Lab 07: BSDS

Adrian S. Volcinschi M.
Universidad de los Andes
https://uniandes.edu.co/en
as.volcinschi@uniandes.edu.co

Abstract

Image segmentation is a task that hasn't been solved completely up to nowadays. The first approach was to think of it as a clustering method since we didn't knew how to accomplish this task. The purpose of this is to be able to separate all the objects inside an image. The two primary clustering methods, Kmeans and Gaussian Mixture Models, were used and compared to the algorithm gPb-OWT-UCM. The clustering methods showed a poor performance compared to gPb-OWT-UCM because of the lack of representation, specially the spatial information. While the clustering methods showed a F-measure of 0.53 gPb-OWT-UCM showed a 0.73 which is a huge leap in performance.

1. Introduction

The idea to segment an image into its different components has been around since the early 1970's. Since then there have been a lot of approaches like clustering [5] and Watersheds [4]. In 2004, Fowlkes et al. created the detector Probability of Boundary (Pb) [7] to calculate a probability of a boundary and with that information segment the image. This probability of boundary was presented alongside the BSDS500 dataset [6] with a benchmark to objectively evaluate segmentation methods. Approximately 10 years later, Arbelez et al. proposed the gPb-OWT-UCM which based on the original Pb detector but with a multiscale approach and a gradient of eigenvectors that come from Normalized cuts. This gave a global probability of boundary (gPb) which later on goes through a Oriented Watershed Transform and uses Ultrametric Contour Maps (UCM) to build a hierarchy of segmentations [3].

2. Materials and Methods

The objective is to segment different images of the BSDS500 dataset that can be downloaded at `https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html` with Kmeans and Gaussian Mixture Models (GMM). This dataset consists of 200 images for test, 200 images for train and 100 images for validation. All the images are RGB and have a different size. The groundtruth for this dataset consists of segmentations and boundaries drawn by a variable number of annotators. Some pictures of this dataset can be seen on figure 1.

Figure 1: Some pictures of the BSDS500 dataset

To do this a function called segmentByClustering was created. The parameters of this functions are a RGB image, a clustering method (Kmeans and GMM's), a color space (RGB, HSV, Lab, RGB+XY, HSV+XY, and LAB+XY), and a number K of clusters. Kmeans and GMM's were the chosen segmentation methods because of the results obtained in a subsampled BSDS dataset.

2.1. Clustering Methods

2.1.1 Kmeans

Kmeans is the simplest clustering method which consists of choosing K random points as centroids, assign labels to all other points depending on which centroid is closer to them using Euclidean distance and then recalculating the centroids. The idea is to iterate this many times until no significant changes in the centroids occur [8]. The hyperparameter in this clustering method is the number of clusters, K, which defines how many regions the segmentation is going to have.

2.1.2 Gaussian Mixture Models (GMM)

Gaussian Mixture Models has the same intuition as Kmeans but has two big differences. First, it assumes the points distribute normally in K Gaussian probability distributions. Second, it doesn't assign a hard label like Kmeans but rather assigns a probability of being part of each Gaussian distribution [9]. The hyperparameter in this clustering method is the number of Gaussians, K, which defines how many regions the segmentation is going to have.

2.2. Color Space

The segmentation methods were chosen based on the results in the subsampled BSDS dataset which were evaluated with a histogram metric that didn't take into account any spatial information. Because of this, 5 images of the BSDS500 dataset were used to test the two methods, Kmeans and GMM's, but evaluating them with the BSDS500 benchmark to find out which color space was better to use.

2.3. Evaluation method

Since the dataset used is the BSDS500 the chosen evaluation method is the BSDS500 benchmark through the Precision-Recall curve. Because of the expensiveness of the clustering methods, only 50 images of test were segmented with the number of clusters varying from 2 to 102 in steps of 10. For the UCM the whole test images were used. Additional to this Precision-Recall curve, the ODS, OIS and Area under the PR curve was calculated to give a more quantitative metric. The ODS and OIS are measures of the F-measure calculated in different ways. The ODS is the maximum F-measure across the whole PR curve for the images under a certain K. On the other hand, the OIS is the maximum F-Measure across the whole PR curve but using the best result of each image, in other words, using the best K for each image [1]. Additionally, the average precision, area under the curve of PR curve, is calculated for a more complete analysis.

