MOVING TOWARD REGION-BASED IMAGE SEGMENTATION TECHNIQUES: A STUDY

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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. In this paper, we compare the performances of the two popular region-based image segmentation methods namely the Watershed method and the Mean-shift method. The watershed method, also called the watershed transform, is an image segmentation approach based on mathematical morphology. Mean-shift method is a data-clustering method that searches for the local maximal density points and then groups all the data to the clusters defined by these maximal density points.

Keywords: *Watershed Method (WS), Mean-Shift Method (MS)*

1. INTRODUCTION

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.

The goal of this paper is to analyze the function performance of region-based segmentation methods. Here we consider the two general-purpose methods of watershed and mean-shift methods. The watershed transform is the traditional segmentation technique used in gray-scale mathematical morphology [1][2][3], and an abundant literature proposes several practical implementations of the algorithm. Intrinsically, the watershed is a gray-level dedicated images and thus not straightforward. The MS method has two main parameters: the level of resolution H_s and the minimum allowed segment area S. Similar to the EG, S is measured as the percentage of the image area.

In the remainder of this paper, Section 2 briefly reviews the related work on image-segmentation evaluation and summarizes the contribution of this paper. Section 3 introduces the methodology involved in this paper . Section 4 briefly introduces the performance measurement details.. Section 5 describes the Experiment results with analysis charts. A brief conclusion is given in Section 6.

2. RELATED WORK AND OUR CONTRIBUTION

There has 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 [7, 8, 9] 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 inhomogeneity 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 region-based image segmentation methods 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: water-shed segmentation and mean-shift segmentation. 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:

- Watershed Method (WS)
- Mean-Shift Method (MS)

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 he following, we briefly overview these two methods.

3.1 Watershed Method (WS)

The Watershed method, also called the watershed transform, is an image segmentation approach based on gray-scale mathematical morphology, to the case of color or, more generally speaking, multi component images. Different strategies are presented and a special attention is paid to the "bit mixing approach". This method bijectively maps multi-dimensional data into a mono-dimensional space. In geography, a watershed is the ridge that divides areas drained by different river systems. By viewing an image as a geological landscape, the watershed lines determine the boundaries that separate image regions. In the topographic representation of an image *I,* the numerical value (i.e., the gray tone) of each pixel stands for the evolution at this point. The watershed transform computes the catchments basins and ridge lines, with catchment basins corresponding to image regions and ridge lines relating to region boundaries. Methods for computing the watershed transform are discussed in detail in Ref. 8 . In our evolution, we use the watershed transform function of Matlab 7. However, the Mat lab implementation of the watershed transform is very sensitive to image noise and usually produces over segmented regions. To solve this problem, we first smooth images with Gaussian smoothing filters of different scales before applying the watershed transform. By varying the parameter of Gaussian filters, we can segment an image into a target number of regions.

The watershed transform usually leads to over segmentation of images due to image noise and other local irregularities. To overcome this problem, researchers have proposed many strategies such as region merging, marker-controlled watershed segmentation, hierarchical segmentation, and multiscale segmentation. In our evaluation, we use the Matlab function of watershed transform. To achieve segmentations with different number of segments, we adopt a strategy that is similar to that of the multiscale segmentation. Before the watershed transform, each image is smoothed using a Gaussian filters, we vary the filter size ***N*** and the standard variation **σ**. Particularly, we set ***N*** = [**σ**]+1;

3.2 Mean-Shift Method (MS)

MS is a data-clustering method that searches for the local maximal density points and then groups all the data to the clusters defined by these maximal density points. When used for image segmentation, each pixel $\mathbf{x}_i$, i=1,…,n, in the image is treated as an input data, and the density at point **x** is estimated by

$$f(x) = \frac{c}{nh^d} \sum_{i=1}^{n} K\left(\left\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\right\|^2\right),$$

1. Where *h* is the bandwidth parameter, *d* is the data dimensionality, *c* is a normalization constant, and **K(-)** is the density estimation kernel. In the implementation of the mean-shift method, the uniform kernel is used. To locate a local maximum of the density, an initial point $\mathbf{y}_1$ is selected and then successively updated by

$$\mathbf{y}_{j+1} = \frac{\sum_{i=1}^{n} \mathbf{x}_i K\left(\left\|\frac{\mathbf{y}_j - \mathbf{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} K\left(\left\|\frac{\mathbf{y}_j - \mathbf{x}_i}{h}\right\|^2\right)}$$

until convergence. With these local maximal-density points, the image can be segmented into regions by grouping each pixel to its corresponding local maximal-density point. In the adopted implementation, there are mainly three free parameters: the spatial bandwidth H_s, the range bandwidth H_r, and the minimum segment area S which has the same meaning to the one in EG. Since all the test images in our benchmark are gray-level images, the range bandwidth H_r, which is mainly related to the color channels, is fixed to its default value. The bandwidth H_s determines the resolution in selecting the local maximal-density points. In other words,
H_s control the number of resulting segments.

