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BOUNDARY DETECTION USING DOUBLE-OPPONENCY AND SPATIAL SPARSENESS CONSTRAINT

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ABSTRACT: Brightness and color are two basic visual features integrated by the human visual system (HVS) to gain a better understanding of color natural scenes. Aiming to combine these two cues to maximize the reliability of boundary detection in natural scenes, we propose a new framework based on the color-opponent mechanisms of a certain type of color-sensitive double-opponent (DO) cells in the primary visual cortex (V1) of HVS. This type of DO cells has oriented receptive field with both chromatically and spatially opponent structure. The proposed framework is a feed forward hierarchical model, which has direct counterpart to the color- pponent mechanisms involved in from the retina to V1. In addition, we employ the spatial sparseness constraint (SSC) of neural responses to further suppress the unwanted edges of texture elements. Experimental results show that the DO cells we modeled can flexibly capture both the structured chromatic and achromatic boundaries of salient objects in complex scenes when the cone inputs to DO cells are unbalanced. Meanwhile, the SSC operator further improves the performance by suppressing redundant texture edges. With competitive contour detection accuracy, the proposed model has the additional advantage of quite simple implementation with low computational cost. Keywords: Boundary, Color Opponent, Receptive Field, Visual System, Texture Suppression

I.INTRODUCTION

Boundaries are responsible for object recognition and shapes in an image. Two essential cues luminosity and color are combined to increase the accuracy of the boundary detection. In computer perception functions, boundary detection is a fundamental application, such as object detection [2]. Among various computational boundary detection, conventional approaches include level set [7], phase congruency [5], zero crossing [4],cannydetector [6]and oriented energy approaches [10]. However, many established edge detection methods consistently excerpt edges by calculating the instantaneous changes of regional luminance are not able to differentiate the boundaries from a generous amount of textured edges. To reach the human-level performance of boundary detection, abundant number of associations have been making considerable attempts. For example, to integrate more ocular features derived from the scenes. As a fundamental feature of extrinsic world, color particulars plays an essential role in the human visual approach, such as object recognition and structure. According to engineering aspect, color is essential for different image processing techniques such as image segmentation, edge detector.

II.RELATED WORK

In order to extract boundaries from color images, abundant early studies had concentrated on extending the standard edge detectors, such as canny [6]. In this method, it

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is difficult to differentiate conspicuous object boundaries and consistent edges due that they acknowledge to all disruptions in the image. Abundant approaches have been advanced for boundary detection in complicated scenes. Some learning based techniques also tried to take various scales, more local features or global information [2] for better results. Resent techniques also enhance contour detection at multiple scales. However accomplishment of many learning based techniques mentioned above relies upon the suitable selection of training sets, which makes these techniques stubborn for individual images. Besides this high computational cost raised for training sets have to be carefully handled. Other issue is to generate the salient contour pop out in cluttering scenes. Contour detection [2] [3] integrates multiple local cues into a globalized frame work. The zero crossing [4] are only inconsequential edges to prevent the detection that complements as the first derivative is above some thresholds. In phase congruency [5] it has been noted that features like edges have many frequency elements in the same phase. This coincides with human perceived edges in an image, where there are salient changes between dark and light. But it is very intensively complicated and sensitive to noise. To restrain unwanted textured edges from the boundaries, texture analysis method can be used. For texture defined boundaries, texture boundary detector [13] responds well, and are not sensitive to unwanted edges. However this technique results in high computational cost for multiple tasks. Some more boundary detecting methods have been proposed. Sketch tokens is a method which is fast and precise, which detects mid-level features. It is attainable to accomplish boundary detection performance by using low dimensions [2] and local information. Various techniques based on the biological methods for edge detection have been introduced, which motivated us to bring a color boundary detection [13]. Color gradients in the color boundaries where calculated here, which surpass the achievement of several traditional object recognition and boundary detection system. Here the restraint is, they are unsighted to luminance defined boundaries.