3. Results

The first experiment consisted in segmenting 5 images from the dataset using various color spaces (RGB, HSV, Lab, RGB+XY, HSV+XY, and Lab+XY) and various number of clusters (2,10,30,50,100). With this segmentations the ODS, OIS and Area under the PR curve were calculated. The results for Kmeans and GMM can be found in Table 1 and Table 2 respectively.

Table 1: ODS, OIS and Area PR for each color space using Kmeans with K = 2,10,30,50,100

Color Space	ODS	OIS	Area PR
RGB	0.59	0.58	0.12
HSV	0.54	0.55	0.08
Lab	0.56	0.56	0.10
RGB+XY	0.58	0.59	0.08
HSV+XY	0.54	0.54	0.16
Lab+XY	**0.58**	**0.57**	**0.19**

Table 2: ODS, OIS and Area PR for each color space using GMM with K = 2,10,30,50,100

Color Space	ODS	OIS	Area PR
RGB	0.58	0.58	0.12
HSV	0.52	0.55	0.07
Lab	0.56	0.59	0.09
RGB+XY	0.57	0.57	0.10
HSV+XY	0.54	0.55	0.16
Lab+XY	**0.58**	**0.59**	**0.19**

With this we were able to choose Lab+XY as the best color space for both Kmeans and GMM methods. This is probably because the Lab color space is considered to be near uniform spacing of perceived colors [2].

The next step was to run the 200 test images with these two methods using Lab+XY. To get a more complete PR curve for both methods the K used went from 2 to 102 in steps of 10. This meant a lot of computational resources were needed since clustering with a high amount of clusters can be really expensive. After approximately 2 days of running Kmeans had only processed 50 images and GMM 82. Taking this into consideration the segmentations used for the following results are based on only 50 test images. Nevertheless, the gPb-OWT-UCM results in the test images were used in their totality. The PR curve of these two methods and the gPb-OWT-UCM are shown in Figure 2. Since both methods, Kmeans and GMM, have almost the same behavior, a zoom in the PR curve was done and it is shown in Figure 3.

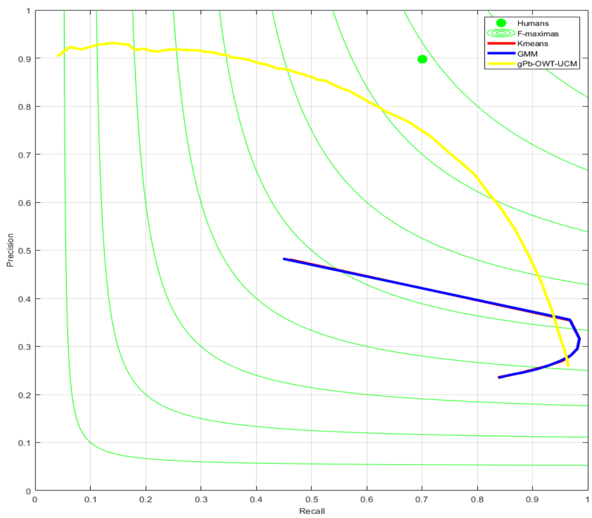

Figure 2: Precision-Recall curve for Kmeans, GMM and gPb-OWT-UCM in the test of BSDS500

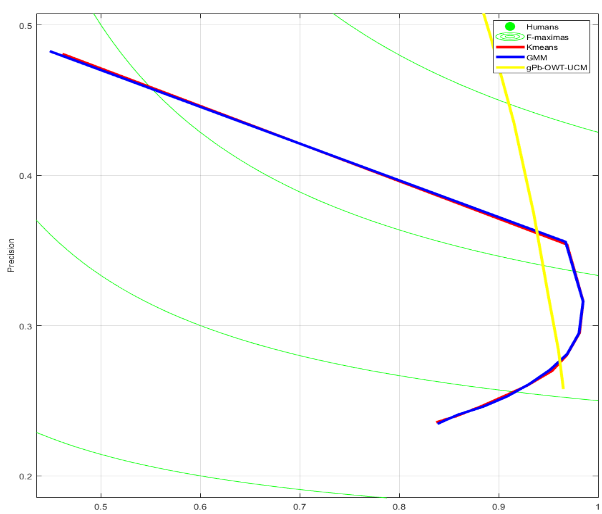

Figure 3: Precision-Recall curve for Kmeans, GMM and gPb-OWT-UCM in the test of BSDS500 zoomed in

Based on these results shown in Figures 2 and 3 we can tell that assuming the representation space of the image as a mixture of Gaussians is the same as not assuming it. Additionally, it is obvious that the gPb-OWT-UCM method is way better because of its considerations of texture, color and brightness in a more local way rather than only using color and a very broad approximation of spatial information with the XY coordinates. Additionally, the fact that gPb-OWT-UCM works in a more local way and uses multi scale analysis it is clear that is going to have better results.

