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Orientation contrast model for boundary detection

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A B S T R A C T

The boundary detection task has been extensively studied in the field of computer vision and pattern recognition. Recently, researchers have formulated this task as supervised or unsupervised learning problems to leverage machine learning methods to improve detection accuracy. However, texture suppression, which is important for boundary detection, is not incorporated in this framework. To address this limitation, and also motivated by psychophysical and neurophysiological findings, we propose an orientation contrast model for boundary detection, which combines machine learning technique and texture suppression in a unified framework. Thus, the model is especially suited for detecting object boundaries surrounded by natural textures. Extensive experiments on several benchmarks demonstrate the improved boundary detection performance of the model. Specifically, its detection accuracy was improved by 10% on the Rug dataset compared with state-of-the-art unsupervised boundary detection algorithm, and its performance is also better or at least comparable with previous supervised boundary detection algorithms.

1. Introduction

Boundary detection is a longstanding problem and a grand challenge in computer vision and pattern recognition [1]. Usually employed as a preprocessing step for high-level vision tasks [2–4], boundary detection algorithm output compressed representation for images. In recent years, it also plays a key role in the inference of high level semantics from low level features in image understanding [5].

Boundary detection has close relationship with texture segmentation. Psychophysical experiments and neurophysiological data show that texture segmentation and visual "pop-out" comes from orientation difference [6] or from orientation gradient [7]. In the preliminary version of this work, we proposed a surround suppression model which combines gradient information and orientation contrast [8], which achieved satisfactory edge detection performance. In this paper, we further addressed two limitations of that work: First, threshold selection is done by trial and error in [8]. Second, only one suppression term (feature) is considered in [8], which is not enough to achieve the best boundary detection performance. To overcome the two limitations, we formulate the boundary detection task as a supervised learning problem and add more features to further improve the edge discrimination power. In this new formulation, trial and error-based threshold selection is avoided since parameters are now adaptively learned from data.

In brief, our boundary detection model works as follows. First, the input image is converted from the RGB to Lab color space. At each channel, candidate boundaries are extracted by the edge focusing algorithm [9]. Second, we propose an orientation contrast model (OCM) to differentiate step edges from texture edges. Third, we extract a set of boundary features (such as edge length, edge density, edge smoothness and suppression magnitude) for each connected edge based on results from the second step. Finally, using the feature representation, we train classifiers for boundary detection. The overall working pipeline of the proposed boundary detection model is illustrated in Fig. 1.

The main contribution of this paper is the development of an integrated supervised learning framework for boundary detection, but not the re-development of the separated parts. First, by training the boundary detection classifier, the OCM is better for differentiating true step edges from false-positive texture edges. Thus, it is more appropriate for detecting object boundaries surrounded by natural textures such as grasses, trees and leaves. Second, since the feature vector is extracted on each connected edge, via supervised learning, the boundary detection classifier outputs coherent pixels for the object boundaries, which greatly reduce the edge fragmentation effects (see experimental results in Section 5.3 for more details).

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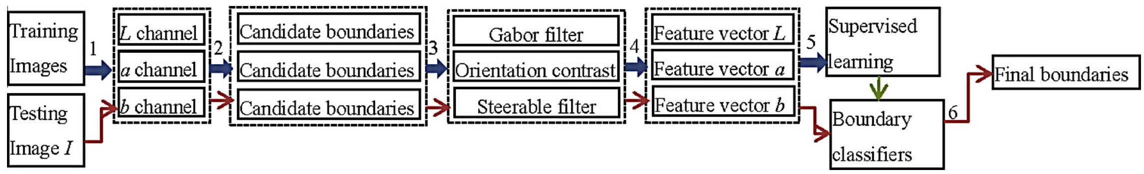

Fig. 1. The overall framework of our boundary detection model. 1: Training images (Testing image) are (is) converted from the RGB to Lab color space. 2: At each channel, candidate connected edges are extracted by the edge focusing algorithm [6] (see Section 3.1). 3: The proposed orientation contrast model, which consists 3 filters: Gabor filter, orientation contrast filter and steerable filter (see Section 3.2). 4: The proposed feature representation (see Section 3.3). 5: Training and testing the boundary classifiers (Section 4). 6: The final boundaries output by the model.

This paper is organized as follows: In Section 2, we briefly review recent algorithms for boundary detection. The proposed OCM model and its feature representation are introduced in Section 3. Section 4 presents the supervised learning of the OCM for boundary detection. We evaluate the performance of the proposed algorithm and compared it with existing ones on several benchmarks in Section 5. Section 6 concludes this work.

