation*: by allowing feature points to vote for the line segments passing through them. *3) Line End Localization:* by filtering detected line segments. *4) Recombination*: of line segments detected at each orientation and spatial scale. Implementation details of each are discussed below.

4.2 The Network

Previous work has shown how the Hough transform can be cast in a connectionist architecture [29]. Pixel based feature properties (thresholded oriented edges) are represented in neuron-like node elements, which cooperatively pass information to similar node elements containing parameter space information. Nodes in the parameter space record a level of confidence (vote totals); totals above some threshold indicates the presence of the parameterized object in the image. The image to parameter space mapping determines the pattern of connections in the network.

Our final architecture is multi-layer feed-forward network. An input image is filtered for oriented edges using a difference of offset Gaussian (DOOG) model [34] at every 22.5° of orientation, and at four separate spatial scales (4, 8, 12 and 14 cycles per degree). Each orientation and spatial scale combination is processed with a separate layer of nodes, where each node in the layer has an identical connection pattern to encode the appropriate edge detection convolution. Within a spatial scale, orientations compete using a winner take all method; each pixel may signal an edge

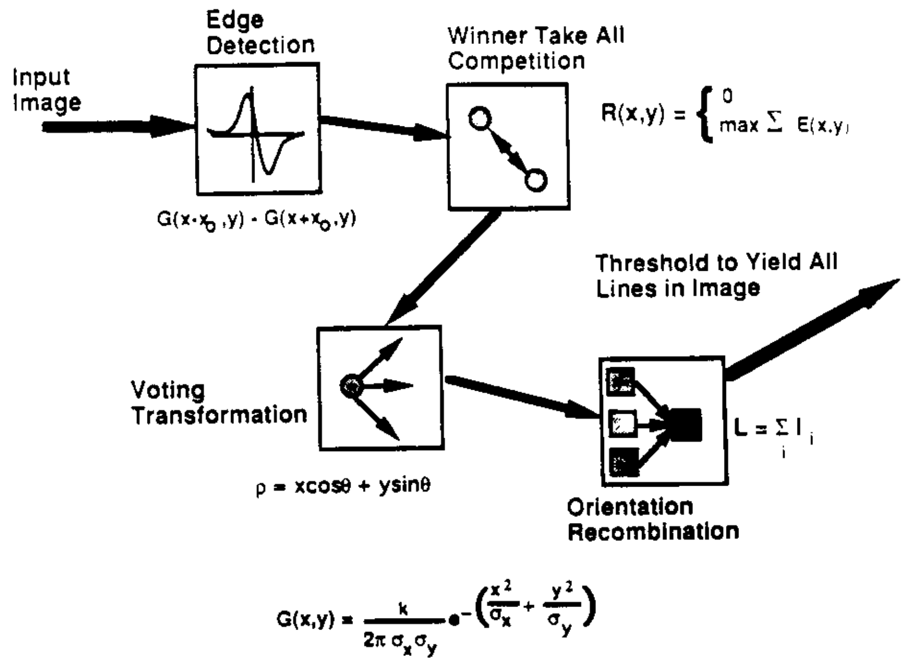


Figure 3: The enhanced Hough transform network. Edges are detected from the image, and then compete using a winner-take-all mechanism. Remaining points vote for lines passing through them using orientation and offset information. Evidence layers are recombined to yield all lines present in the image.

at only one orientation. Remaining edge points increment the confidence counter of nodes lying on an oriented line centered at the edge. The thresholded outputs of these nodes signal the presence of a line passing the corresponding spatial position.

End points of the detected line segments are then localized using the line end filter described above. As with edge detection, the filter mask is encoded in the connection strengths of a layer of processing nodes. For a given spatial scale, all oriented line information is then combined by simply "and"ing information from the separate orientation layers. Spatial scales are combined by taking final line segments to be those which persist across two or more scales.

