Color- Opponent Mechanism For Boundary Detection

S.Amulya.
Department of Electronics and Communication Engineering
Narayana Engineering College, Nellore, Andhra Pradesh, India.

C. Leela Mohan
Associate Professor.
Department of Electronics and Communication Engineering
Narayana Engineering College, Nellore, Andhra Pradesh, India.

S. Girish Gandhi
Asst. Professor.
Department of Electronics and Communication Engineering
Narayana Engineering College, Nellore, Andhra Pradesh, India.

Abstract: Color and luminosity are essential aspects to explain thecolor natural scenes,which are used to improve the accuracy of boundary detection. Here we use anew mechanism depending on the color-opponency technique,of a certain kindof color-sensitive double-opponent cells in the human visual system of the primary visual cortex. Doubleopponent cells have adapted spatially and picturesquely antithetical structure,which has direct analogue to the color- opponent structure involved from the retina to visual cortex. In human visual system cones and rods are opposite in nature. Responses of two opposite colors are antagonistic to each other. Double opponent cells can easily apprehend both the chromatic and achromatic boundaries of important objects in convoluted scenes, when the cone inputs to double opponent cells are unequal. The spatial sparseness constraint operator is used to upgrade the response by concealing repetitious texture edges. With contentious contour detection efficiency, this technique has the further benefit of simple, understandable applicationwith very limited computational cost.

Key words— color opponent, boundary, visual system, texture suppression, receptive field.

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, edgedetector.

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 is difficult to differentiate conspicuousobject boundaries and consistent edges due thatthey acknowledgeto 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 colorboundary 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 areunsighted 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.
- Coloropponency**:** 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.

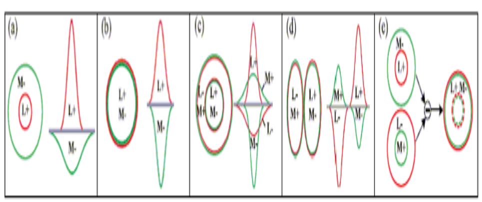

Fig 1: The Color opponent cells. (a) Type1, (b) type2, (c) concentric center surrounds receptive field, (d) side by side spatially orient receptive field, (e)illusion to explain type2 in the ganglion.

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

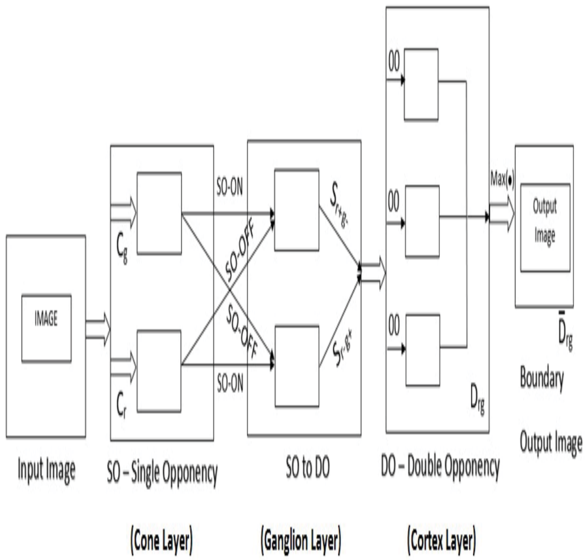

Fig.2:Block diagram of color opponent processing in the R-G channel.

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) GanglionLayer:

The majority of ganglion cells in retina have center-surround RFs, which send information to (Lateral geniculate nucleus) LGN, a place that is widely regarded as a relay center between the retina and visual cortex (V1). Many physiological findings reveal that the ganglion and LGN cells have similar receptive field(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 couldbe constructed by differencingtwo 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

$$Ck(x, y; \sigma) = Ik(x, y) * gf(x, y; \sigma); \; k \epsilon\{r, g, b, y\} \quad (1)$$

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

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

$$S_{rg}(x, y) = \omega_1 . C_r(x, y; \sigma) + \omega_2 . C_g(x, y; \sigma) \quad (3)$$

$$where \begin{cases} \omega_1 . \omega_2 \leq 0 \\ |\omega_1|, |\omega_2| \in [0,1] \end{cases} \quad (4)$$

Where *w*1 and *w*2 are the connection weights from cones to RGCs. *w*1 and *w*2 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 modelled using the first-order (partial) derivative of a two-dimensional (2D) Gaussian given by

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

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

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

Here γ is Gaussians spatial aspect ratio that handlesellipticity of receptive field, set γ=0.5. Most suitable orientation of a given cell isθ. Receptive field size of visual cortex neurons is $k\sigma$.Always set k=2.

Double opponent cells response is calculated by convoluting the single opponent cells response in lateral geniculate nucleus given by (3) with the orientedreceptive field filters. Given as

$$D_{rg}(x, y; \theta_i, \sigma) = S_{rg}(x, y) * RF_1(x, y; \theta_i, \sigma) - S_{rg}(x, y) * RF_2(x, y; \theta_i, \sigma) \quad (8)$$

$$RF_1(x, y; \theta_i, \sigma) = \mathbb{H}\left(V(x, y; \theta_i, \sigma)\right) \quad (9)$$

$$RF_2(x, y; \theta_i, \sigma) = \mathbb{H}\left(-V(x, y; \theta_i, \sigma)\right) \quad (10)$$

$$\mathbb{H}(s) = \begin{cases} s, & s > 0 \\ 0, & s \leq 0 \end{cases} \qquad (11)$$

Here * is used for convolution operation. $\theta_i \in [0,2\pi)$ *are* N_θ Orientations which are computed at $\theta_i = \frac{(i-1)2\pi}{N_\theta}, i = 1,2 \ldots\ldots, N_\theta$. Here we set $N_\theta = 16$.The neurons with $\theta = \alpha$ value responds preferably to the R to G boundaries. The neurons with $\theta = \alpha + \pi$ can detect the G to R boundaries.