2. Related works

In general, previous boundary detection algorithms can be broadly classified into three categories: gradient-based, machine learning-based and saliency-based methods.

In the category of gradient-based methods, the most classical and well-known edge detector is the Canny edge operator [10]. Despite its success in the early years, the edge detection result is largely dependent on the scale parameter, which is not easy to tune. Bergholm [9] partially addressed the scale selection problem by the edge focusing approach, which integrates information at multiple scales. However, both the Canny edge detector and the edge focusing algorithm were designed to detect local edges, which had the problem that not only true image boundaries, but also false positive texture edges are detected. To reduce texture edge detections, Grigorescu et al. [11], Papari and Petkov [12] proposed the surround suppression model, which operated on gradient image features. Specifically, the design of suppression model in [11] borrowed the "nonclassical receptive field" concept from biology. Essentially, this approach can be seen as a filter operating in the gradient space. As pointed by the authors, the method had two problems: unwanted self-inhibition and undetermined inhibition level [12]. Even using more sophisticated steerable filter [13], the self-inhibition problem still could not be completely resolved.

With the recent popularity of machine learning techniques in computer vision and the presence of human labeled image databases [14–16], the boundary detection task is increasingly formulated as a machine learning problem. Martin et al. [17] presented a learning based boundary detector called Pb using local brightness, color and texture cues. The key idea was to compute the χ^2 distance of two half-disc intensity histograms along candidate edge orientations. Dollár et al. presented boosted edge learning (BEL) [18], which used a lot of image features to generate a probabilistic boosting tree classifier. The advantage of [18] is that it could learn object-specific edges; however, the edge classes should be first defined in the training set. Recently, Arbeláez et al. [19] presented a high performance boundary detector called gPb that was an improved version of Pb [17]. It used multiscale color features and texture features to obtain an initial boundary detection result, which is called mPb. Then, global information was added to construct the gPb detector. There were lots of parameters in gPb, which has to be tuned for optimization of the performance of edge detection (quantified by the F-measure). The gPb detector further improved the performance of boundary detection at the cost of using more computational time and memory consumption when compared with the Pb detector. To speed up the gPb detector, Catanzaro et al. [20] present a GPU-based implementation. However, it is still not clear whether the GPU implementation of the gPb detector could run smoothly on large images. Other machine learning-based boundary detection approaches have also been proposed. For example, Kokkinos [21] used Pb [17] and Canny edge operator to generate candidate edges, which are subsequently refined by a machine learning approach for boundary detection and grouping. Compared to the supervised-learning-based boundary detection algorithms, our OCM model explicitly incorporated texture suppression term in the boundary feature representation, which enabled its better performance in texture dominant scenes than the Pb [17] and BEL [18] algorithms.

The third category is saliency-based method. Itti et al. [22], Sun and Fisher [23] used color and orientation contrast map as initial features to construct a saliency map. Feng et al. [24] then used the saliency map to detect salient edges and regions for content-based image retrieval. Shimodaira [25] defined edge saliency measure and used the boundary likelihood for edge detection. However, the approach [25] has too many parameters to be tuned, which limits its potential application scope. Kennedy [26] presented a contour cut algorithm for salient contour detection. Although there are connections between saliency and boundary maps, the two concepts still have large difference.

Another related domain to boundary detection is perceptual organization, in which one of the key focuses there is contour completion. Kovacs and Julesz [27] argued that closure contours are more useful than incomplete contours for figure-ground segmentation. To this end, Elder and Zucker [28] presented a method to compute contour closures. Ren [29] also developed a probabilistic model for contour completion, while Ming et al. [30] employed a higher-order conditional random fields model to compute close contours. These works are relevant to the low-level image boundary detection task, but with different emphasis.

3. Orientation contrast model

The proposed orientation contrast model is composed of three modules: the edge focusing algorithm, computation of orientation contrasts and the boundary feature description. First, the edge focusing algorithm is used to generate a set of candidate boundaries before extracting connected edges. Then, we compute orientation contrasts to effectively discriminate step edges from texture edges. Finally, we compute feature representations of these connect edges.

3.1. Computing candidate boundaries using the edge focusing algorithm

Classical gradient-based edge detectors, such as the Canny edge detector [10] are able to detect edges quickly. However, the detection results are sensitive to the scale parameter. If large Gaussian window is used, the detection result will contain less noisy edges, but the localization of edges will be not accurate. On the other hand, if small Gaussian window is used, the localization of edges will be accurate, but too much false-positive detections, like texture edges will also be detected.