III.COLOR MECHANISMS:

Trichromacy:Photoreceptors are two types, they are rods and cones. Color vision is done by cones. Cones wave lengths are classified into three, long (L), middle (M), short (S). This is responsible for conveying color information which is known as trichromacy. x Color opponency: In the visual pathway, color statistics are handled in an opposing way. That is red is opposite to green, blue is opposite to yellow respectively. Opponent color responses are antagonistic to each other.

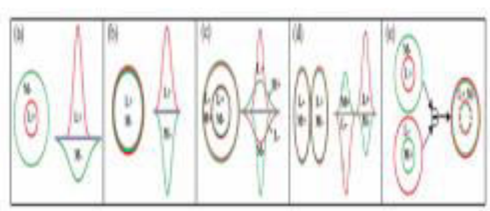

Fig 1: The Color opponent cells. (a) Type1, (b) type2, (c) concentric center surrounds receptive field, (d) side by side spatially orient receptive field, (e)illusion to explain type2 in the ganglion.

x Color opponent cells:The ganglion cells have a single opponent receptive field. Some cells in

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visual cortex (V1) have a double opponent receptive field. Single opponent cells are classified into two, type 1 cells have center surrounded opponent receptive field and type 2 cells are centered only opponent receptive field. Double opponent (DO) receptive field is both chromatic and spatially opponent to each other.

IV. PROPOSED SYSTEM

our new boundary detection system is based on the double component mechanism and has the amazing property of jointly extracting colors and luminances defined edges which is really different from the two steps way of some existing models that explicitly extract the color and luminance edges in separate channels and then combine them e.g. with a supervised learning.

A new strategy of spatial sparseness constraint was introduced to weight the edge responses of the proposed system which provides a simple while efficient way for texture suppression.

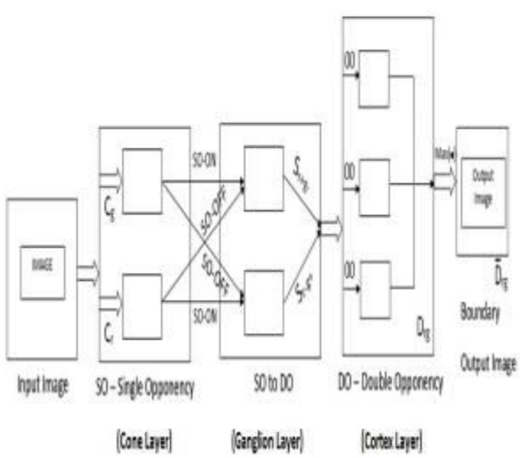

Fig.2:Block diagram of color opponent processing in the R-G channel.A.

From Single- to Double-Opponent Processing Our framework shown in Fig.2 is a feed forward hierarchical model including three layers, which correspond to the levels of retina, lateral geniculate nucleus (LGN), and V1 of the visual system, respectively. Based on the physiological hypothesis that the two sub regions of the RF of oriented DO cells resemble the RF of a Type II cell, we model that each DO V1 cell receives the neuronal responses of two single opponent LGN cells of Type II. In Fig. 2, we just show the computational steps in the R-G channel, and information processing along another channel of B-Y shares the similar computational steps.

1) Cone Layer: At the layer of cone photoreceptors, the input color image is first separated into three components:

Ir (x, y) for red (R), Ig(x, y) for green (G), and Ib(x, y) for blue (B), which are respectively sent into L, M, and S cones In addition, when the information from the cones is passed forward via horizontal cells, bipolar cells, etc., to the retinal ganglion cells, the output layer of the retina, a yellow (Y) component is constructed by a kind of bipolar cells that receive both R and G cone signals, i.e., Iy (x, y) = 0.5(Ir (x, y) +Ig(x, y)), which will be then sent to the single-opponent ganglion cells of B-Y type.