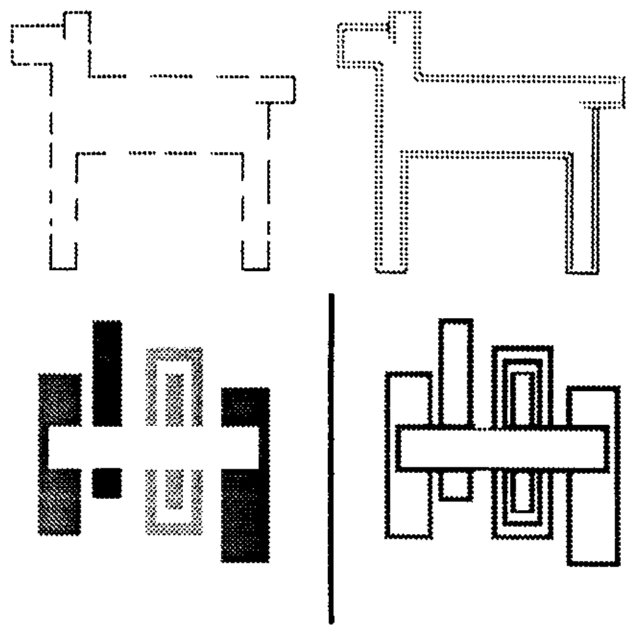


Figure 4: (a) An input image showing the broken outline of a figure. The network was able to detect lines corresponding to the complete boundary of the figure despite gaps in the border. (b) An input image containing an illusory bar. Lines detected correspond to both normal contours and to the boundaries of the illusory surface.

4.3 Simulation Results

The network is able to detect most real and illusory contours in simple input images (Fig. 4). Lines corresponding to the outline of a figure completed despite gaps in the border are shown in Figure 4a. The network was also able to fill-in illusory contours which were collinear with their inducing segments (Fig. 4b). Here, normal contours as well as contours bounding the illusory bar were found.

However, the network was unable to fill-in across gaps when they became too large. Increasing the size of the voting neighborhood expanded the gap size that could be crossed, but resulted in localization errors which could not be corrected through the line end filtering process. The network also had problems in disambiguating when to fill-in across a gap by completing lines which were not boundaries of surfaces, real or illusory. Varying the size of the local voting neighborhood across spatial scales might provide a method for addressing problems of this nature; our architecture

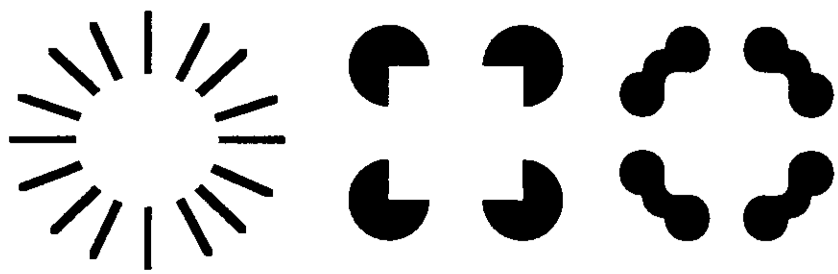


Figure 5: Visual cues for occlusion. (a) A perceptual occluding surface bounded by an illusory contour (after Kennedy, 1975). (b) Discontinuities present in the image allow inference of an occluding surface. (c) Without this discontinuity information, the perception is removed.

transforms each scale separately, making this possible. We feel that a more intelligent (adaptive; uneven weightings of various cues) transformation and evidence collection scheme will prove to be a valuable tool for some perceptual completion tasks.

5 Illusory Contours and Perceptual Completion

Our simulation results with the Hough transform based network suggest that some contour information can be completed on the basis of line continuity. The network performs well with completion of broken boundaries of objects (possibly due to occlusion), and filling in the boundaries of some illusory surfaces. However in many cases, discontinuity information is a stronger cue for the existence of occluding surfaces than partial contour (Fig. 5). In (5a), an illusory occluding boundary is given strictly by aligned discontinuities; (b) and (c) demonstrate the necessity of this discontinuity information for the perception of occlusion.

Occluding (modal) and occluded (amodal) contours obviously play an important and mutually interactive role in visual scene analysis; additional evidence for occluding surfaces may provide the cues necessary for completion of boundaries occluded by those surfaces, allowing incomplete or partially defined objects to be recognized. In complex, real-world scenes, this type of partial occlusion is extremely common, justifying the need for a system to quickly detect and analyze occlusions in early stages of vision. The next section describes a hypothetical neural model of illusory contour processing based on discontinuity information.

