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Performance of Efficient Closed-Form Solution to Comprehensive Frontier Exposure

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Abstract:*Boundary detection is essential for a variety of computer vision tasks such as segmentation and recognition. We propose a unified formulation for boundary detection, with closed-form solution, which is applicable to the localization of different types of boundaries, such as intensity edges and occlusion boundaries from video and RGB-D cameras. Our algorithm simultaneously combines low- and mid-level image representations, in a single eigenvalue problem, and we solve over an infinite set of putative boundary orientations. Moreover, our method achieves state of the art results at a significantly lower computational cost than current methods. We also propose a novel method for soft-segmentation that can be used in conjunction with our boundary detection algorithm and improve its accuracy at a negligible extra computational cost.*
Keywords:*boubdary, edges, localization, segmentation*

I. Introduction

The field of image processing is broad and contains many interesting applications. Some ofthe common image processing areas are image restoration, compression, and segmentation.Many times, the size of the raw data for the images can require gigabytes of data storage.Researchers have developed routines to compress an image into a reversible form to savestorage space. In this area, there are methods for the compression via wavelets,using general compression schemes that are applicable to any type of file, and methods whichallow some loss of data.

The area of segmentation distinguishes objects from the background in an image. This is particular useful for satellite imagery from an intelligence standpoint. It isalso useful for identification purpose by using facial imagery in a database. Segmentation isused in robotics, where it is important to locate the correct objects to move or manipulate.Another area of image processing is image restoration. In image restoration, a distortedimage is restored to its' original form. This distortion is typically caused by noise in transmission, lens calibration, motion of the camera, or age of the original source of the image.We focus on image restoration in this dissertation.

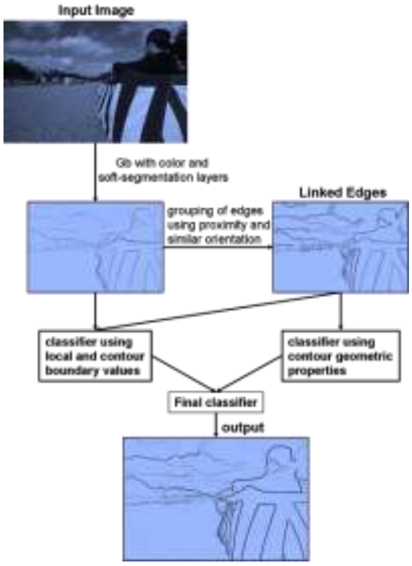
II. Methodology

Boundary detection is a fundamental computer vision problem that is essential for a variety of tasks, such as contour and region segmentation, symmetry detection and object recognition and categorization. We propose a generalized formulation for boundary detection, with closed-form solution, applicable to the localization of different types of boundaries, such as object edges in natural images and occlusion boundaries from video. Our generalized boundary detection method (Gb) simultaneously combines low-level and mid-level image representations in a single eigenvalue problem and solves for the optimal continuous boundary orientation and strength. The closed-form solution to boundary detection enables our algorithm to achieve state of the art results at a significantly lower computational cost than current methods. We also propose two complementary novel components that can seamlessly be combined with Gb: first, we introduce a soft-segmentation procedure that provides region input layers to our boundary detection algorithm for a significant improvement in accuracy, at negligible computational cost; second, we present an efficient method for contour grouping and reasoning, which when applied as a final post-processing stage, further increases the boundary detection performance.

Following are the areas of application of segmentation and recognition in images:

1. **Digital library:** For maintenance of images in large database.
2. **Image modification:** Useful under modification of information's in images.
3. **Cinematographic applications:** For enhancing the image information in movievideo clips.

Our proposed step/ramp boundary model can be seen in different layers of real-world images. Left: A step is often visible in the low-level color channels. Middle: In some cases, no step is visible in the color channels yet the edge is clearly present in the output of a soft segmentation method. Right: In video, moving boundaries are often seen in the optical flow layer. More generally, a strong perceptual boundary at a given location may be visible in several layers, with consistent orientation across layers. Our multi-layer ramp model covers all these cases.



