A Biologically Inspired Model Using Laplacian of Gaussian Improves Contour Detection

Mayuri Vidhate¹, L.B.Randive²

¹P.G Student, Computer Science and Engineering, M.I.T Aurangabad
²Assistant Professor, Computer Science and Engineering, M.I.T Aurangabad

Abstract-A model for detecting contours in gray scale images is presented by combining three features. We present an overview of various approaches to contour detection that have been proposed in the last two decades. The goal of this work is to accurately detect contour in gray level images by combining multiple visual features. Majority of neurons in the primary visual cortex respond to a line or an edge of a certain orientation in visual field. In this study, a biological model (Multi Feature Surround suppression) is proposed to improve performance of contour detection. Weighted feature difference is combining as in fine scale. The combined weights are then used to modulate the final surround prohibition of the neurons. The proposed framework compared with other contour detection methods. Output of this method matched against ground truth binary images to count precision and recall values. We test this method on RuG40 dataset. Defining the limits of the receptive field of a neuron in visual cortex has never been a simple issue; however, a fundamental distinction can be made between the region of visual space in which stimuli evoke spike discharges the so called ‘classical receptive field’, Our proposed model use only image intensity as the source of contour detection.

Index terms- Classical Receptive Field, Laplacian of Gaussian, Surround Inhibition

I. INTRODUCTION

Computer vision include methods of processing, analyzing images and high dimensional data to form high level understanding and recognition of the scene or images. Contour detection is one of the intermediate step in computer vision applications such as shape-based object recognition[1], pattern matching[2]. The extraction of meaningful information from images by means of digital image processing approaches is an important task in many application domains.

Precise difference given in edge and contour Edge refers to variations in intensity level in gray level image whereas contours are salient course edges that belong to object and region boundaries in that image[3] Many methods has been studied early for edge or contour detection, examples include local differential[4,5], phase congruency[5,6], snake contour[8,9] statically inference[10] etc. Research has been made according to progress in accuracy and efficiency. Contour judgment is one of the important functions of human visual system. Primary visual cortex which is present in a brain give much attention in contour judgment, The beginning work of hubel and wise linearly 1960’s [11] publish that the majority of V1 neuron are gracefully sensitive to oriented bars or edges in classical receptive field (CRF) which is particular region of sensory visual space. There is slight difference in between CRF and non-CRF i.e. surrounding CRF region is non-CRF this will understand by below figure In fig 1.1 center small circle is CRF and large circle i.e. surround part of CRF is non-CRF. Our proposed method has been tested on the RuG40 dataset [12], and experimental results exhibit promising performances. The remainder of this paper is organized as follows. In Section 2, we present related work in contour detection and Then, we describe the details of our biologically-inspired Multi Feature Surround suppression model and biologically-inspired multi
feature prohibition algorithm in Section 3. In Section 4, we evaluate the performance of the proposed method on the RuG40 dataset. Finally, we discuss our model and draw conclusions in Section 5.

![Difference in CRF and NON-CRF](image)

**II. RELATED WORK**

Contour detection and edge detection are classical problems in computer vision. There is a huge Literature on these topics. It is hard for this paper to give a full survey on the topic, so only a small relevant subset of works will be reviewed here.

Contour detectors are classified in three main classes [12] 1. location oriented or Region oriented [13,14] in which location of Steady or slowly varying texture are first identified; Contours are then determined as closed boundaries; 2. edge or line oriented [15] in which lines are explained using some feature of image like contrast, intensity level. 3. hybrid in which there is mix of above two classes. These three classes also classify in two methods [15,16], (i) Local method, which have local differences of intensity, color, texture of image. (ii) Global methods which is based on good continuation and closure of pixels. There are two main categories of contour detection techniques First is the computational or this can also known as Learning based method in which machine learning approaches are used like supervised or supervised methods. A regression classifier is used to predict contour strength from these features. Examples include global probability of boundary (gPb)[17], Multi-scale Probability of boundary[18], and next is the biologically inspired or non learning based methods which attempts to model some structural features of the Human Visual System More precisely, our contour detection approach attempts to model the Primary visual cortex concept[19,20]. It means that any picture or image that captures from our eye first its reflection goes to photoreceptor in retina. The optics of the eye create an image of the visual world on the retina. Visual perception is the ability to interpret the surrounding environment using light in the visible spectrum reflected by the objects in the environment. The resulting perception is also known as visual perception, eyesight, sight, or vision. The classical receptive field [21] of an individual sensory neuron is the particular region of the sensory space i.e. retina. In the visual system, receptive fields are volumes in space. combination of two parts is equal to receptive field first is the center part which is called as classical receptive field and second is surround part of that particular space which is known as non-classical receptive field[22]. Receptive fields of cells in the visual cortex are larger and have more-complex stimulus requirements than retinal ganglion cells or lateral geniculate nucleus cells. Hubel and Wiesel (e.g., Hubel, 1963; Hubel-Wiesel 1959) so, our purpose is to find the contours which is detect on line that is between CRF and NON-CRF i.e. detects on line between center and surround part of receptive field[20,21]. Neurons in primary visual cortex react to orientation, intensity, contrast etc extract applicable information from natural images. The neuronal responses are strongly inhibited when the stimuli within the CRF and non-CRF share similar features. Here we apply non-maxima suppression and hysteresis thresholding, Non-Maximum suppression is applied to "thin" the contours. After applying gradient calculation, the
contour extracted from the gradient value is at rest highly blurred. There should only be one accurate response to the contour. Thus non-maximum suppression can help to suppress all the gradient values to 0 except the local maximal, which indicates location with the sharpest change of intensity value. And hysteresis thresholding is next process after non-maxima suppression in which filter out contour pixels with a weak gradient value and preserve contour pixels with a high gradient value.

