STUDYING THE FEASIBILITY AND IMPORTANCE OF GRAPH-BASED IMAGE SEGMENTATION TECHNIQUES

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ABSTRACT

Image segmentation and its performance evaluation are very difficult but important problems in computer vision. A major challenge in segmentation evaluation comes from the fundamental conflict between generality and objectivity: For general-purpose segmentation, the ground truth and segmentation accuracy may not be well defined, while embedding the evaluation in a specific application, the evaluation results may not be extensible to other applications. This paper analyzes the performance of Normalized Cut (NC) and Efficient Graph (EG) methods of Image Segmentation. We treat image segmentation as graph partitioning problem and propose novel global criterion, NC for segmenting the graph. The NC criterion measures both total dissimilarity between the different groups as well as the total similarity within the groups. We apply efficient graph based image segmentation method to image segmentation using two different kinds of local neighbourhood in constructing the graph. We also present a special strategy to compare and analysis the above two graph-based methods

Key words: *Normalized Cut (NC), Efficient Graph (EG), Minimum Spanning Tree (MST)*

1. INTRODUCTION

We take a graph-based approach to segmentation. Let G = (V, E) be an undirected graph with vertices $v_i \in V$, the set of elements to be segmented, and edges $(v_i; v_j) \in E$ corresponding to pairs of neighboring vertices. Each edge $(v_i; v_j) \in E$ has a corresponding weight $w(v_i; v_j)$, which is a non-negative measure of the dissimilarity between neighboring elements v_i and v_j . In the case of image segmentation, the elements in V are pixels and the weight of an edge is some measure of the dissimilarity between the two pixels connected by that edge (e.g., the difference in intensity, color, motion, location or some other local attribute). In Sections 5 and 6 we consider particular edge sets and weight functions for image segmentation. However, the formulation here is independent of these definitions.

In the graph-based approach, a segmentation S is a partition of V into components such that each component (or region) $C \in S$ corresponds to a connected component in a graph G' = (V, E'), where $E' \subseteq E$. In other words, any segmentation is induced by a subset of the edges in E. There are different ways to measure the quality of segmentation but in general we want the elements in a component to be similar, and elements in different components to be dissimilar. This means that edges between two vertices in the same component should have relatively low weights, and edges between vertices in different components should have higher weights.

By partitioning an image into a set of disjoint segments to represent image structures, image segmentation leads to more compact image representations and bridges the gap between the low-level and the higher-level structures. As the central step in computer vision and image understanding, image segmentation has been extensively investigated in the past decades, with the development of a large number of image-segmentation methods. However, general-purpose image segmentation is still an unsolved problem; we still lack reliable ways in performance evaluation for quantitatively positioning the state of the art of image segmentation. In many prior works, segmentation performance is usually evaluated by subjectively or objectively judging on several sample images. Such evaluations on a small number of sample images lack statistical meanings and may not be generalized to other images and applications.

In this paper, section 2 describes the related works, section 3 explains the methodology applied section 4 details about performance measurements and section 5 demonstrates the experiment with results.

2. RELATED WORKS

In this section we briefly consider some of the related work that is most relevant to our approach: early graph-based methods, region merging techniques, techniques based on mapping image pixels to some feature space and more recent formulations in terms of graph cuts and spectral methods.

Graph-based image segmentation techniques generally represent the problem in terms of a graph G = (V, E) where each node v_i $\in$ V corresponds to a pixel in the image, and the edges in E connect certain pairs of neighboring pixels. A weight is associated with each edge based on some property of the pixels that it connects, such as their image intensities. Depending on the method, there may or may not be an edge connecting each pair of vertices. The earliest graph-based methods use fixed thresholds and local measures in computing a segmentation. The work of Zahn [11] presents a segmentation method based on the minimum spanning tree (MST) of the graph. This method has been applied both to point clustering and to image segmentation. For image segmentation the edge weights in the graph are based on the differences between pixel intensities, whereas for point clustering the weights are based on distances between points.