6 Physiologically Based Model

Physiological results from alert, fixating rhesus monkeys revealed an early-vision neuronal correlate to illusory contour perception [20,33,32]. Some cells (roughly 40%) in area V2 responded to both normal contrast boundaries, as well as to stimuli which produce illusory contour perception in human subjects. All cells sensitive to illusory contours also responded to normal contours. Orientation and directional selectivity were roughly equivalent for both types of contour. No attempt was made to classify the cells into traditional hierarchies (simple, complex, etc.), although it was noted that all identified cells were binocularly driven.

The model proposed to explain responses [21], sums two sets of cortical inputs, one carrying luminance defined edges, and a second providing an illusory contour component (Fig. 6). This component was driven by image features which appear to contribute to illusory contour perception, such as line endings or corners. Responses from cells sensitive to these features (example: hypercomplex I and II) were summed in a spatially specific manner; rows of perpendicularly oriented endstopped cells sum discontinuity information across an area overlapping the normal edge response. Endstopped responses were gated by similar activity on the opposite side of the receptive field center; evidence of a physical contour is needed on both sides of the gap in order to perform perceptual completion. Contributions from normal edge responses and from collections of gated

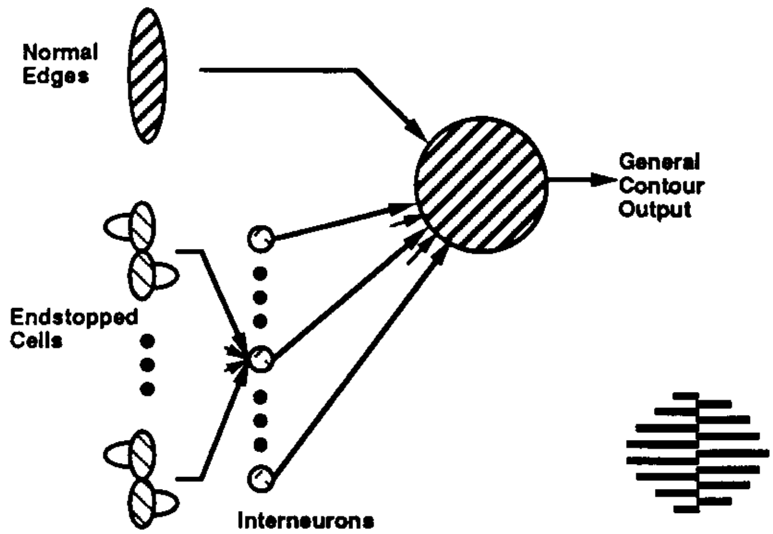


Figure 6: The general contour neuron (after Peterhans et al., 1986). Rows of orthogonal endstopped cells sum information to be combined with normal oriented edge information.

endstopped responses are summed at a final "general contour neuron".

We examined the performance of the model using the UCLA-SFINX simulation environment. General contour neuron inputs were filtered from the input image by earlier layers of the network. Edges were obtained using the difference of offset gaussian (DOOG) model; edge layers of the network $E_1 \ldots En$ filterted responses from an images intensity profile $I(x,y)$ based on this model:

$$E_i(x,y) = (G(x - x_o, y) - G(x + x_o, y)) \otimes I(x,y) \tag{1}$$

$$G(x,y) = \frac{k}{2\pi\sigma_x\sigma_y} e^{-(\frac{x^2}{\sigma_x} + \frac{y^2}{\sigma_y})} \tag{2}$$

Terminations are detected using a derivative of this approach, based on the hypercomplex cell model proposed by Dobbins et al. [4]. Here, the responses of two oriented edge detectors (generated using the DOOG model) varying in spatial size are combined with a slight spatial offset to yield asymmetrical endstopping inhibition.

$$T(x,y) = \lambda_1 E_1(x,y) - \lambda_2 E_2(x+x_o,y) \tag{3}$$

Features were again detected at every 22.5° of orientation.

To integrate outputs across feature space, we used a competition and normalization scheme modified from Heeger [9]. At each spatial position, a feature response was normalized by the responses of similar features at all other orientations (ie edges compete with edges at same spatial scale across all orientations). For a given feature response $R_i(x,y)$:

$$R_i(x,y) = \frac{R_i(x,y)}{\Phi + \sum_{j\epsilon\Theta} R_j(x,y)} \tag{4}$$

The result is to introduce a degree of contrast independence, as well as response stabilization into the network. For example, a 22° line terminator with high contrast may give a higher response at 45° than an actual 45° degree line ending with low contrast; the normalization scheme helps to elicit proper responses in these cases.