The first category is connected component-based method, which can locate image quickly but have difficulties when image is embedded in complex background or touches other graphical objects.

The second category is texture-based, which is hard to find accurate boundaries of image areas and usually yields many false alarms in "image-like" background texture areas.

The third category is edge-based method. Generally, analyzing the projection profiles of edge intensity maps can decompose regions and can efficiently predict the image from a given video image clip.

Image region usually have a special texture because they consist of identical character components. These components contrast the background and have a periodic horizontal intensity variation due to the horizontal alignment of many characters. As a result, text regions can be segmented using texture feature.

III. Edge Detection For Images

Edges are boundaries between different textures. Edge also can be defined as discontinuities in image intensity from one pixel to another. The edges for an image are always the important characteristics that offer an indication for a higher frequency. Detection of edges for an image may help for image segmentation, data compression, and also help for well matching, such as image reconstruction and so on.

There are many methods to make edge detection. The most common method for edge detection is to calculate the differentiation of an image. The first-order derivatives in an image are computed using the gradient, and the second-order derivatives are obtained using the Laplacian. Another method for edge detection uses Hilbert Transform. And we have proposed a new method called short response Hilbert transform (SRHLT) that combines the differentiation method and the Hilbert transform method.

However, SRHLT improved the differentiation method and HLT, it still cannot fulfil our request. We can view SRHLT as the medium between the differentiation operation and the Hilbert transform (HLT) for edge detection. Now, we will introduce improved harris' algorithm and new corner detection algorithm. A more accurate algorithm for corner and edge detections that is the improved form of the well-known Harris' algorithm is introduced. First, instead of approximating |L [m+x, n+y]–L [m, n]|2 just in terms of x2, xy, and y2, we will approximate |L[m+x, n+y]–L[m, n]|(L[m+x, n+y]–L[m, n]) by the linear combination of x2, xy, y2, x, y, and 1. There are 6 basis different from 3 basis. We can observe the sign of variation with this modification. It can avoid misjudging the pixel at the wrong location and is also helpful for increasing the robustness to noise. Moreover, we also use orthogonal polynomial expansion and table looking up and define the cornet as the "integration" of the quadratic function to further improve the performance. From simulations, our algorithm is effective both for corner detection and edge detection.

Fist-Order Derivative Edge Detection

$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}. \quad (1)$$

An important quantity in edge detection is the magnitude of this vector, denoted ∇f, Where

$$\nabla f = |\nabla \mathbf{f}| = \sqrt{G_x^2 + G_y^2}. \quad (2)$$

Another important quantity is the direction of the gradient vector. That is,

$$\text{angle of } \nabla \mathbf{f} = \tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (3)$$

Computation of the gradient of an image is based on obtaining the partial derivatives of ∂f/∂x and ∂f/∂y at every pixel location.

Represent the gray levels in a neighbourhood of an image. One of the simplest ways to implement a first-order partial derivative at point z5 is to use the following Roberts

Cross-gradient operators:

$$G_x = (z_9 - z_5) \quad (4)$$

and

$$G_y = (z_8 - z_6) \quad (5)$$

These derivatives can be implemented for an entire image by using the masks with the procedure of convolution.

Another approach using masks of size 3×3 which is given by

$$G_x = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3) \quad (6)$$

and

$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (7)$$

A slight variation of these two equations uses a weight of 2 in the centre coefficient:

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \quad (8)$$

$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (9)$$

A weight value of 2 is used to achieve some smoothing by giving more importance to the centre point Sobel operators, are used to implement these two equations.

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Fig. 1.1**:** A 3×3 Area of an Image.

0	0	0
0	−1	0
0	0	1

0	0	0
0	0	−1
0	1	0

Fig. 1.2**:** The Roberts Operators.

–1	–1	–1
0	0	0
1	1	1

–1	0	1
–1	0	1
–1	0	1

Fig. 1.3**:** The Prewitt Operators.