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 WS and MS 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

5. RESULTS OF EXPERIMENTS

We performed the comparison with the two region-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.

Watershed Method (WS)

We consider the beach image to analyze the performance of WS method. Fig. (a) is the original beach image, Fig.(b) is it’s gray image and Fig. (c) represents segmented view using this method.

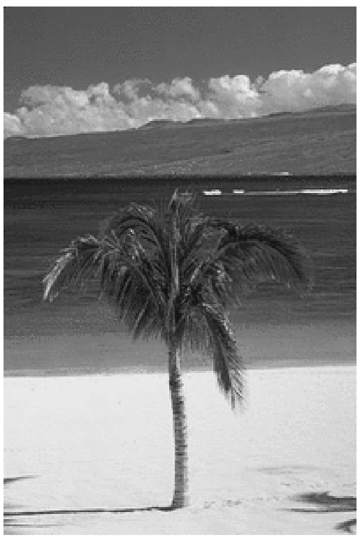

Fig. 1(a) Original Image

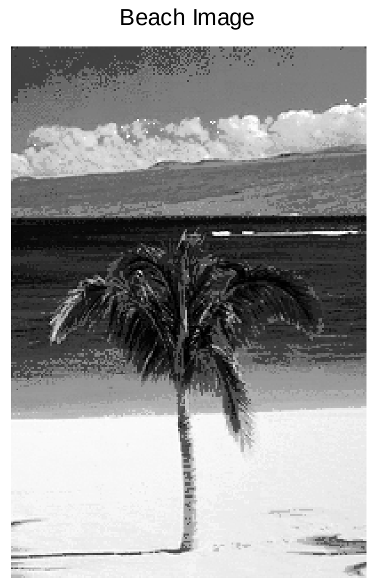

Fig. 1(b) Gray Image

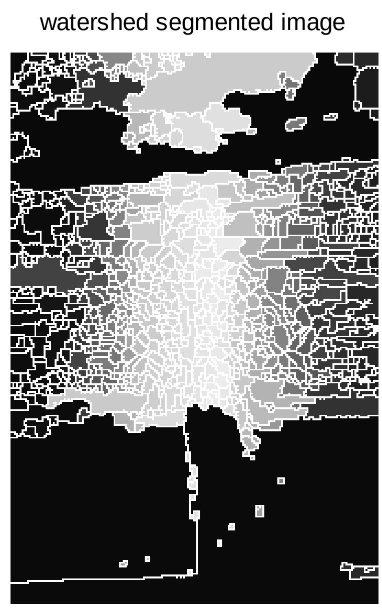

Fig. 1(c) Segmented Image

In this method, the average performance of portions of images is visualized in Fig.1. It shows 5-segment portion of images with its average performance of 0.5885. Fig.2 shows the performance curve of 10-segment portion of images with its average performance of 0.5313