The illusory component of the general contour neuron is obtained by summing orthogonal terminator responses in the region coextensive with the area of edge sensitivity. Responses on each side of the receptive field center are gated together; there must be terminator evidence on both sides to perform boundary completion.

$$SG(x,y) = \left(\int_{x-x_o}^{x} T(\chi,y)\delta\chi - \Theta\right) \;\&\&\; \left(\int_{x}^{x+x_o} T(\chi,y)\delta\chi - \Theta\right) \tag{5}$$

Determining the neighborhood size over which to integrate terminator information was an open

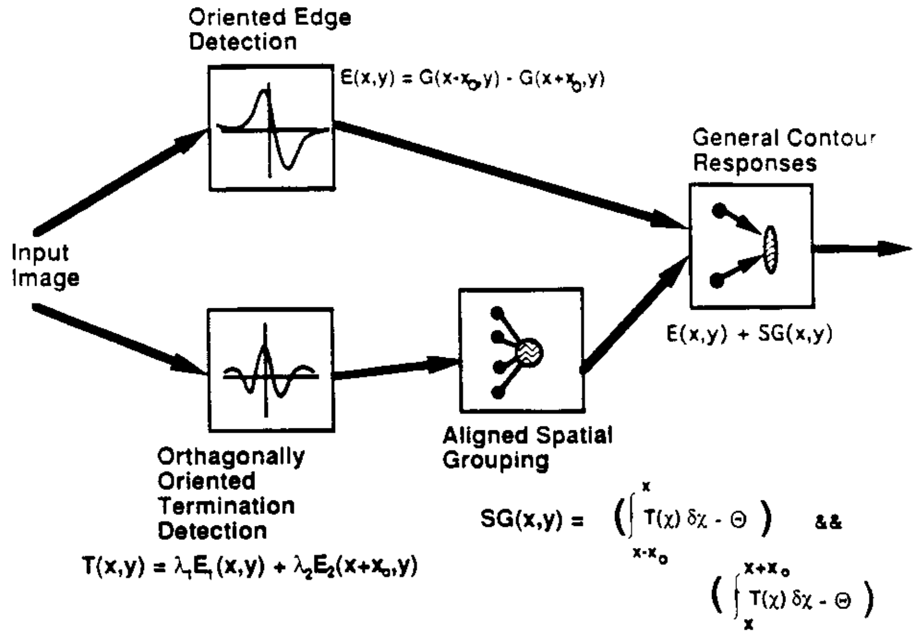


Figure 7: The network architecture. Edges and line terminations are filtered from an input image by layers of the network. Termination information is combined by layers of interneurons which serve as the illusory component of the generalized contour neuron.

parameter in the model; we used values between 0.5 and 1.0 visual degrees, in correspondence with psychophysical measurements of the maximum size gap which can be perceptually crossed by an illusory contour [30]. Terminator information was combined in a layer of interneurons; the illusory contour component merely pooled the interneurons on each side of its receptive field center to determine whether or not to fill-in.

Responses from both component parts, real and illusory, were summed in layers of general contour neurons; each node in these layers signaled the magnitude of real and illusory contour response at a given orientation and spatial position.

$$GCN(x,y) = \sum E(x,y) + \sum SG(x,y) \tag{6}$$

The network diagram is shown in Figure 7.

6.1 Simulation Predictions

Figure 8(Ia) shows an input image with an illusory "Kanizsa" square partially occluding four disks. "Normal" contour responses are shown in Figure 8(Ib). Responses of all layers of terminator cells are shown in Figure 8(Ic); they correspond to corners of the broken disks. The network was able to find normal boundaries as well as the illusory contours corresponding to boundaries of the occluding square (Fig. 8(Id)). The importance of terminator information is shown in Figure 8(II). Here, the sharp discontinuity information in the image is reduced, resulting in suppression of both the perceptual salience of the illusory square, and in the completion responses of the network. The result of the network when using an abutting grating illusory contour stimulus pattern is shown in Figure 8(III).

However, in more ambiguous images, the network had a tendency to generate spurious contour completion (Fig. 8(IV)). Here, the network found all physical contours, as well as contours corresponding to the illusory occluding bar. However, contour completion was also done in places where no perceptual occluding contour exists. These results suggest that although the proposed neural circuit contains many of the salient aspects of illusory contour perception, there must be a more complex process involved.

