An improved surround suppression model based on orientation contrast for boundary detection

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Abstract

This paper proposes an unsupervised bottom-up boundary detection algorithm, which is an improved surround suppression model based on orientation contrast. First, the candidate boundary set is obtained by the edge focusing algorithm. Second, the orientation contrast map is constructed using the response of Gabor filter. The suppression term is computed on orientation contrast map using steerable filter, which can effectively differentiate step edge from texture edge. Using low-level image features, the boundary map can be used as preprocessing step for image segmentation and/or object detection. The detection approach has been validated on Rug dataset and the average of figure of merit shows an improvement of 15%.

1 Introduction

Boundary detection is a fundamental problem in image processing and computer vision. Early works mostly focus on edge detection, which aim to provide a compress representation of image [5]. Boundary detection, having close relationship to edge detection, pays more attention to global image feature detection. Boundary detection can be served as preprocessing step before the mid-level or high-level image processing such as image segmentation, shape matching and object detection [7], [14], [13].

As low-level feature detection method, boundary detection is expected to provide useful information for later specific task. Although there are many large image datasets on the web, only a small part of image datasets provide ground truth boundary, since artificial boundary labeling is a huge work and different people may label the same image with different level of granularity. Thus an unsupervised boundary detection algorithm is promising and potentially has wide applications.

In this paper, an unsupervised bottom-up boundary detection algorithm is proposed. The candidate boundary set is generated by edge focusing algorithm [2]. Then connected edges are extracted from candidate boundary set. Orientation contrast map is used to differentiate step edge from texture edge on connected edge level, which is an instance of second-order texture segmentation model [9].

1.1 Related Work

Boundary detection algorithm can be classified into two categories: gradient-based method and machine learning-based method. In the category of gradient-based method, the most classical edge detector was Canny edge operator [3]. Canny detection produced different results with different scale. Bergholm [2] proposed an edge tracking algorithm, called edge focusing, with the scale parameter changing from coarse to fine. Both Canny edge operator and edge focusing were designed to detect local edge, of which detection results contained not only image boundaries, but also texture edges that were not expected. Grigorescu et al. [8], Papari and Petkov [11] had made some improvement, operating on gradient image, to inhibit texture edges called surround suppression. Surround suppression [8] had a biological explanation to the suppression of texture edge. In fact, it can be seen as a filter operation on gradient image. Just as the author said, it has two

With rapid progress of machine learning and the presence of more ground truth database\(^1\), boundary detection is increasingly formulated as a machine learning problem. Martin et al. [10] gave a learning based boundary detector called Pb using local brightness, color and texture cues. Dollár et al. presented boosted edge learning [4], which used lots of image features to generate a probabilistic boosting tree classifier. Recently, Arbeláez et al. [1] gave a high performance boundary detector and applied it to image segmentation which is an improved version of Pb [10]. It used multiscale color feature and texture feature to obtain an initial boundary map called mPb. Then global information was added to formulate the gPb detector.

This paper focuses on unsupervised boundary detection algorithm. Compared to [11], we have two advantages. First, we conduct suppression on orientation contrast space, which can effectively differentiate step edge from texture edge. Second, the suppression value is computed on connected edge instead of on pixel level, which can effectively reduce edge fragments. The detection algorithm has been validated on Rug dataset and the average of figure of merit shows an improvement of 15% than [11].

2 Proposed Method

The proposed boundary detection algorithm consists of two phases. First, candidate boundary set is obtained by the edge focusing [2]. Second, orientation contrast map, using Gabor filter as the building block, can effectively differentiate step edge from texture edge. It can be seen as an instance of second-order texture segmentation model [9].

2.1 Candidate Boundary Set

Classical gradient-based edge detector such as Canny edge detector [3] can quickly detect edges. However, the detection results are highly depended on scale parameter. Using large Gaussian window, the details of image were smoothed out. The edge map contained less noise edges, but the edge location was not accurate. Using small Gaussian window, the details of image were reserved. The edge location was more accurate, but the edge map contained more noise edges.

To resolve the scale problem, Bergholm [2] proposed the edge focusing algorithm. The transformation of edge was derived mathematically in the scale space. The algorithm began with an initial edge map obtained at the largest scale, then made edge detection on sub-region that is composed of edge map points and their neighbors with a subsequently small scale. New edge map was obtained and the process continued until the reach of the smallest scale. Edge focusing made a trade-off between detection accuracy and noise reduction. Edge focusing tracked the transformation of edge in scale space with scale parameter change from large to small, which gave a way to resolve the scale problem.

