ISSN XXXX XXXX © 2018 IJESC

IJESC

Research Article Volume 8 Issue No.2

Effective Object Boundary Detection using Color Double Opponency

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Abstract:
In this system we are aiming two basic visual features, Brightness and color and to combine these two facts 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 of HVS(human visual system). 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-opponent 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 modelled 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 whitlow computational cost.

I. INTRODUCTION

Boundaries of Objects represent important cues for visual perception such as scene understanding and object recognition. Boundary detection characterizes object boundaries and is useful features for segmentation, registration and object identification in scenes. Goal of boundary detection is Identify sudden changes or discontinuities in an image. Boundary detection is also a fundamental building block for a large variety of computer vision applications, such as image segmentation and object detection. However, most traditional edge detection methods usually extract edges by computing the abrupt change of local luminance. As a basic feature of external world, color information plays an important role in human visual perception such as shape and object recognition.

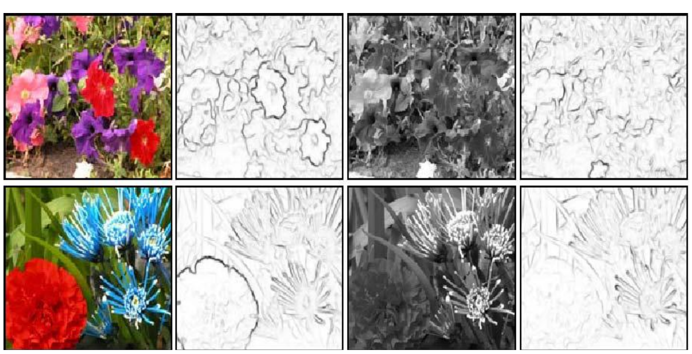

Figure.1.1 Example of Boundary Detection

From the perspective of engineering, color is also necessary for various image processing tasks, such as edge detection, image segmentation, and junction/corner detection. Fig. 1 shows typical examples illustrating that some important contours of objects (e.g., flowers in the first column) in color images are lost in the gray-scale space, especially for those boundaries with only color contrast in regions of iso-luminance.

1.1.1 Why do we care about edges?

- **Extract information, recognize objects**

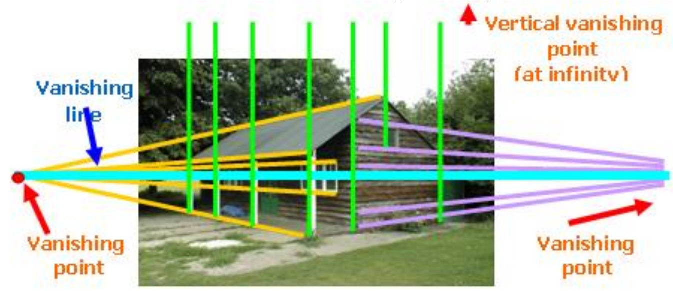

Figure.2. Recognition of Object

- **Recover geometry and viewpoint**

1.1.2 Origin of Edges

- **Edges are caused by a variety of factors**

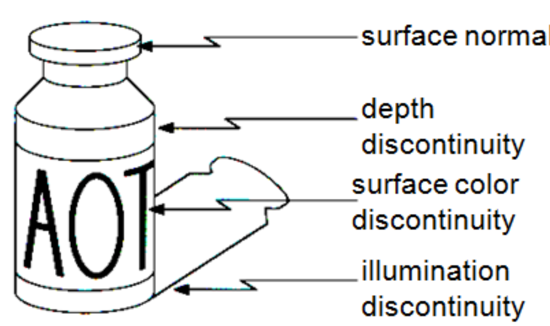

Figure.3. Cause of Edges

1.2 CRITERIA FOR A GOOD BOUNDARY DETECTOR

- **Criteria for a good boundary detector:**
- **Good detection:** the optimal detector should find all

real edges, ignoring noise or other artifacts

– **Good localization**

• the edges detected must be as close as possible to the true edges

• the detector must return one point only for each true edge point

• **Cues of boundary detection**

– Differences in color, intensity, or texture across the boundary

– Continuity and closure

– High-level knowledge.

II. EXISTING SYSTEM

• Among numerous computational boundary detection, typical methods include:

➢ **Canny detector :**

This is probably the most widely used edge detector in computer vision Theoretical model: step-edges corrupted by additive Gaussian noise Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of signal-to-noise ratio and localization Note about Matlab's canny detector

Small errors in implementation:

Gaussian function not properly normalized First filters with a Gaussian, then a difference of Gaussian (equivalent to filtering with a larger Gaussian and taking difference).

➢ Zero crossing

➢ phase congruency

• In these above methods, to detect boundaries from color images, many early studies focused on extending the standard edge detectors, such as Canny to color space.

• However, most traditional edge detection methods usually extract edges by computing the abrupt change of local luminance.