There have been a large number of literatures on the image segmentation evaluation developed in the past decades. Most of previous works are focused on developing better ways to measure the accuracy/error of the segmentation. Some of them do not require the ground-truth image segmentation as the reference. In these methods, the segmentation performance is usually measured by some contextual and perceptual properties, such as the homogeneity within the resulting segments and the in homogeneity across neighboring segments.

Most of the prior image-segmentation evaluation methods, however, need a ground-truth segmentation of the considered image and the performance is measured by calculating the discrepancy between the considered segmentation and the ground-truth segmentation. Since the construction of the ground-truth segmentation for many real images is labor intensive and sometimes not well or uniquely defined, most of prior image-segmentation methods are only tested on: (a) some special classes of images used in special applications where the ground-truth segmentations are uniquely defined, (b) synthetic images where ground-truth segmentation is also well defined, and/or (c) a small set of real images.

Different from these methods, the paper presents a comparison of two general-purpose image segmentation methods [1] on a large variety of real images with well-defined objects as ground truth.

In this paper we present the results of an objective evaluation of two popular segmentation techniques: mean shift segmentation, and the efficient graph-based segmentation methods. As well, we look at a hybrid variant that combines these algorithms. For each of these algorithms, we examine three characteristics:

1. *Correctness*: the ability to produce segmentations which agree with human intuition. That is, neither segmentations which correctly identify structures in the image at neither too fine nor too coarse a level of detail.

2. *Stability with respect to parameter choice*: the ability to produce segmentations of consistent correctness for a range of parameter choices.

3. *Stability with respect to image choice*: the ability to produce segmentations of consistent correctness using the same parameter choice on a wide range of different images.

If a segmentation scheme satisfies these three characteristics, then it will give useful and predictable results which can be reliably incorporated into a larger system.

3. METHODOLOGY

We evaluate the following two image-segmentation methods:

- Efficient graph-based method (EG) [3]
- Normalized-cut method (NC) [2]

We choose these two methods based on three considerations: (a) they well represent different categories of image-segmentation methods; (b) all of them are relatively new methods and/or implementations that well represent the current state of the art of general-purpose image segmentation.

In the following, we briefly overview these two methods.

3.1 Efficient graph-based method (EG)

Similar to NC, EG adopts a graph model and finds the evidence of a boundary between two segments based on the intensity differences across the boundary and the intensity differences within each segment. However, the intensity difference within a segment is defined as the largest edge weight of the minimum spanning tree built from this segment, and the intensity difference across the boundary is defined as the minimum edge weight that connects these two segments. EG takes only O (n log n) computational time to segment an n-pixel image. In the adopted implementation, there are three free parameters: a smoothing factor σ that is related to the Gaussian smoothing scales, a constant parameter K that controls how coarsely or finely an image is segmented, and a parameter S that constrains the minimum area of the resulting segments. Varying S usually results in different number of segments. In our evaluation, we fix the smoothing factor σ to its default value and vary K and S to measure the segmentation performance.

3.2 Normalized-cut method (NC)

In NC, an image is modeled by a graph G = (V, E), where V is a set of vertices corresponding to image pixels and E is a set of edges connecting neighboring pixels. The edge weight w(u, v) describes the affinity between two vertices u and v based on their intensity similarity and spatial proximity. Using this graph model, segmenting an image into two segments corresponds to a graph cut (A, B), where A and B are the vertices in two resulting subgraphs. In NC, the segmentation cost is defined by

$$Ncut(A,B) = cut(A,B)/ assoc(A, V) + cut(A,B) /assoc(B, V), \quad (1)$$

where $cut(A,B) = \Sigma_{u \in A, v \in V} w(u, v)$ is the cut cost of (A,B) and $assoc(A, B) = \Sigma_{u \in A, v \in V} w(u, v)$ is the association between A and V . NC segments the image by finding the cut (A, B) with the minimum cost (1). Since this is a NPcomplete problem, a spectral-graph algorithm was developed to find an approximate solution. This algorithm can be easily repeated on the resulting subgraphs to get more segments. In the NC method, the most important parameter is the number of regions to be segmented. In our evaluation, we are going to vary this parameter to measure its performance.