The final response in another three double opponent channel like $\widetilde{D}_{rg}, \widetilde{D}_{by}$ *and* $\widetilde{D}_{yb}$, could be computed with

$$\widetilde{D}_{rg}(x, y; \sigma) = \max\{D_{rg}(x, y; \theta_i, \sigma) \qquad (12)$$

$$\mathrm{i} = \{1,2, \ldots, \mathrm{N}_\theta\}$$

To compare four double opponent channels, the output of each double opponent channel should be separately normalized linearly to [0,1].

V. Simulation Results:

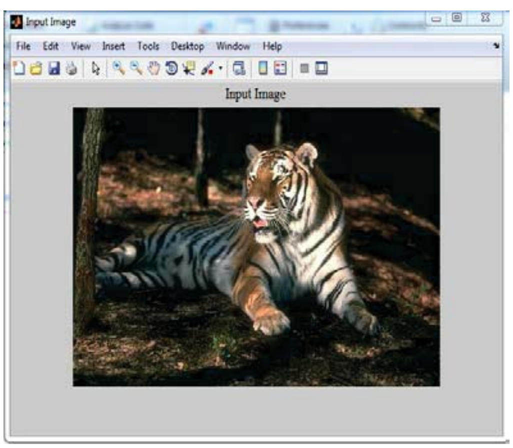

Fig: input Image

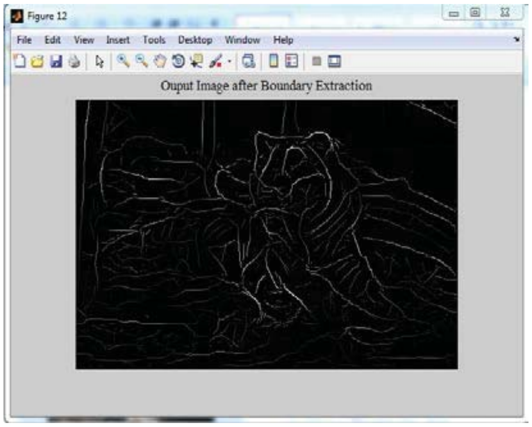

Fig: Output Image after Boundary Extraction

VI.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.

REFERENCES

[1] D. B. Walther, B. Chai, E. Caddigan, D. M.Beck, and L. FeiFei, "Simple line drawingssuffice for functional MRI decoding of naturalscene categories," *Proc. Nat. Acad. Sci.*, vol.108, no. 23, pp. 9661–9666, 2011.

[2] P. Arbeláez, M. Maire, C. Fowlkes, and J.Malik, "Contour detection and hierarchical image segmentation," *IEEE Trans. Pattern Anal.Mach.Intell.*, vol. 33, no. 5, pp. 898–916, May2011.

[3] G. Papari and N. Petkov, "Edge and line Oriented contour detection:State of the art," *Image Vis. Comput.*, vol. 29, nos. 2–3, pp.79–103,2011.

[4] D. Marr and E. Hildreth, "Theory of edgedetection," *Proc. Roy. Soc.London B, Biol. Sci.*, vol. 207, no. 1167, pp. 187–217, 1980.

[5] P. Kovesi, "Image features from phasecongruency," *Videre, J. Comput.Vis. Res.*, vol. 1,no. 3, pp. 1–26, 1999.

[6] J. Canny, "A computational approach to edgedetection," *IEEE Trans.Pattern Anal. Mach.Intell.*, vol. PAMI8,no. 6, pp. 679–698, Nov.1986.

[7] X. Yang, X. Gao, D. Tao, and X. Li,"Improving level set method for fast auroral ovalsegmentation," *IEEE Trans. Image Process.*,vol. 23,no. 7, pp. 2854–2865, Jul. 2014.

[8] X. Yang, X. Gao, J. Li, and B. Han, "Ashapeinitializedand intensityadaptive level setmethod for auroral oval segmentation," *Inf. Sci.*,vol. 277, pp. 794–807, Sep. 2014.

[9] X. Yang, X. Gao, D. Tao, X. Li, and J. Li,"An efficient MRF embedded level set methodfor image segmentation," *IEEE Trans. ImageProcess.*,vol. 24, no. 1, pp. 9–21, Jan. 2015.

[10] P. Perona and J. Malik, "Detecting andlocalizing edges composed of steps, peaks androofs," in *Proc. 3rd ICCV*, Dec. 1990, pp.52–57.

[11] M. C. Morrone and R. A. Owens, "Featuredetection from local energy,"*Pattern Recognit.Lett.*, vol.6, no. 5, pp. 303–313, 1987.

[12] W. T. Freeman and E. H. Adelson, "Thedesign and use of steerable filters," *IEEE Trans.Pattern Anal. Mach. Intell.*, vol. 13, no. 9,pp. 891–906, Sep. 1991.

[13] D. R. Martin, C. C. Fowlkes, and J. Malik,"Learning to detect natural image boundariesusing local brightness, color, and texture cues,"*IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26,no. 5, pp. 530–549,May 2004.