However, to the best of our knowledge, similar algorithms or frameworks have been rarely used to detect contours. In our work, a biologically-inspired Character Based surround suppression is proposed for contour Detection. We introduce a laplacian of Gaussian to obtain oriented CRF response and then modulate surround suppression using different scale based planning.

III. MATHEMATICAL MODEL

Proposed model shown in fig 2 in which First we compute CRF stimulus with orientation using Laplacian of Gaussian to describe their effects on different orientations. After that we extract three features of image then we find weighted feature difference between CRF and non-CRF.then combine that weighted feature difference at fine scale. Then find final contours by subtracting maximum of weighted feature difference from CRF stimuli.

3.1 Find CRF Stimulus

The Laplacian of Gaussian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for contour detection. Here we find CRF stimulus,

\[
CRF(x, y, \theta, \sigma) = \frac{\partial^2 G_\sigma(x,y)}{\partial x^2} + \frac{\partial^2 G_\sigma(x,y)}{\partial y^2}
\]  
(1)

Where, \(\theta\) is preferred orientation and \(\sigma\) is the standard deviation define the size of CRF.

For an input image \(I(x, y)\), the CRF response of a V1 cell with preferred orientation \(\theta_i\) is computed as

\[
e_i(x, y; \theta_i, \sigma) = |I(x, y)| \ast CRF(x, y; \theta, \sigma)
\]  
(2)

Then, at each location, the maximum CRF response over all \(N_\theta\) cells with different orientations is selected as the final CRF response, which is written as

\[
E(x, y; \sigma) = \max \{e_i(x, y; \theta_i, \sigma) | i = 1, 2, \ldots, N_\theta \}
\]  
(3)
3.2 Extraction of Feature

In this section, we will describe how to extract the multiple visible features, i.e. orientation $\theta(x,y)$, Luminance $L(x,y)$, and Contrast $C(x,y)$.

We code the orientation information of the local stimuli around $(x,y)$ with a vector as,

$$\theta(x,y) = [e_1, e_2, ..., e_{N\theta}]^{T}_{(x,y)}$$

(4)

This vector will be used to compute the orientation difference of the stimuli between CRF and non-CRF.

Luminance:

$$L(x,y) = 1/\mu \sum_{(x_i,y_i) \in S_{xy}} w(x_i,y_i) I(x_i,y_i)$$

(5)

Luminance Contrast:

$$C(x,y) = \sqrt{1/\mu \sum_{(x_i,y_i) \in S_{xy}} w(x_i,y_i) \frac{(I(x_i,y_i) - L(x,y))^2}{L(x,y)^2}}$$

(6)

Where, $w(x_i,y_i)$ is a raised weighted cosine window used to find difference between Luminance and Luminance contrast. Note that the values of luminance and luminance contrast are linearly normalized to $[0, 1]$ (i.e., $L, C \in [0, 1]$) for convenience of computation.

3.3 Weighted Feature Difference:

In this find weighted feature difference between CRF and non-CRF.

For Orientation:

$$W_\theta(x,y) = \exp\left(-\frac{\Delta\theta(x,y)^2}{2\sigma^2_{\theta}}\right)$$

(7)
Where, $\Delta \theta(x,y)$ is the difference of CRF and non-CRF for orientation, and the standard deviation $\sigma_{\Delta \theta}$ establishes the sensitivity of inhibitory strength with orientation difference.