IV. Outputs

We presentthe output of Gb using only the first 3 dimensions ofour soft-segmentations as input layers (no color information was used). We came to the following conclusions:

1) while soft-segmentations do not separate the image intodisjoint regions (as hard-segmentation does), their boundaries are correlated especially with occlusionsand wholeobject boundaries (as also confirmed by our results onCMU Motion Dataset [46]);
2) soft-segmentations cannotcapture the fine details of objects or texture, but, in combination with raw color layers, they can significantly improveGb's performance on detecting general boundaries in staticnatural images.

Fig. 1.4**:**Input Image

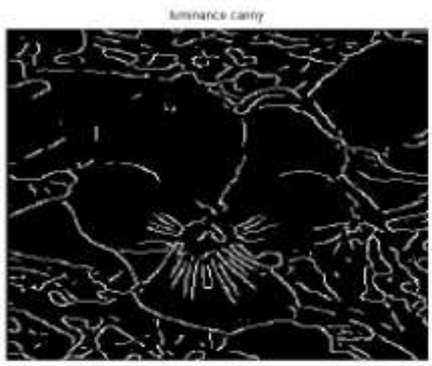


Fig. 1.5**:**GB Luminanace Image

Fig. 1.6**:**GB Image Color Canny

Fig. 1.7**:**Input Image

Fig. 1.8**:**Soft Segmented Gradient

Fig. 1.9**:**Shadoe Shading Inverse Image

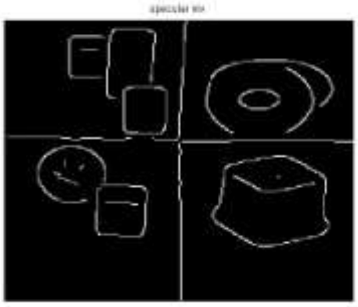


Fig. 1.10**:**Specular Segmented Image

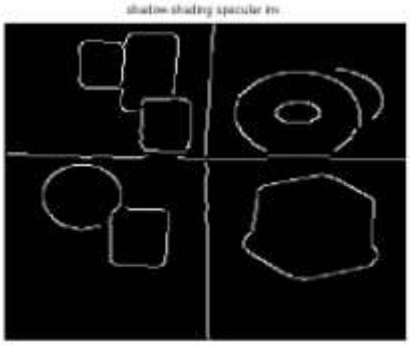


Fig. 1.11**:**Complete Specular Shadow Image

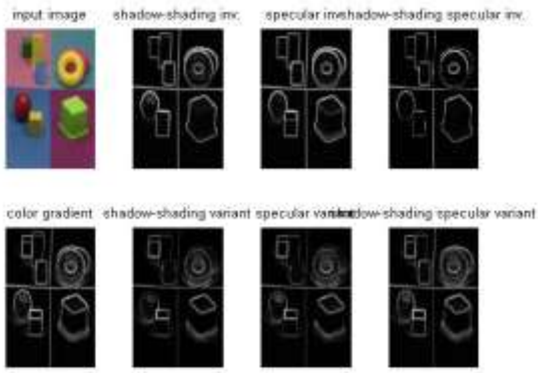


Fig. 1.12**:**Genaralized Boundary Presentation of Image

V. Conclusion

We have presented Gb, a novel model and algorithm forgeneralized boundary detection. Gb effectively combinesmultiple low- and mid-level interpretation layers of animage in a principled manner, and resolves their constraintsjointly, in closed-form, in order to compute the exact boundary strength and orientation. Consequently, Gb achievesstate of the art results on published datasets at a significantly lower computational cost than current methods.For mid-level inference, we present two efficient methodsfor soft-segmentation, and contour grouping and reasoning, which significantly improve the boundary detectionperformance at negligible computational cost. Gb's broadreal-world applicability is demonstrated through quantitative and qualitative results on the detection of boundariesin natural images and the identification of occlusion boundaries in video.

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