A study of observation scales based on the FH dissimilarity measure

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Abstract

Hierarchical image segmentation provides a region-oriented scale-space, *i.e.*, a set of image segmentations at different detail levels in which the segmentations at finer levels are nested with respect to those at coarser levels. Guimarães *et al.* proposed a hierarchical graph based image segmentation (HGB) method based on the Felzenszwalb-Huttenlocher dissimilarity. This HGB method computes, for each edge of a graph, the minimum scale in a hierarchy at which two regions linked by this edge should merge according to the dissimilarity. In order to generalize this method, we first propose an algorithm to compute the intervals which contain all the observation scales at which the associated regions should merge. Then, following the current trend in mathematical morphology to study criteria which are not increasing on a hierarchy, we present various strategies to select a significant observation scale in these intervals. We use the BSDS dataset to assess our observation scale selection methods. The experiments show that some of these strategies lead to better segmentation results than the ones obtained with the original HGB method.

1 Introduction

Hierarchical image segmentation provides a multi-scale approach to image analysis. Mathematical morphology has been used in hierarchical image analysis with, *e.g.*, hierarchical watersheds [3, 8], binary partition trees [10], quasi-flat zones hierarchies [7], and tree-based shape spaces [12]. Other methods for hierarchical image analysis consider regular and irregular pyramids [6], scale-set theory [4], multiscale combinatorial grouping [9] and series of optimization problems [11]. A hierarchical image segmentation is a series of image segmentations at different detail levels where the segmentations at higher detail levels are produced by merging regions from segmentations at finer detail levels. Consequently, the regions at finer detail levels are nested in regions at coarser levels. The level of a segmentation in a hierarchy is also called an *observation scale*. In [5], Guimarães *et al.* proposed a hierarchical graph based image segmentation (HGB) method based on the Felzenszwalb-Huttenlocher dissimilarity measure. The HGB method computes, for each edge of a graph, the minimum observation scale in a hierarchy at which two regions linked by this edge should merge according to the dissimilarity.

This article is part of our work presented in [2], where we provide a formal definition of the criterion which is implicitly used in the HGB method and we show that this criterion is not increasing with respect to the observation scales. An important consequence of this observation is that selecting the minimum observation scale for which the criterion holds true, as done with the original HGB method, is not the unique strategy that makes sense with respect to practical needs. Hence, following a recent trend of mathematical morphology (see, *e.g.*, [12]) to study non-increasing criteria on a hierarchy, we investigate scale selection strategies, leading to new variations of the original HGB method. In

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Table 1: Average F_r scores for BSDS dataset. In the table, avg., param. and med. stands for average, parameter, and median, respectively.

Strategy	Param.	ODS		OIS	
		avg.	med.	avg.	med.
Min	-	0.463	**0.453**	**0.570**	0.555
Lower p-rank	0.005	0.432	0.431	0.551	0.546
	0.01	0.432	0.431	0.551	0.544
	0.05	0.431	0.427	0.552	0.547
	0.1	0.431	0.426	0.543	0.531
Lower $\alpha-$*length*	10	**0.465**	0.450	0.563	**0.564**
	100	0.439	0.430	0.552	0.537
	500	0.420	0.416	0.546	0.536

Strategy	Param.	ODS		OIS	
		avg.	med.	avg.	med.
Max	-	0.547	0.543	0.638	0.642
Upper p-rank	0.005	0.552	**0.553**	0.646	**0.649**
	0.01	**0.553**	0.541	**0.647**	0.648
	0.05	0.553	0.541	0.643	0.637
	0.1	0.548	0.541	0.641	0.637
Upper $\alpha-$*length*	10	0.548	0.545	0.638	0.640
	100	0.547	0.545	0.638	0.638
	500	0.546	0.543	0.640	0.643

this work, the proposed methods are assessed with the evaluation framework of [1]. The assessment shows that some of the proposed variations significantly outperform the original HGB method (see illustration in Fig. 1).

Figure 1: Saliency maps resulting from the HGB method using the original observation scale (middle) and from one of our proposed observation scale (right).

2 Experiments

In this section we aim to compare the segmentation results obtained from the original HGB method against the segmentations obtained by our strategies. To this end, we use the Berkeley Segmentation Dataset (BSDS) and associated evaluation framework [1] for our experiments. This dataset consists of 500 natural images of size 321×481 pixels. In order to perform a quantitative analysis, we use the F-measures defined from the precision-recall for regions F_r. The segmentation is perfect when $F_r = 1$ and totally different from the ground-truth when $F_r = 0$. From each pair made of an image segmentation and the associated ground truth, we obtain one F-measure value. Then, we keep the best F_r-measure obtained for each image of the database. Alternatively, we can also keep the F_r-measure for a constant scale over the database, such that the constant scale is chosen to maximize the average F_r-measure of the overall database. They are called optimal image scale (OIS) and optimal database scale (ODS) respectively.

In Table 1, we see the average F_r scores for ODS and OIS on the BSDS dataset. As we can observe, we obtain much better segmentation results from the selection strategies that use max-rule over the selection strategies using min-rule. Furthermore, among the selection strategies that use max-rule, the *upper p-rank* selection shows a slight improvement over the max selection. In Fig. 1, we can see a qualitative comparison between the saliency maps resulting from the HGB method using the min selection strategy over our *upper p-rank* strategy which shows a significant improvement.

3 Conclusions

In this article, we study the HGB method with the aim of proposing new strategies for selecting an observation scale that can lead to better segmentation results. To this end, we propose an algorithm that computes all the scales for which the Felzenswalb-Huttenlocher dissimilarity measure indicates that the regions should merge. Dually, we are able to obtain based on the min- and max-rule selection with filtering techniques the negative intervals. Then, we propose several strategies to select scales at both positive and negative intervals. We validate the performance of our strategies on the BSDS dataset. The best performance was achieved by our *upper p-rank* strategy.

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