6.2 Perceptual Surfaces and an Enhanced Model

Examining even simple illusory contour examples reveals that subjective surfaces become more perceptually salient when the corners (or points of high curvature) of the surface are present as physical luminance discontinuities. A simple demonstration of the perceptual importance of these points is shown in Figure 9. The perceptual significance of corners and points of high curvature

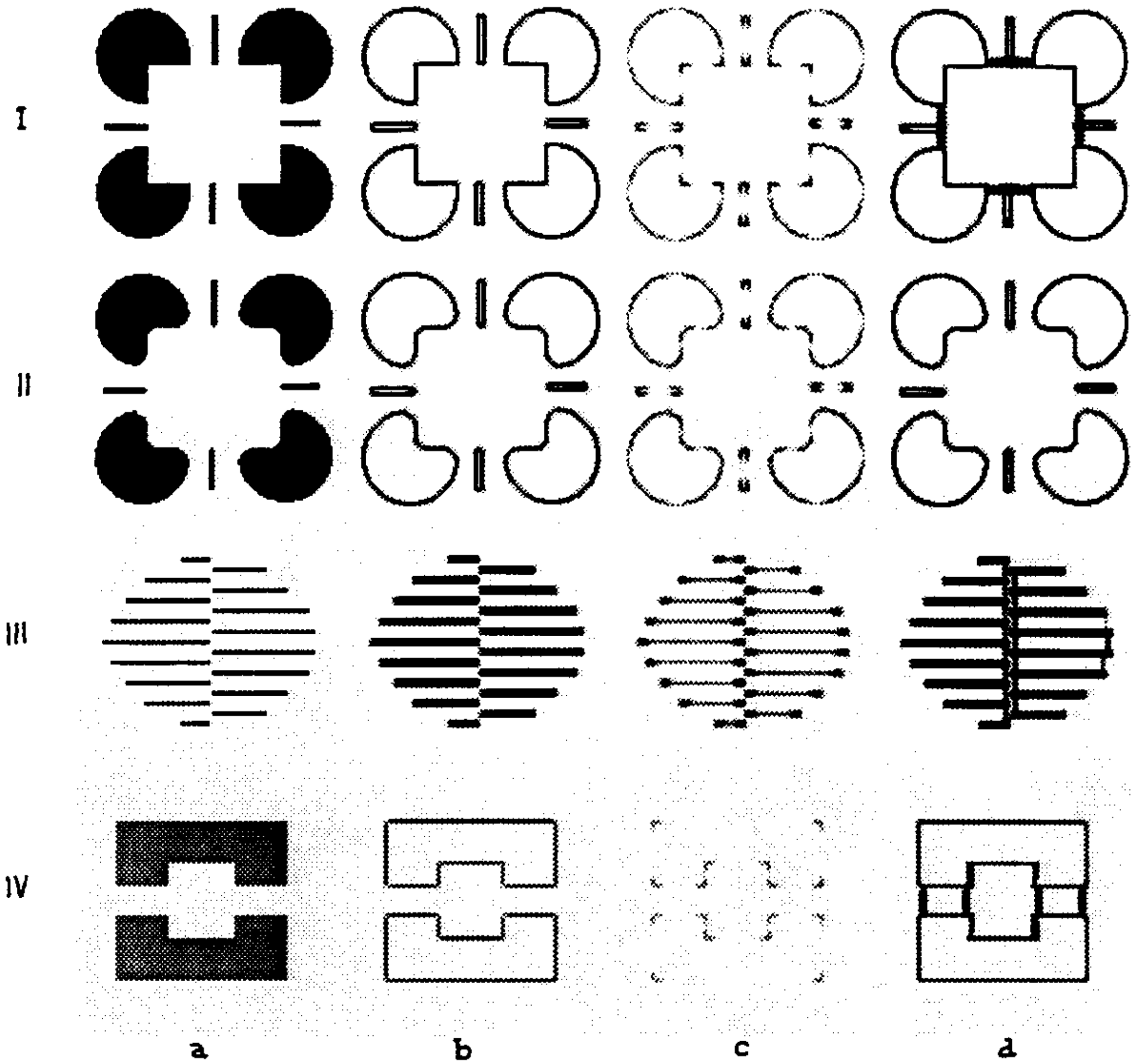


Figure 8: Typical simulation results. Each image is a response profile of a layer or layers of the network. (a) The input intensity profile. (b) Normal edge responses. (c) Terminator responses. (d) Response of generalized contour neurons.