4. PERFORMANCE MEASURE

To evaluate segmentation using this benchmark, the most desirable form of segmentation output is certainly figure ground-style segmentation, i.e., the image is partitioned into two segments with one as the foreground and the other as the background. However, in most cases, the segmentation methods produce more than two regions. All the methods partition an image into a set of disjoint segments without labeling the foreground and background. Consequently, we develop a region-merging strategy so that they can be fairly evaluated in the benchmark.

In this paper, we use the following Performance Measure Algorithm to determine and compare average performance of EG and NC methods of Segmentation.

Algorithm for Performance Measure:

1. Find the no. of Segment Labels
2. Compute the Ratio

3. Find the names of Segment Labels
4. Determine the Average Performance Measure

Efficient-graph method (EG). The EG has two main parameters: K, which controls the splitting process of a segment, and S, which constrains the minimum area of each resulting segment. For all tested values of K, the average performance $\bar{P}$ increases as the minimum region area S decreases.

However, when S gets very small, $\bar{P}$ reaches a limit and cannot be improved any further.

Normalized-cut method (NC). In NC, we vary the parameter k, the target number of segments. The maximum possible value of k is the total number of pixels; in that case $p(x) \equiv 1$, x □ [0, 1]. As shown in Fig. 6(c), while the curve p(x) moves up (not surprisingly) as k increases, it does not move up in a linear way in terms of the increase of k. The largest move-up of p(x) happens when k increases from 2 to 5, and after that the move-up of p(x) is not substantial even if we increase k logarithmically. While a larger k improves the upper-bound performance p(x), such an upper-bound becomes more difficult to achieve because of the required post processing of region merging. Thus we need to find an appropriate k by seeking a compromise.

5. RESULTS OF EXPERIMENTS

We performed the comparison with the two graph-based image segmentation methods to analyze their average performances. The images are taken from the benchmark databases. After applying image segmentation method for 1030 images, the average performance for each method is observed.

Efficient graph-based method (EG)

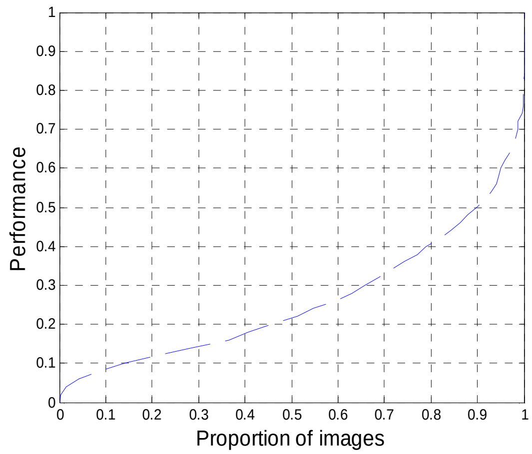
We take the grain image to analyze the performance of EG method. Fig. (a) is the original grain image and Fig.(b) is it's segmented view using this method.

Fig. (a) Original grain image

Segmentation parameters: sigma = 0.5, K = 1000, min = 100.

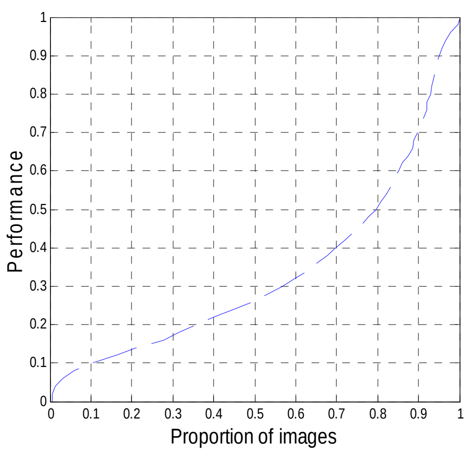
Fig. (b) Segmented grain image

In this method, the average performance of portions of images is visualized in Fig.1. It illustrats two-segment portion of images with its average performance of 0.2598. Fig.2 shows the performance curve of five-segment portion of images with its average performance of 0.3342. Fig.3 shows the performance curve of 10-segment portion of images with its average performance of 0.4374. Fig.4 shows the performance curve of 40- segment portion of images with its average performance of 0.6454 and Fig.5 shows the performance curve of 100-segment portion of images with its average performance of 0.7610.



