Laboratory 5 - Berkeley Segmentation Data Set and Benchmarks 500 (BSDS500)

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Abstract

Object boundary and region recognition in an image are important tasks for object identification and extraction in computer vision. In this report, results from different clustering methods and the watershed transform, tested on the Berkeley Segmentation Dataset (BSDS) are presented and compared against the gPb-owt-ucm algorithm. F-measure values and area under the precision-recall curve for boundary quality, showed that clustering methods based on color features with or without spatial information perform poorly on the BSDS dataset. However, the watershed transform, with some minor adjustments to prevent over-segmentation, outperformed the mentioned clustering methods obtaining ratter acceptable results. On the other hand, the performance of the gPb-owt-ucm algorithm was significantly higher than all the methods tested, proving that boundary identification is a hard problem that require models of higher complexity than the ones used.

1. Report

Object boundary and region recognition in an image are important tasks for object identification and extraction in computer vision. One initial approach to object identification is to label pixels with similar features (color, intensity) trough a clustering algorithm, in hope that this labeling create perceptually meaningful regions. Another approach is the watershed transform, that models an image as a topographic surface, and considers the water basins formed when this surface is submerged as regions. In this report, results on different clustering methods and the watershed transform are presented when tested on the Berkeley Segmentation Dataset (BSDS) and compared against the gPb-owt-ucm algorithm by Arbeláez et al. [1]

1.1. Methods

First, each method was tested on the train dataset with images in RGB, Lab and HSV color spaces, with or without the inclusion of spatial information (x,y coordinates), for a total of 6 feature spaces. Then, boundary quality was evaluated using $F{-}measure$ and Area under the precision-recall curve Apr as performance measures was used to select two different methods with superior scoring along with its corresponding parameters: color space and number of clusters; being not a clustering procedure,the watershed transform parameter for number of clusters was reinterpreted as a minimum suppression and energy threshold selection value (details are given below). The methods selected: k-means in HSVxy space and watershed in Lab space, were finally tested on the BSDS test image-set and compared against the gPb-owt-ucm algorithm.

It is well known that the watershed transform suffers of over-segmentation. Also, to obtain a desired level of segmentation resolution or "level" a threshold th is required. In order to account for this problems, additional filtering with was employed and a criteria was designed as part of the watershed implementation. Given a selection value nC, a minimum suppression procedure is carried out by computing the intensity value ρ corresponding to the 50th percentile of the gradient image (after applying a sobel filter) along with its min and max values. Then the threshold is computed using the formula:

$$th = ((min + max)\alpha * nC) + \rho)/2 \tag{1}$$

The corresponding threshold value th is used as input of a minimum imposition function on the gradient image. This transformation takes care in part of the problem of over-segmentation and level selection, given a selection value. For the training dataset, a nC value of 0.02 was used, and for the test dataset nC equals 0.008. Finally, a Gaussian 3x3 filter with $\sigma = 1.5$ was applied to the gradient image, before the minimum suppression step. This filtering step, helped to remove the effects of low energy contours and texture response, reducing the overall over-segmentation of the image.

1.2. Results

For each method and color space, a segmentation was created using a different number of clusters, starting form

