Contour Detection

Project Proposal Report

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1 Introduction

Contour detection of objects is essential in human vision. With damages in certain brain area responsible for the perception of contours, a person will be unable to recognize objects [1]. To develop a more powerful computer vision system, contour detection is also a must. In fact, contour detection is one of the most fundamental problems in computer vision. People can have a deep knowledge of the structural information in the images based on object contours, which many other tasks such as image segmentation, object recognition and scene understanding rely heavily on. Due to the importance of contour detection, among these years a lot of related work has been done and many methods have been developed to achieve better results.

In this project, our goal is to investigate how to detect contours. Our future work mainly focuses on two parts: (1) One is to study the existing methods comprehensively, implement them and compare their performances. (2) The other is to find a niche to improve current algorithms, or to apply the state-of-the-art techniques to other possible areas in computer vision.

2 Related Work

To evaluate contour detection algorithms in a quantitative manner, we will be using a dataset and its corresponding benchmark called Berkeley Segmentation Data Set and Benchmarks 500 (BSDS 500) [2]. It consists of natural images and their corresponding human-annotated ground truth contours. The benchmark includes the evaluation results of almost all modern approaches to contour detection.

A number of recent methods with satisfactory performance are based on the posterior probability of boundary (Pb) developed Martin et al. [3], which uses brightness, color and textures to detect both global and local contours. These techniques include the conditional random fields model developed by Ren et al. [4], the untangling cycle algorithm designed by Zhu et al. [5] and the idea of globalized probability boundary (gPb) raised by Maire et al. [6]. Other progressive work not based on Pb includes the min-cover approach developed by Felzenszwalb and McAllester [7], the boosted edge learning algorithm invented by Dollar et al. [8], the method using sparse code gradients (SCG) proposed by Ren and Bo [9] and sketch tokens designed by Lim et al. [10].

3 Technical Thoughts

Above all, since Pb serves as a basic idea which is further developed by several methods in contour detection, we plan to delve deeper into its mechanism and try to implement it. In addition to Pb, we are also interested two machine learning approaches for this problem, SCG and sketch tokens.

For SCG, the aim of sparse coding is to learn a basis of a given set of data (images in this problem) which enables a sparse representation, and then the basis can be used for contour detection. We will not only implement this algorithm but try to find its application to other type of data, for example, medical images or images taken by 3D cameras.

Sketch tokens is also an interesting method since it can achieve a result with similar accuracy but in much shorter time compared to other modern methods. They are supervisedly learned using mid-level information in the form of hand drawn contours in images. Patches of human generated contours are clustered to form sketch token classes and a random forest classifier is used for efficient detection in novel images.

At the end of this project, we hope to have a more detailed study on these techniques, with both the implementation of the algorithms and our improvements on some specific parts in the methods.

4 Milestones

Date	Progress
Feb 15 – Feb 28	In-depth paper review (3-5 papers)
Feb 29 – Mar 20	Implementation of papers (gPb, SCG, sketch tokens, etc.)
Mar 21 – Mar 27	Midterm report writing
Mar 28	Midterm report due
Mar 29 – Apr 18	Original work (improvement and other applications)
Apr 19 – Apr 24	Presentation preparation
Apr 25 – May 5	Presentation and final report writing

References

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