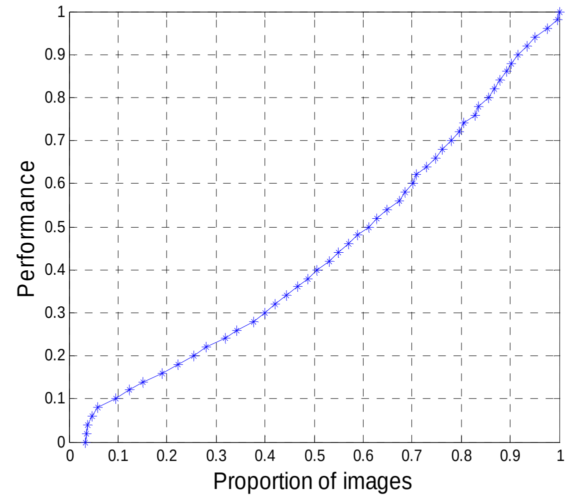
Average Performance = 0.2598

Fig.1 EG Method for 2-Segment Images



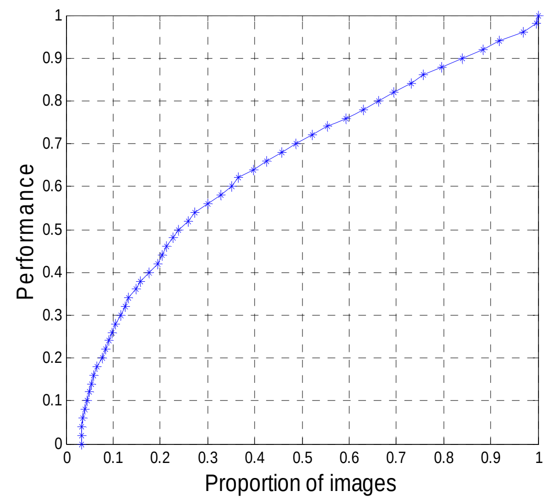
Average Performance = 0.3342

Fig.2 EG Method for 5-Segment Images



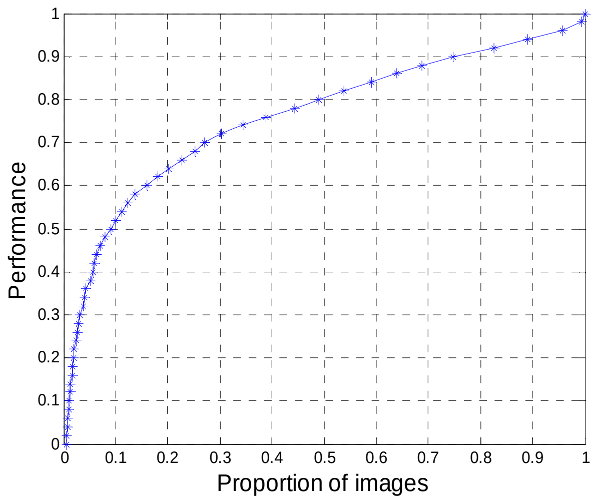
Average Performance = 0.4374

Fig.3 EG Method for 10-Segment Images



Average Performance = 0.6454

Fig.4 EG Method for 40-Segment Images



Average Performance = 0.7610

Fig.5 EG Method for 100-Segment Images

Normalized-cut method (NC)

We take the bear image to analyze the performance of EG method. Fig. (a) is the original bear image, Fig.(b) is it's gray image for segmentation view Fig.(c) is the edges of the image and Fig.(d) is it's segmented view using this method.