• The performances of most learning-based methods mentioned above are dependent on the appropriate selection of training sets.

2.2 LIMITATIONS OF THE EXISTING SYSTEM

The existing or traditional Boundary detection system has some limitations which can be overcome by adopting new methods.

• These methods are inherently difficult to discriminate salient object boundaries and texture edges due that they respond to all the discontinuities in image intensity, color or texture.

• Normally are not capable of distinguishing boundaries from abundant of textured edges.

III. RELATED WORK

In order to detect boundaries from color images, many early studies focused on extending the standard edge detectors, such as Canny [1], to color space. These methods are inherently difficult to discriminate salient object boundaries and texture edges due that they respond to all the discontinuities in image intensity, color or texture. In recent decades, many new approaches have been developed for boundary detection in complex scenes. Typically, in the famous *Pb* method, Martin *et al*. [2] took into account multiple local cues (i.e., color, brightness, and texture) and combined these cues with certain learning technique to detect and localize the boundaries. Other learning-based methods tried to take multiple scales [3], more local features [4] or global information [5], [6] for better results. Recent methods also improve contour detection by learning to classify the various SIFT features [7] or sparse code features [8], [9] extracted at multiple scales. However, the performances of most learning-based methods mentioned above are dependent on the appropriate selection of training sets, which makes the methods inflexible for individual images. Furthermore, the high computational cost resulted from training needs to be carefully dealt with. Another important issue is to make the salient contours pop out in cluttered scenes. There are mainly two classes of methods including contour grouping and texture suppression. Contour grouping methods usually integrate low-level elements produced by basic edge detectors into mid-level features. For example, Zhu *et al*. [10] proposed a contour grouping method with the topological formulation called Untangling Cycles. Ren *et al*. [11] presented a model to enforce the curvilinear continuity with Conditional Random Fields framework. By utilizing the Gestalt rules (i.e., good-continuation, proximity, contour-closure, etc.), existing methods introduced the local interactions between contour segments [12], [13] and global effect [14] to extract perceptually salient contours. Salient contours were also extracted by solving the min-cover problem [15] or building Ultrametric Contour Maps [5], [16]. Texture analysis methods have also been used to suppress the undesired textured edges while extracting boundaries. For example, texton-based approaches have been developed for texture analysis and image segmentation [17], [18]. Martin *et al*. further developed the Texture-Gradient (TG) for texture boundary detection [2]. These detectors respond well to texture-defined boundaries and are insensitive to unwanted edge segments within homogeneous textured regions. However, texton-based methods usually take high computational cost on multiple convolution operations and high-dimensional analysis. Recently, some more time-saving texture boundary detection algorithms have been proposed. For example, biologically inspired surround inhibition methods make texture boundaries pop out by suppressing the unwanted short edges surrounded by similar textured patterns [19]. Hidayat *et al*. detected texture boundaries almost in real-time by extracting ridges in the standard deviation space [21]. It is exciting to see that several more recent models are capable of obtaining a quite well balance between boundary detection accuracy and computational cost, especially for the multi-scale and learning-based frameworks. For example, Leordeanu *et al*. [22] proposed a generalized boundary detection model (termed *Gb*), which estimates a measure of boundary strength for each location in a closed-form computation by utilizing multiple layers of image representations of various features at both low- and mid-levels. Then a logistic model learned from training set is used to obtain the probability of boundary. This *Gb* model achieves competitive results at a quite lower computational cost. More recently, Lim *et al*. [23] proposed a quite fast and accurate edge detector that learns and detects mid-level features, called *Sketch Tokens*, to capture local edge structure. They learn the features of sketch tokens using supervised mid-level information from human labeled edges in natural images, and then classify edge patches of new images into sketch tokens using random forest classifiers. In order to discard the requirement of pre-defined classes of edge patches in sketch tokens based model, Dollár and Zitnick [24] proposed a novel framework of structured random forests to learn more subtle variations in edge structure by taking advantage of the inherent structure in edge patches. This model can achieve state-of-the-art results almost in real-time. Contrary to the recent trends employing higher-order or higher-level information for boundary detection as mentioned above, Isola *et al*. [25] introduced a very local variance termed point wise mutual information (*PMI*) as the statistical association between pixels to predict whether or not two pixels belong to the same object. Then a spectral clustering was used to get segments and boundaries. The state-of-the-art results obtained by this model suggest that with the help of certain grouping operation, it is possible to achieve excellent boundary detection performance by only using very local information and low-dimensional feature spaces [5], [25]. Along another line, it has a long history that to employ early visual mechanisms for image analysis, such as texture discrimination in gray-scale images [26], [27]. Recently, the increasing success of biologically based methods for edge detection in gray-scale images [19], [28], [29] motivated us to build a biologically inspired framework for color boundary detection in natural images in an effective way. Several methods based on the color-opponent channels, i.e., Red-Green (R-G) and Blue-Yellow (B-Y) channels found in the visual system, have exhibited promising performance on color boundary detection. Martin *et al*. [2] computed the color gradients in these two single-opponent channels for color boundary detection. Zhou and Mel [30] applied custom "pairwise difference" oriented edge detector on the smoothed R-G and B-Y. More recently, Zhang *et al*. [31] proposed a new color descriptor based on color-opponent mechanisms, which improves the performances of several classical object recognition and boundary detection systems by extending them from grayscale to color space. However, one of the key limitations of these coloropponency based approaches is that the color-opponent channels in them are blind to the luminance-defined boundaries when no luminance channel is explicitly included [2], [31].