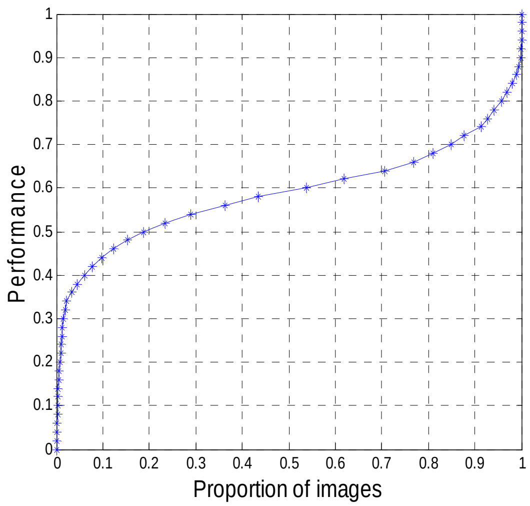

Fig. 1 WS Method for 5-Segment Images

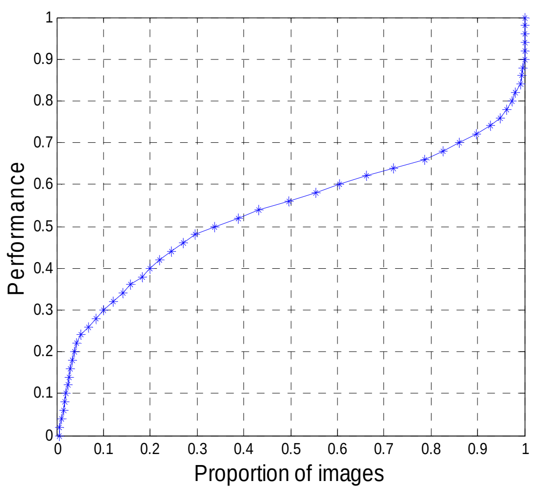

Fig. 2 WS Method for 10-Segment Images

Mean-Shift Method (MS)

We take the outdoor image to analyze the performance of MS method. Fig. (a) is the original outdoor image, Fig.(b) represents the boundaries of the image, Fig. (c) represents the filtered image and Fig. (d) represents the segmented image.

Fig. 2(a) Original Image

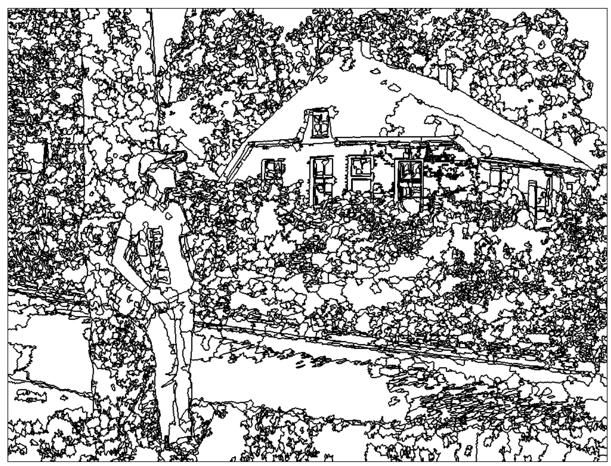

Fig. 2(b) Boundaries of the Image

Fig. 2(c) Filtered Image

Fig. 2(d) Segmented Image

In this method, the average performance of portions of images is visualized in Fig.3. It shows two-segment portion of images with its average performance of 0.3987. Fig.4 shows the performance curve of five-segment portion of images with its average performance of 0.4925

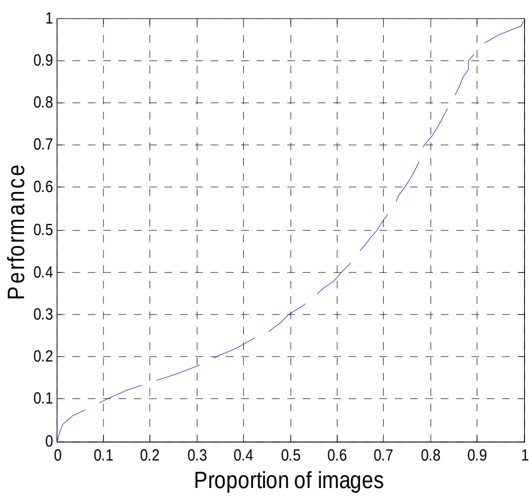

Fig. 3 MS Method for 5-Segment Images

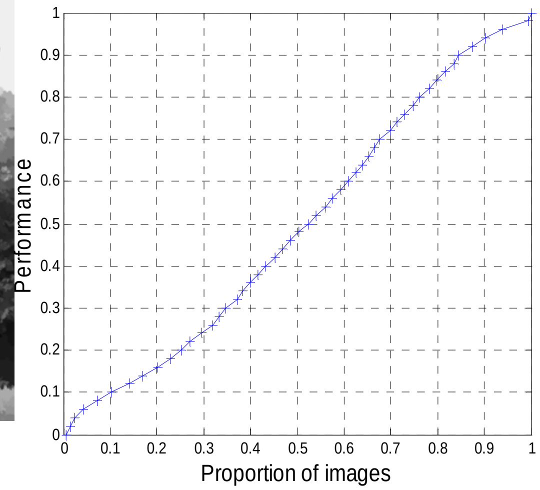

Fig. 4 MS Method for 10-Segment Images

6. CONCLUSION

Our framework consists of comparing the performance of two region-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 Watershed image segmentation method has shown better performance than the Mean-Shift image segmentation method. It is clear that the Watershed Method is efficient for images with a small number of segments. Moreover, we propose in future to develop a combination of above-said methods to enhance segmentation.

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