Fig. (a) Original bear image

Fig. (b) Gray image for segmentation

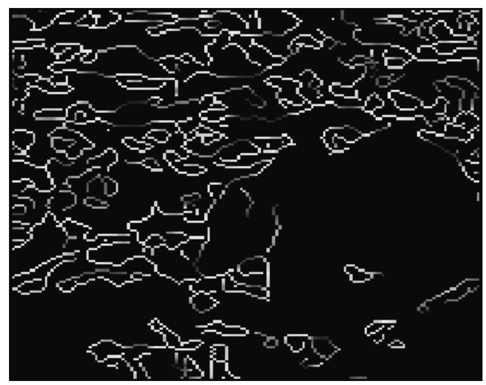


Fig. (c) Edges of the image

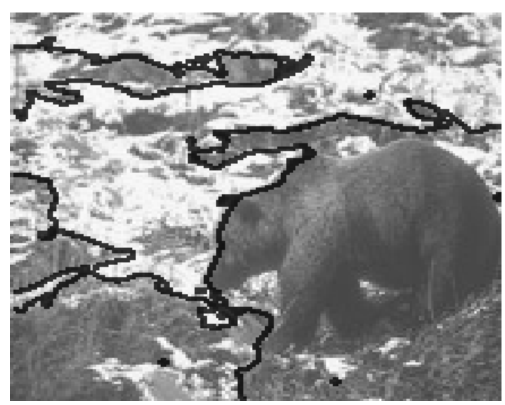
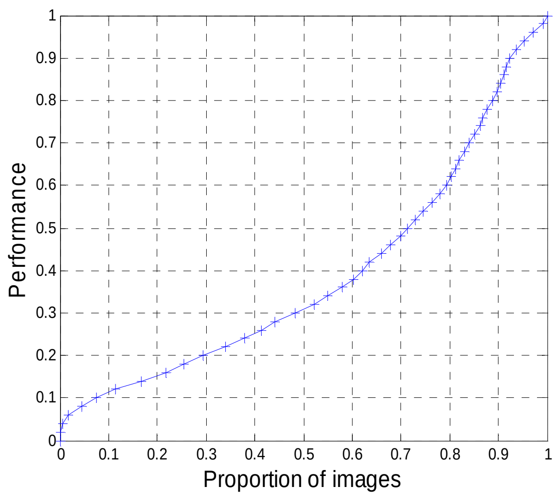
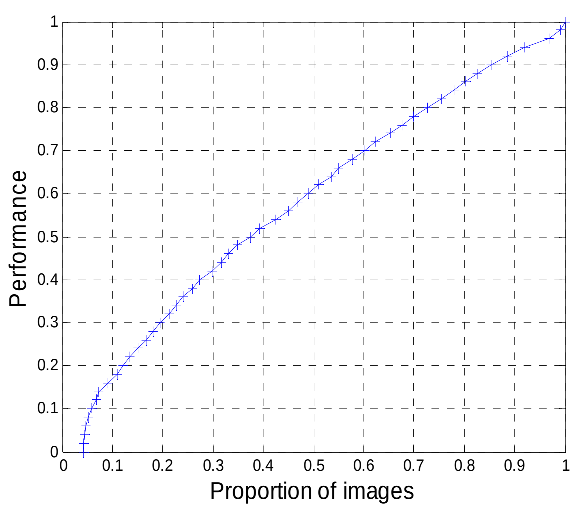