It was also possible to calculate the better K for each method and it was shown that for Kmeans and GMM the better results was using K = 3. Additionally, gPb-OWT-UCM showed the best result with a threshold of 0.13. These results are shown in Table 3. With this in mind, the image 107072 of test was segmented. This segmentations were transformed into boundary images and compared with the original image, the gPb-OWT-UCM result and the groundtruth. This comparison can be shown in Figure 4.

Table 3: ODS, OIS, Area PR, and Threshold for Kmeans, GMM and gPb-OWT-UCM in test images

Method	ODS	OIS	Area PR	Threshold
Kmeans	0.53	0.54	0.17	1.66 (3)
GMM	0.53	0.54	0.18	1.68 (3)
gPb-OWT-UCM	0.73	0.76	0.73	0.13

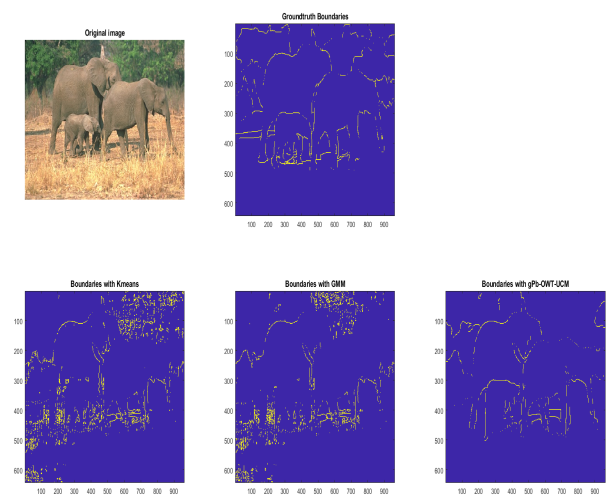

Figure 4: Boundaries obtained with Kmeans, GMM and gPb-OWT-UCM for a test image

It is obvious that the boundaries of Kmeans and GMM have a lot of noise whereas the gPb-OWT-UCM has very little noise and compares pretty good with the groudtruth. It is also worth noting that the threshold for both Kmeans and GMM is 3, which is a low number, and it must be because of the lack of spatial information these methods have. If it was a higher K the number of boundaries across the image would only increase the noise.

4. Conclusions

The approach of segmenting using clustering methods is not a very good idea as it was shown. The lack of coarse spatial information leads these methods to a lot of noise in the segmentations as well as in the boundaries. Additionally, the use of only color to represent these images ends up in a huge loss of information such as texture and brightness which the gPb-OWT-UCM doesn't. One way to improve these clustering methods can be by upscaling the representation of this images to texture and brightness as well and maybe even orientations with the help of HOG or SIFT.

References

[1] Project 2: pb-lite: Boundary detection. http://cs.brown.edu/courses/cs143/2011/results/proj2/lbsun/.

[2] Lab color values. https://www.xrite.com/blog/lab-color-space, oct 2018.

[3] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik. Contour detection and hierarchical image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 33:898–916, 05 2011.

[4] S. Beucher and C. Lantujoul. Use of watersheds in contour detection. volume 132, 01 1979.

[5] M. Celenk. A color clustering technique for image segmentation. *Comput. Vision Graph. Image Process.*, 52(2):145–170, Sept. 1990.

[6] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *Proc. 8th Int'l Conf. Computer Vision*, volume 2, pages 416–423, July 2001.

[7] D. R. Martin, C. C. Fowlkes, and J. Malik. Learning to detect natural image boundaries using brightness and texture. In S. Becker, S. Thrun, and K. Obermayer, editors, *Advances in Neural Information Processing Systems 15*, pages 1279–1286. MIT Press, 2003.

[8] A. Trevino. Introduction to k-means clustering. `https://www.datascience.com/blog/k-means-clustering`, 2016. [Online; accessed 07-03-2019].

[9] J. VanderPlas. In depth: Gaussian mixture models. `https://jakevdp.github.io/PythonDataScienceHandbook/05.12-gaussian-mixtures.html`, 2016. [Online; accessed 07-03-2019].