2) Ganglion/LGN Layer: The majority of ganglion cells in retina have center-surround RFs, which send information to LGN, a place that is widely regarded as a relay center between the retina and V1. Many physiological findings reveal that the ganglion and LGN cells have similar RF properties (e.g., single-opponent), and the main difference is that LGN cells have relatively larger RFs. Meanwhile, physiological studies have also reported that Type II cells with center-only RFs do exist in the dorsal layers of LGN, though they are in the minority. It has been suggested that the RF of a Type II LGN cell could be constructed by differencing two center-surround SO ganglion cells. Based on this idea, we unify the ganglion and LGN layers into a single processing by center-only LGN cells. We first define

$$C_k(x, y; \sigma) = I_k(x, y) * gf(x, y; \sigma); k \in \{r, g, b, y\} \tag{1}$$

$$gf(x, y; \sigma) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{2}$$

Where * is a convolution operator. Then, the response of the SO cells of R-G type (including R-on/G-off and G-on/R-off) is computed as

$$S_{rg}(x, y) = w_1 \cdot C_r(x, y; \sigma) + w_2 \cdot C_g(x, y; \sigma) \tag{3}$$

$$where \begin{cases} w_1 \cdot w_2 \leq 0 \\ |w_1|, |w_2| \in [0, 1] \end{cases} \tag{4}$$

Where $w1$ and $w2$ are the connection weights from cones to RGCs. $w1$ and $w2$ always have opposite signs.

3) Cortex Layer: In the cortex layer of V1, the RFs of most color- and color-luminance-sensitive neurons are both chromatically and spatially opponent. Mathematically, the DO RF with two side-by-side spatially antagonistic regions can be modeled using the first-order (partial) derivative of a two-dimensional (2D) Gaussian given by

$$V(x, y; \theta, \sigma) = \frac{\partial f(x, y; \theta, \sigma)}{\partial \tilde{x}} \tag{5}$$

$$f(x, y; \theta, \sigma) = \frac{1}{2\pi(k\sigma)^2} exp\left(-\frac{\tilde{x}^2 + \gamma^2\tilde{y}^2}{2(k\sigma)^2}\right) \tag{6}$$

$$\begin{bmatrix} \tilde{x} \\ \tilde{y} \end{bmatrix} = \begin{bmatrix} x\cos(\theta) + y\sin(\theta) \\ -x\sin(\theta) + y\cos(\theta) \end{bmatrix} \tag{7}$$

VI.RESULTS

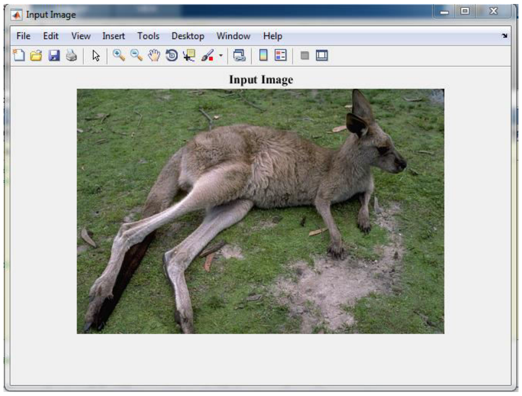

Fig 3: Input Image.

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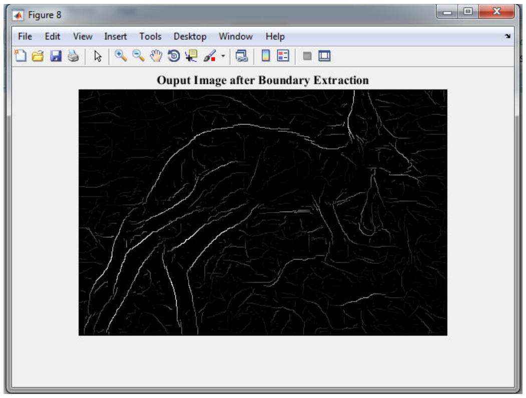

Fig 4: Output Image after Boundary Extraction.

VII.CONCLUSION

This work offers the property of responding well to the diversity of edges including both color and luminancedefined ones. With competitive performance in comparison to the state of the art approaches. We hope that the proposed double opponent based detector shows a way for the challenging task of detecting salient boundaries in complex color scenes, inspired by the information processing mechanisms emerging in the early visual stages. In specific, the SO ganglion cells function to enhance regionalinformation, and the oriented Double opponent cells in Visual cortex serve to detect the boundaries among regions.

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