Figure 9: The importance of corner information to illusory surface perception.

were first demonstrated by Attneave [1]. The corner of a surface generates termination information of opposite polarity from that provided by broken boundaries; thus a possible enhancement to the bottom-up processing of the model is to incorporate unequal contributions from opposite polarity terminator responses. OFF channel responses would then be weighted more heavily when completing across a dark-to-light gap, and vice-versa for light-to-dark gaps. With this unbalanced weighting incorporated into the network, responses begin to converge better on perceptual results; we predict that cells in V2 possibly perform this sort of unbalanced weighting.

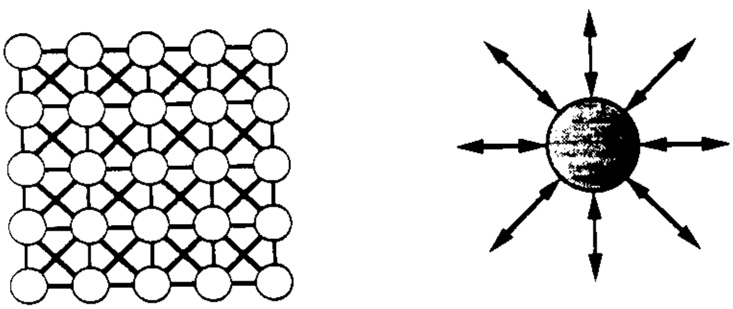
However, it is unlikely that this enhancement alone (or even with the requisite adaptive thresholding scheme) will suffice to adequately model the illusory contour phenomenon. Contours, both real and illusory, bound surfaces. Thus, attempting to construct a purely edge driven solution to the problem will most likely be inadequate; some information about surfaces existing in an image must be extracted to constrain the excess contour filling-in. However, constructing surface information using a purely local, bottom-up, feed forward network has proven to be difficult. The next section describes our work in progress towards developing a recurrent processing based model to accurately constrain the completion of general contour neurons.

7 Recurrent Networks

The visual world consists of intricate arrangements of possibly overlapping contour delineated surfaces. Hence, even primitive surface computations might provide the additional information needed to constrain activity of contour neurons. A surface (region in 2D) can be computed by grouping two dimensional features, including color, texture and motion according to qualities such as symmetry, closure and similarity. Nevertheless, illusory contours can be clearly perceived using only intensity based features. We therefore choose to work with a simplest set of features, intensity based contour and curvature.

In the primate visual system, the cells corresponding to the general contour neurons were speculated to exist in area V2 [21]. Locating processing responsible for the computation of surface information is a much more tangled endeavor. Most likely, multiple visual areas are involved in this function, with preliminary brightness levels being computed in the retina and LGN, contours and features being extracted in V1 and V2, and form assessments being made in higher visual areas (V3, V4, V5 and beyond). However, visual area V5 seems to play the major role in the type of computations under examination here [13].

The visual system is marked by modules roughly associated with somewhat independent visual tasks, with interactions between the areas (and visual tasks) carried out through rich sets of interconnections between them [13,35,6]. Information is normally thought to flow forward, but in fact most inter-cortical module connections are backward or recurrent connections. Of particular interest here are the excessive recurrent connections in the primate visual system from area V5 to area V2 [35,6]. Further, the manner in which these connections might affect information processing at the lower levels seems to match up well with the type of computation called for in the model partially described above; "...backward connections seem not to excite cells in lower areas, but instead influence the way they respond to stimuli within their smaller receptive fields" (Zeki and Shipp, 1988). In our model, surface or region information, possibly obtained in area V5, affects the processing of discontinuity information by cells in area V2 signalling illusory contours.



$$\frac{\partial x_a}{\partial t} = -K\, x_a(t) + 1/n \sum_{i,j} \psi x_{i,j}(t) + I_a$$

K is the decay rate.

ψ determines the connection strengths at position a, and is a function of the control.

I is the input at postion a.

Figure 10: The diffusion process. Activity levels are communicated through connections between cells. Each cell connects only to its 8 immediate neighbors.