2.2 Orientation Contrast Map

The candidate boundary set, combining edge maps with different scale, contains most part of boundaries. Nevertheless, it usually contains texture edge which is not boundary, thus further processing is needed to differentiate step edge from texture edge. A basic assumption is that there are more orientations in texture zone. Although some artificial texture images do not satisfy the assumption, it is useful to deal with most of natural images.

Gabor filter is used to define the orientation contrast map. In texture zone, the response of Gabor filter with different orientations have high variation, while in flat zone, the response of Gabor filter with different orientations have low variation. Suppose \( u_x(\theta) = \langle u_x(0), u_x(\pi/4), u_x(\pi/2), u_x(3\pi/4) \rangle \) is the output of Gabor filter with four orientations on pixel \( x \). The orientation difference between pixel \( x \) and pixel \( y \) can be defined as the inner product of \( u_x(\theta) \) and \( u_y(\theta) \). The orientation contrast of pixel \( x \) is defined as:

\[
C_{ori}(x) = \sum_{x \in N(x)} \langle u_x, u_{x'} \rangle
\]

where \( N(x) \) is \( 3 \times 3 \) neighborhood of \( x \) and \( \langle \cdot, \cdot \rangle \) is inner product. The orientation contrast \( C_{ori}(x) \) characterizes the orientation variation of \( N(x) \). Instead of operating on pixel level, our method operates on connected edge level. From candidate boundary set, the connected edges are detected. Steerable filter [6] is implemented on orientation contrast map \( C_{ori}(x) \), the filter function is \( W_\theta(x, y) \), where \( \theta \) is the local orientation of detected edge. With \( W_\theta(x, y) \) as following:

\[
W_\theta(x, y) = x^2 \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)
\]

From the outputs of steerable filter, the filter output on a connected edge can be computed. According to the filter outputs, a threshold \( T \) is selected to classify

3 Experimental Results

3.1 Boundary Detection Illustration

The boundary detection is a sequential process. Candidate boundary set is generated by edge focusing [2]. The orientation contrast map is computed according to equation 2. Orientation contrast map is used to differentiate step edge from texture edge. Gabor filter with four directions are employed to compute the orientation response. A connected edge is classified to texture edge if its value of steerable filter exceeds a threshold $T$. Suppose the mean (on all edge segments) of the steerable filter outputs is $\mu_{sf}$, we empirically find that $T = \mu_{sf}$ can give good results. Furthermore, the results are not very sensitive to threshold $T$, the detection results will not change dramatically when $0.8 \mu_{sf} < T < 2\mu_{sf}$. All detection results obtained in our experiment use the threshold $T = 1.6\mu_{sf}$. The boundary detection method is illustrated in figure 1.

3.2 Comparison with Surround Suppressions

Surround suppression [11] is an unsupervised boundary detection algorithm. It operates on gradient space. To resolve the self inhibition problem, a steerable filter edition of surround suppression is presented in [11]. Only gradient feature is used in [11], and it operates on pixel level. Comparing to Canny edge detection, the inhibition can be regarded as an additional step to suppress texture edge. The comparison conducts on Rug image dataset, which consists of 40 grayscale images with ground truth boundary. Figure 2 shows the comparison results. It can be seen that our method can detect more truth boundaries than surround suppression. At the same time, our method can inhibit more texture edges.

To quantitatively validate the detection accuracy, we compute the Pratt’s figure of merit (FOM) [12], which is used in [11]. The figure of merit is defined as

$$FOM = \frac{1}{\max(B_G, B_D)} \sum_{i=1}^{B_D} \frac{1}{1 + \alpha d_i^2}$$

where $B_G$ and $B_D$ are the number of boundary pixel in ground truth and actual detected boundary. $\alpha$ is a scaling parameter, with the same setting in [11], we set $\alpha = 1/4$. $d_i$ is the separation distance of the ith actual detected edge point normal to a line of ideal edge points (ground truth). We obtain the binary boundary using a thresholding step. We compute the average value of FOM for edge focusing (EF) [2], surround suppression (SS) [11] and our method on Rug image dataset, the results are show in table 1. The average of FOM of our method shows an improvement of 15% than [11]. Of 40 images, our method has obtained higher value of FOM than [11] on 30 images.

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<td>FOM</td>
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Figure 1. Boundary detection scheme.

Table 1. The average value of FOM for edge focusing (EF) [2], surround suppression (SS) [11] and our method on Rug image dataset

4 Conclusion

In this paper, an unsupervised bottom-up boundary detection algorithm is presented. It uses edge focusing to generate the candidate boundary set, then orientation contrast and steerable filter are used to differentiate step edge from texture edge. Experimental results show the improvement of performance on Rug dataset.

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Figure 2. Comparison with surround suppressions [11]. First row, image froms Rug database. Second row, ground truth of boundary. Third row, surround suppressions results. Fourth row, our results.

References