For Luminance and Luminance contrast:

$$W_L(x,y) = \sum_{(x_i,y_i)} W_{\Delta \theta}(x,y,x_i,y_i; \sigma_{\Delta \theta}) W_d(x_i - x, y_i - y)$$

(8)

$$W_L(x,y) = \sum_{(x_i,y_i)} W_{\Delta c}(x,y,x_i,y_i; \sigma_{\Delta c}) W_d(x_i - x, y_i - y)$$

(9)

Where, $(x_i,y_i)$ are the pixels from non-CRF, $W_d$ is a distance related weighting function used to find distance between CRF and non-CRF, and $\sigma_{\Delta \theta}$ and $\sigma_{\Delta c}$ feature difference of Luminance and Luminance contrast.

### 3.3 Contour Extraction

After the surround Inhibition weights of three features are computed we combine above that three max of Weighted Difference of features (surround Inhibition) i.e., Orientation $W_\theta$, Luminance $W_L$ and Luminance contrast $W_C$ as $W_{com}(x,y) = \max (W_\theta, W_L, W_C)$, combination at fine scale we take here max of three surround Inhibition weights because weights should stronger at that pixel. In contrast the pixel at min of weights should be weaker so we get unwanted contours not salient. and we take also CRF response computed by (1) at fine scale as $E(x,y;\sigma)$. Why we take combination of weights and CRF response at fine scale reason behind that is generally the gradient magnitude map at a large scale gives reliable contours but misses the detailed edge and may be inaccurate in localization. In the opposite at fine scale, responses at fine scale covers more details. Considering the case that at fine scale contour information add more details with more accurate localization we construct the final response by subtracting max of combined weights from CRF response at fine scale:

$$c(x,y) = H(E(x,y;\sigma) - \alpha W_{com}(x,y))$$

(10)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Equations</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma$</td>
<td>Size of CRF</td>
<td>1</td>
<td>2.0</td>
</tr>
<tr>
<td>$N_\theta$</td>
<td>Number of Orientation</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>$\sigma_{\Delta \theta}$</td>
<td>Feature Difference of orientation</td>
<td>(3.7)</td>
<td>0.2</td>
</tr>
<tr>
<td>$\sigma_{\Delta l}$</td>
<td>Feature Difference of Luminance</td>
<td>(3.11)</td>
<td>0.05</td>
</tr>
<tr>
<td>$\sigma_{\Delta c}$</td>
<td>Feature Difference of Luminance contrast</td>
<td></td>
<td>0.05</td>
</tr>
</tbody>
</table>

Where $H(a)$ is used to guarantee that neuronal responses should not be negative and $\alpha$ denotes the connection strength between the neurons within CRF and its surrounding non-CRF.

### IV. EXPERIMENTAL RESULT

Finally we apply biologically motivated contour detection using Laplacian of Gaussian to find contours in natural images. Various contour detection algorithms are analyzed to find the best and worst performance of edge detection algorithm on various image types.
We carry Experimental results on RuG40 dataset which have 40 images of gray scale with ground truth images to compare f-score values. The performance evaluation will be based on a technique that calculate True Positive (TP), False Positive (FP) and False Negative (FN) pixels on the basis of ground truth images given in dataset in order to calculate Recall and Precision metrics. Precision, Recall and F-score calculate as:

\[
\text{Precision: } PR = \frac{C_{TP}}{(C_{FP} + C_{TP})}
\]
\[
\text{Recall: } RC = \frac{C_{TP}}{(C_{FN} + C_{TP})}
\]

**Where,**
- A pixel is classified as True Positive (TP) if it is present in both the GT and the Proposed Result images.
- A pixel is classified as False Positive (FP) if it is present only in the Proposed Result image.
- A pixel is classified as False Negative (FN) if it is present only in the GT image.

\[
\text{F-Score: } FM = \frac{2 \times RC \times PR}{(RC + PR)} \times 100\%
\]

Quantitative comparision i.e F-score or Measure value for various Biological Model of contour Detection algorithms is given in Figure 3.1.

From Quantitative comparison our model give better f-score as compared to other biologically inspired models.

**Fig. 3.1.** Quantitative comparison of various models on the whole RuG40 dataset

**Fig 3.2:** Experimental results and compared with ground truth values of images from RuG40 dataset.
V. CONCLUSIONS AND FUTURE SCOPE

This paper presented a biologically motivated model using Laplacian of Gaussian to find contours. The integration of multiple features and use of laplacian of Gaussian to find CRF resulted in improvement of performance and robustness of contour detection system. Comparing with other methods give better Efficiency and Accuracy. It can be designed for coloured natural images. Contour detection improved by adding different features like frequency, spatial aspect ratio. Also it can be design for video in future

REFERENCES

[1] Alexander Toshev · Ben Taskar · Kostas Daniilidis “Shape-based Object Detection via Boundary Structure Segmentation” Received: 03/02/2011