Fig. (d) Image Segmentation

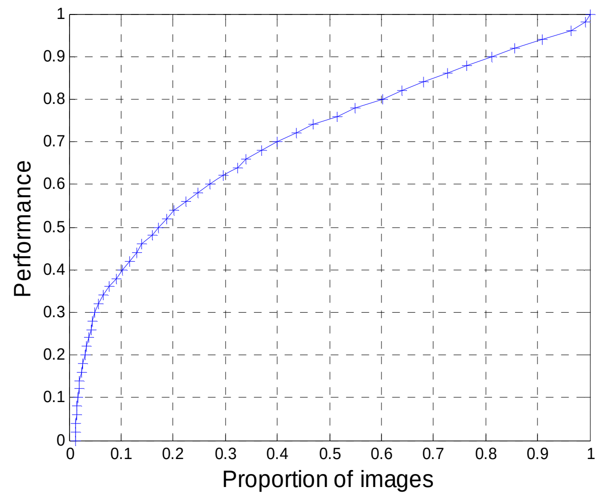
In this method, the average performance of portions of images is visualized in Fig.6. It illustrates two-segment portion of images with its average performance of 0.3837. Fig.7 shows the performance curve of five-segment portion of images with its average performance of 0.5739. From the Fig.8, we can find the performance curve of 10-segment portion of images with its average performance of 0.6991. The performance curve for 40-segment portion of images with its average performance of 0.8157 and 100-segment portion of images with its average performance of 0.8553 in Fig.9 and Fig.10.



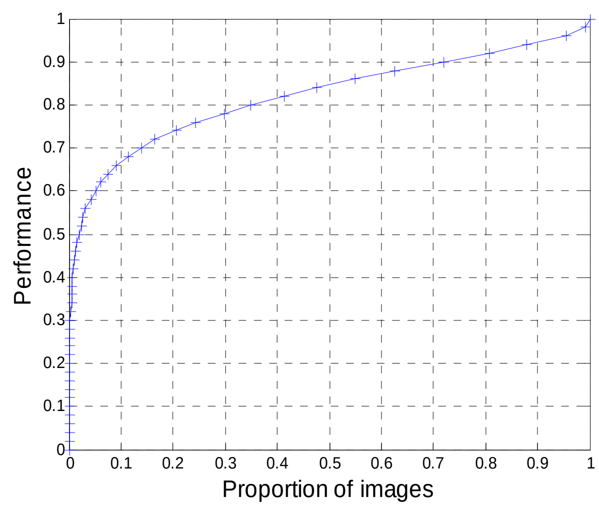
Average Performance = 0.3837
Fig.6 NC Method for 2-Segment Images



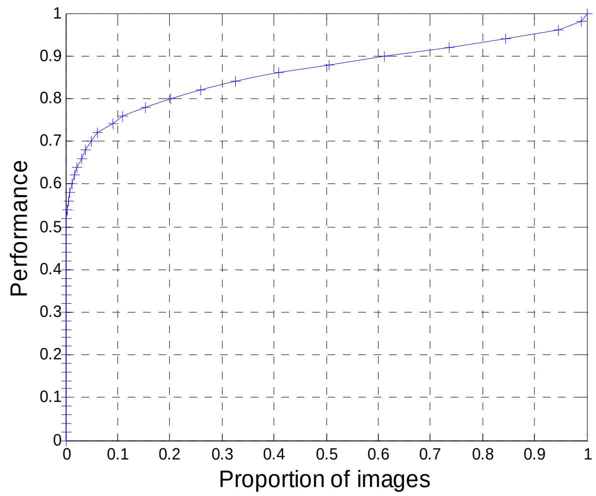
Average Performance = 0.5739
Fig.7 NC Method for 5-Segment Images



Average Performance = 0.6991
Fig.8 NC Method for 10-Segment Images



Average Performance = 0.8157
Fig.9 NC Method for 40-Segment Images



Average Performance = 0.8553

Fig.10 NC Method for 100-Segment Images

6. CONCLUSION

Our framework consists of comparing the performance of two graph-based segmentation methods on the basis of important characteristics such as correctness, stability with respect to performance choice and stability with respect to image choice.

Finally we conclude that the normalized-cut based image segmentation method has shown better performance than the efficient graph-based segmentation method. Moreover, we propose in future to develop a combination of above-said methods to enhance segmentation.

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