7.1 Surface Computation

We construct a primitive estimate of surface information to asses the mechanism by which such information could be used to constrain the contour filling-in process. The chosen features are curvature and contour, which interact using a diffusion process. The features serve as sources of the process, diffusing activity levels through a syncytium of cells (Fig. 10). Steady state activity levels allow inference of surfaces present in the image - varying activity levels correspond to different surfaces. Activity level gradients provide cues for localization of contour information.

Because corners and points of high curvature seem to contain the most important information for constructing surface regions, they are used as higher level sources in the diffusion process, with contours serving as slightly lower sources. Typical ratios used are in the neighborhood of 4 : 1. The actual strength of the source is set as a function of the strength of the underlying feature detected in the image. Once set, these sources are allowed to diffuse through the syncytium.

Formally, given a set of variable strength sources $I(x, y)$ across the image, the activity level of a cell (x_a) obeys the following dynamics:

$$\frac{\delta x_a}{\delta t} = -Kx_a(t) + 1/n \sum_{i,j} \psi x_{i,j}(t) + I_a \tag{7}$$

where K is the decay rate, n is the number of neighbors of the cell and ψ is a connection strength control. ψ is a function of the strength of the contour level at the cell position:

$$\psi = \frac{1}{N + E_{i,j}} \tag{8}$$

where $E_{i,j}$ is the edge strength response at position (i,j) and N represents a control constant. Cells contributing to the activity level via the summation are those in an eight connected neighborhood. Systems of this nature characteristically settle into steady states relatively quickly; our simulations usually converged in 20-30 iterations.

7.2 Surface Contour Neuron

For maximal robustness, surface information should be computed interactively with contour information, corresponding to an iterative, concurrent region and edge based segmentation approach. Existing segmentation algorithms incorporating both edge and region based mechanism typically operate in a sequential manner, performing one type of segmentation, followed by the other with only a single interaction period between the two [8,19]. We feel that the processes must be allowed to evolve concurrently, as information from surfaces helps to constrain contours and vice-versa. This approach adheres to the the anatomy described earlier, consisting of feedforward and feedback connections between cortical areas V2 and V5.

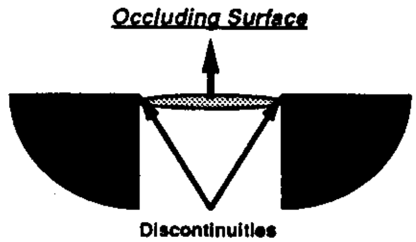


Figure 11: Orientation of discontinuity information yields an implicit occluding surface polarity.

The contour to surface interaction is given by the the mechanics of the diffusion process (Eq: 8). Here, contours provide both the sources and shunting of the diffusion. To complete the recurrence, a technique is needed to update contours based on surface information. Here we focus only on adjusting filled-in contours; contours marked by luminance discontinuities are maintained throughout the process. Our goal is to realize a system where filled-in contours not consistent with surface information are removed.

A simple consistency check can be derived from the "surface polarity" associated with any filled-in contour. When an illusory contour is completed between discontinuities, it is to mark the boundary of an occluding surface. The contours thus have an implicit foreground surface polarity associated with them. For example (Fig. 11) aligned corner elements may indicate that a surface occludes the elements from the top of the image. This is given by odd symmetric terminator information at 90 degrees, of either polarity type. Summing only these types of discontinuity information yields an implicit surface polarity in the inferred contour.

Interaction is modeled through inhibitory and excitatory "surface" inputs to the general contour neuron. Surface information on the proper side of the contour will provide the additional excitatory connections necessary to fire the cell; surface information on the opposite side will trigger inhibitory interactions which will suppress signaling of a contour.

8 Discussion

Recent studies of computer vision and computational modeling of biological vision systems have stressed the important role illusory contours may play in the visual segmentation process [15,8,25]. This paper has attempted to quantify that role, by developing a cogent framework for the need for illusory contours in the processing of images (ie in processing of occluding and discontinuity impaired surfaces), and in terms of providing computational analysis of current physiologically based theories of illusory contour perception.

The model of the general contour neuron proposed by Peterhans et al. [21] represents the most detailed physiologically motivated model of illusory contours. However, the enormous complexity and detail of the primate visual system often makes it impossible to accurately evaluate the value of such models without simulation.