IV. PROBLEM STATEMENT

Goal of boundary detection is Identify sudden changes or discontinuities in an image. Object boundaries represent important cues for visual perception such as scene understanding and object recognition. 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

Introduction to Feed forward Neural Network

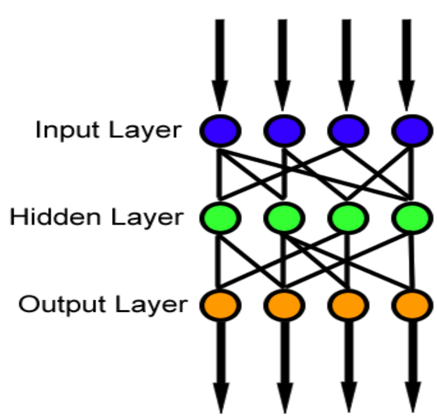

Fig 4.1 Feed Forward Neural Networks

In a feed forward network information at a later level. A feed forward neural network is an artificial neural network where connections between the units do *not* form a directed cycle. This is different from recurrent neural networks. The feed forward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network

V. PROPOSED SYSTEM

Our new boundary detection system is based on the double-opponent (DO) mechanism and has the amazing property of jointly extracting color- and luminance-defined edges, which is really different from the two-step way of some existing models that explicitly extract the color and luminance edges in separate channels and then combine them. A new strategy of spatial sparseness constraint (SSC) was introduced to weight the edge responses of the proposed CO system, which provides a simple while efficient way for texture suppression. This system proposes a novel contour detection model based on the color-opponent mechanisms of the biological visual system by specifically simulating the DO cells with oriented RF. The new model includes three layers simulating the levels of retina, LGN, and V1 (Fig. 3). Particularly, in the last layer (Cortex layer), a pool of oriented DO cells with different preferred orientations is used at each location to extract boundaries by receiving the responses of SO LGN cells, followed by a max operator across all orientations to combine responses to boundaries in separate DO channels. Finally, we compute the maximum to combine the boundaries across all DO channels. To our knowledge, this work is the first attempt to introduce the DO mechanism of color-sensitive V1 cells with oriented RF, a very important group of cells in V1, for detecting boundaries. Second, this work also develops a new texture suppression method with spatial sparseness constraint (SSC). We suppress the neuronal responses to the edges in the local regions with low sparseness measure. This operator works well because the local regions containing (unwanted) regularly distributed textures tend to exhibit lower local sparseness measure, while the regions covering salient boundaries usually have high spatial sparseness in response.

As briefly mentioned above, in this work, we simulate the biological mechanisms of color information processing along the Retina-LGN-Cortex visual pathway and propose a feed forward hierarchical system for boundary detection in real natural scenes by using only low-level local information. The results on a commonly used dataset will show that our model has the capacity of jointly detecting the color- and luminance-defined boundaries and efficiently suppressing textural edges.

VI. REFERENCES

[1]. J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, Nov. 1986.

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

[3]. X. Ren, "Multi-scale improves boundary detection in natural images, "in *Proc. ECCV*, 2008, pp. 533–545.

[4]. P. Dollar, Z. Tu, and S. Belongie, “Supervised learning of edges and object boundaries,” in *Proc. IEEE CVPR*, vol. 2. Jun. 2006,pp. 1964–1971.

[5]. 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, May 2011.

[6]. M. Maire, P. Arbeláez, C. Fowlkes, and J. Malik, “Using contours to detect and localize junctions in natural images,” in *Proc. IEEE CVPR*,Jun. 2008, pp. 1–8.

[7]. I. Kokkinos, “Highly accurate boundary detection and grouping,” in *Proc. IEEE CVPR*, Jun. 2010, pp. 2520–2527.

[8]. J. Mairal, M. Leordeanu, F. Bach, M. Hebert, and J. Ponce, “Discriminative sparse image models for class-specific edge detection and image interpretation,” in *Proc. ECCV*, 2008, pp. 43–56.