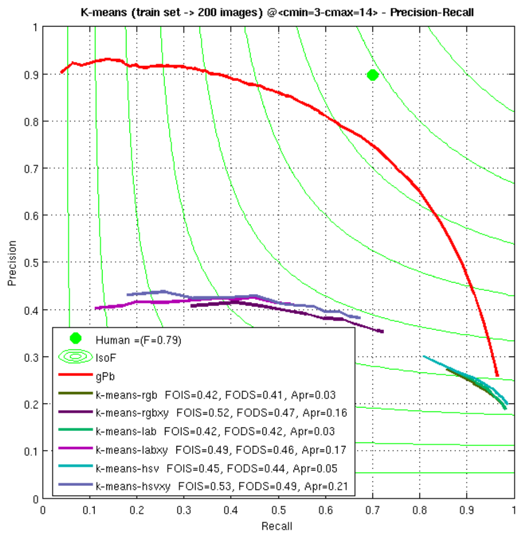

Figure 1. results for k-means method in train image-set

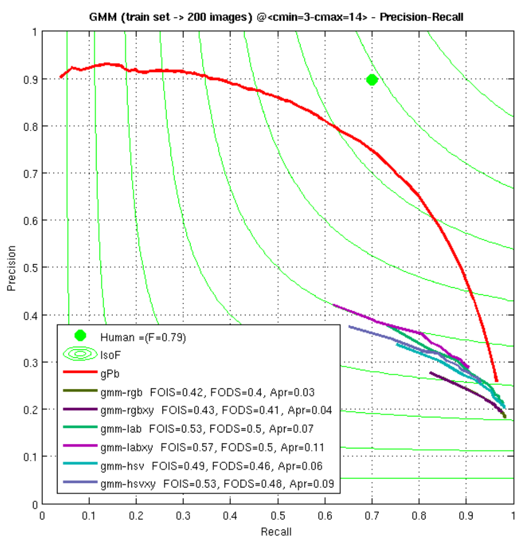

Figure 2. results for GMM method in train image-set

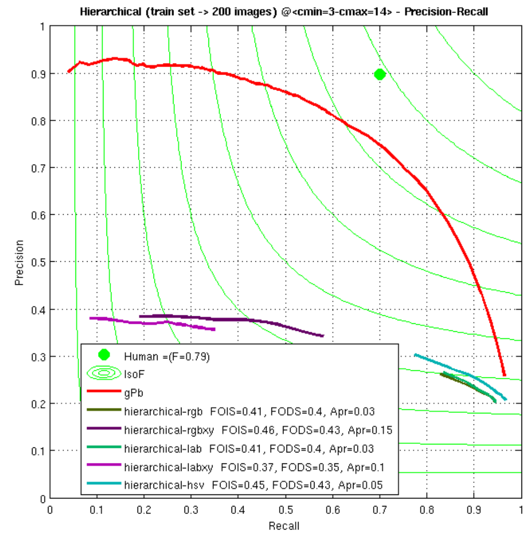

Figure 3. results for hierarchical method in train image-set

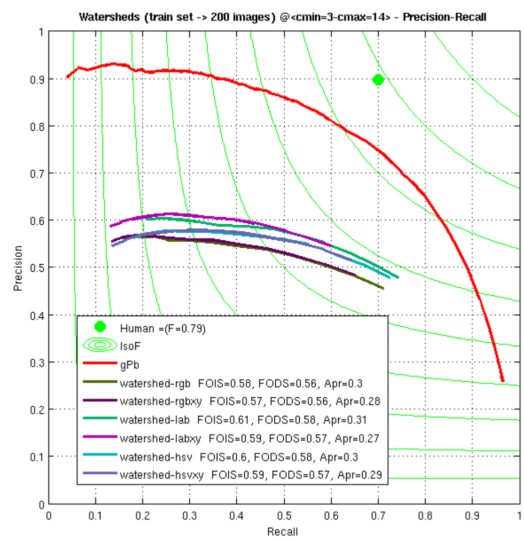

Figure 4. results for watershed method in train image-set

2 to 14 for 200 images in the BSDS train image-set. The results for k-means, Gaussian mixture, hierarchical clustering and watersheds transform are shown in figures 1, 2, 3 and 4 . On these graphs, can be seen that k-means in HSVxy space ($F - measure = 0.49$, $Apr = 0.21$) and watershed transform in Lab space ($F - measure = 0.58$, $Apr = 0.29$) were the best performants among the different methods.

Finally, the selected methods where tested in the BSDS test image-set (200 images), using a wider range for cluster parameter nC, starting at 2 and ending in 50. Results are presented in figure 5, which shows the superiority of the watershed transform ($F - measure = 0.59$, $Apr = 0.45$) over k-means ($F - measure = 0.$, $Apr = 0.$)

1.3. Discussion

Figures 6, 7 and 8, show some segmentation examples using the watershed transform. In those can be seen the its close resemblance between the human segmentation. However, watershed transform, continues to over-segment the image, so its precision is affected by those additional boundaries. On the other hand, results derived from cluster-

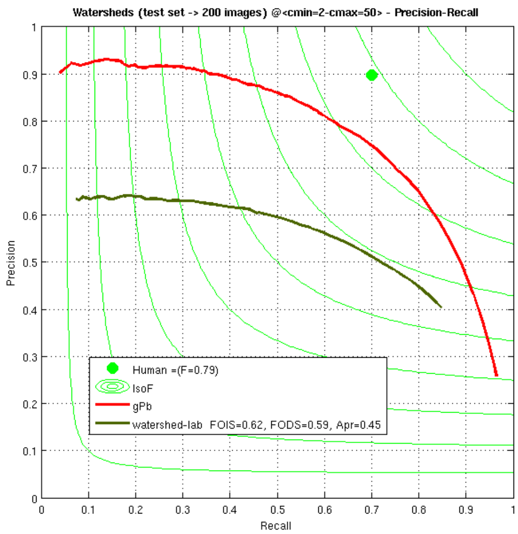

Figure 5. results for k-means (HSVxy) and watershed transform (Lab) in test image-set

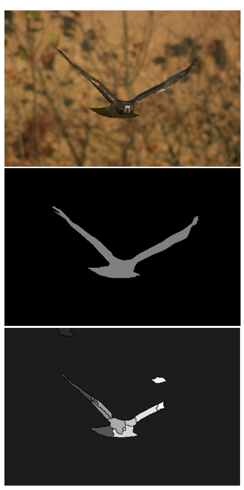

Figure 6. example 1 of watershed transform. First row: original image; middle row: human ground-truth; lower row: watershed transform

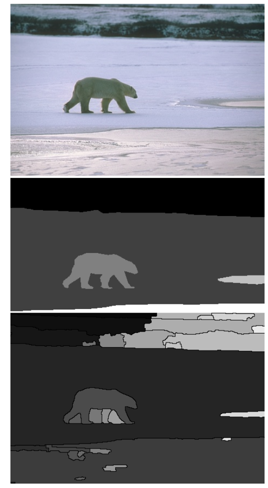

Figure 7. example 2 of watershed transform. First row: original image; middle row: human ground-truth; lower row: watershed transform

Figure 8. example 3 of watershed transform. First row: original image; middle row: human ground-truth; lower row: watershed transform

ing algorithms in color space only, tends to be grainy and commonly labels pixels at object interior with the same label as background. Furthermore, in the case of color space plus spatial coordinates, the segmentation is usually biased by the large value of the coordinates, fussing different regions together.

References

[1] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik. Contour detection and hierarchical image segmentation. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 33(5):898–916, 2011.