Our results suggest that the proposed model displays salient aspects of illusory contour perception, but lacks the necessary computational complexity. For simple cases, the model performs well, however excessive contour completion is produced between arbitrarily aligned discontinuities that are indistinguishable from boundaries of occluding surfaces. Simple enhancements made to the model, such as the unequal weighting of terminator polarity information, improve the results. We feel that these results represent a significant advancement for computer vision; some of the seemingly complex cognitive methods by which humans efficiently extract information from images are captured through interactions of fairly simple features.

Illusory contours reflect the strong correlation between occlusion boundaries and depth effects [3]. Gregory and Harris [7] demonstrated that the ability to perceive illusory contours becomes impaired when stereoscopic depth information is present which contradicts the implicit occlusion

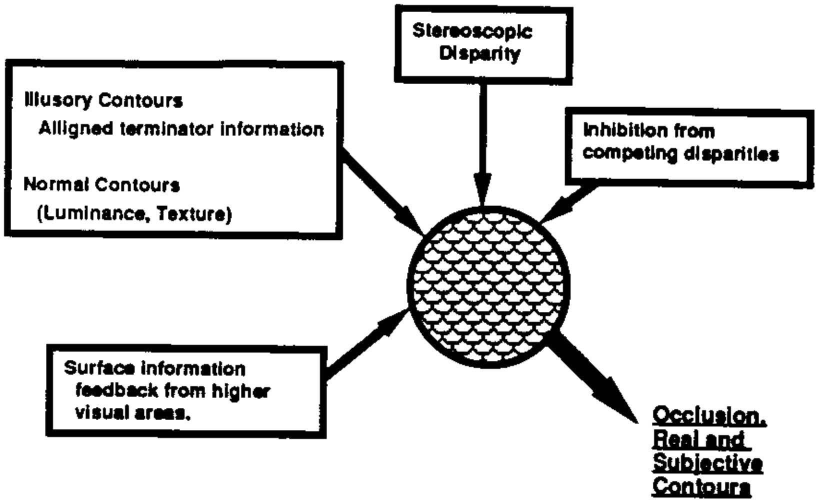


Figure 12: An occlusion neuron. The neuron is stimulated by converging excitatory inputs from illusory and real contours, as well as stereoscopic (and other forms of) depth, and inhibited by competing disparity information.

information of the illusory contour. It is conceivable that this is dealt with by early layers of the visual system using occlusion as a visual primitive [31]. We hypothesize the existence of "occlusion neurons" (Fig. 5) which are sensitive to stereoscopic depth effects, and are correspondingly inhibited by competing depth estimates. Furthermore, they are sensitive to edges which may mark these occlusion borders, such as sharp luminance or illusory edges. The model is thus consistent with observations that cells in V2 which are responsive to illusory contours are also binocular. It would be interesting to test whether these neurons would respond similarly to stereoscopic edges, as well as other occlusion associated discontinuities, such as from motion parallax.

Other computational models of visual processing have addressed the issue of illusory contour perception in the past. One of the most well known of these is the Boundary Contour System (BCS) proposed by Grossberg and Mignolla [8]. This system has shown the ability to complete simple illusory contours; completions are made on the basis of both collinear information and aligned line endings. However, the model fails to provide any sort of constraint on this contour completion, resulting in excessive completion between coincidently aligned segment pieces and line ends.

More sucessfull recent attempts have been made towards detection of illusory contours based in part on the principles of the Peterhans general contour neuron. Manjunath and Chellapa [14] includes orthogonally oriented terminator information as an additional input into their long range grouping mechanism. However, two immediate problems arise: 1) by not gating terminator information with similar sides on opposite sides of a gap lines are completed stretching well passed their true end points, and 2) the size of the grouping neighborhood must be set differently to perceive illusory contours in contrast to normal contours. The network similarly contains no method for monitoring spurious responses.

The model with which we can most closely identify is that proposed by Finkel and Edelman [6]. Their network is based fairly closely on the properties of the general contour neuron, and represent a fairly realistic implementation of such a circuit. Additionally, they recognize the strong relationship between illusory contours and occluding surfaces; illusory contours are filled-in through an occlusion processor. They further recognize the failure of the standard general contour neuron model to respond correctly in cases such as in Fig. 8(IV) (where spurious completions are generated); they require that contour completions have terminator information of both polarities present. This is similar to the unequal weighting of polarity information described as an enhancement to the standard general contour neuron above. However, it is clearly not the case the illusory contours require the existence of both types of polarity information, as for example shown in Figure 5(a).

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