[9]. X. Ren and L. Bo, “Discriminatively trained sparse code gradients for contour detection,” in *Proc. NIPS*, 2012, pp. 593–601.[23] Q. Zhu, G. Song, and J. Shi, “Untangling cycles for contour grouping, “in *Proc. IEEE 11th ICCV*, Oct. 2007, pp. 1–8.

[10]. X. Ren, C. C. Fowlkes, and J. Malik, “Scale-invariant contour completion using conditional random fields,” in *Proc. 10th IEEE ICCV*, vol. 2.Oct. 2005, pp. 1214–1221.

[11]. R. Kennedy, J. Gallier, and J. Shi, “Contour cut: Identifying salient contours in images by solving a Hermitian eigenvalue problem,” in *Proc .IEEE CVPR*, Jun. 2011, pp. 2065–2072.

[12]. S. Mahamud, L. R. Williams, K. K. Thornber, and K. Xu, “Segmentation of multiple salient closed contours from real images,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 4, pp. 433–444, Apr. 2003.

[13]. Y. Ming, H. Li, and X. He, “Connected contours: A new contour completion model that respects the closure effect,” in *Proc. IEEE CVPR*,Jun. 2012, pp. 829–836.

[14]. P. Felzenszwalb and D. McAllester, “A min-cover approach for finding salient curves,” in *Proc. Comput. Vis. Pattern Recognit. Workshop (CVPRW)*, Jun. 2006, p. 185.

[15]. P. Arbelaez, “Boundary extraction in natural images using ultrametriccontour maps,” in *Proc. Comput. Vis. Pattern Recognit. Workshop (CVPRW)*, Jun. 2006, p. 182.

[16]. J. Malik, S. Belongie, J. Shi, and T. Leung, “Textons, contours and regions: Cue integration in image segmentation,” in *Proc. ICCV*, vol. 2.1999, pp. 918–925.

[17]. J. Malik, S. Belongie, T. Leung, and J. Shi, “Contour and texture analysis for image segmentation,” *Int. J. Comput. Vis.*, vol. 43, no. 1, pp. 7–27, 2001.

[18] C. Grigorescu, N. Petkov, and M. A. Westenberg, “Contour detection based on no classical receptive field inhibition,” *IEEE Trans. ImageProcess.*, vol. 12, no. 7, pp. 729–739, Jul. 2003.

[19]. K.-F. Yang, C.-Y. Li, and Y.-J. Li, “Multifeature-based surround inhibition improves contour detection in natural images,” *IEEE Trans. Image Process.*, vol. 23, no. 12, pp. 5020–5032, Dec. 2014.

[20]. R. Hidayat and R. D. Green, “Real-time texture boundary detection from ridges in the standard deviation space,” in *Proc. BMVC*, 2009,pp. 1–10.

[21]. M. Leordeanu, R. Sukthankar, and C. Sminchisescu, “Efficient closed form solution to generalized boundary detection,” in *Proc. ECCV*, 2012,pp. 516–529.

[22]. J. J. Lim, C. L. Zitnick, and P. Dollár, “Sketch tokens: A learnedmid-level representation for contour and object detection,” in *Proc.IEEE CVPR*, Jun. 2013, pp. 3158–3165.

[23]. P. Dollár and C. L. Zitnick, “Structured forests for fast edge detection,”in *Proc. IEEE ICCV*, Dec. 2013, pp. 1841–1848.

[24]. P. Isola, D. Zoran, D. Krishnan, and E. H. Adelson, “Crisp boundary detection using point wise mutual information,” in *Proc. ECCV*, 2014,pp. 799–814.

[25]. J. Malik and P. Perona, “Retentive texture discrimination with earlyvision mechanisms,” *J. Opt. Soc. Amer. A*, vol. 7, no. 5, pp. 923–932, 1990.

[26]. N. Petkov and P. Kruizinga, “Computational models of visual neurons specialised in the detection of periodic and aperiodic oriented visualstimuli: Bar and grating cells,” *Biol. Cybern.*, vol. 76, no. 2, pp. 83–96, 1997.

[27]. G. Papari, P. Campisi, N. Petkov, and A. Neri, “A biologically motivated multiresolution approach to contour detection,” *EURASIP J. Appl. Signal Process.*, vol. 2007, no. 1, 2007, Art. ID 071828.

[28]. N. Petkov and M. A. Westenberg, “Suppression of contour perception by band-limited noise and its relation to non classical receptive field inhibition,” *Biol. Cybern.*, vol. 88, no. 3, pp. 236–246, 2003.

[29]. C. Zhou and B. W. Mel, “Cue combination and color edge detection innatural scenes,” *J. Vis.*, vol. 8, no. 4, pp. 1–25, Apr. 2008.

[30]. J. Zhang, Y. Barhomi, and T. Serre, “A new biologically inspired color image descriptor,” in *Proc. ECCV*, 2012, pp. 312–324.