Segmentation and evaluation on BSDS 500

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Abstract

There are many methods to segment images. These methods are based on the characteristics of the image, in this way the pixels corresponding to each group can be clustering. Therefore, in this practice it is proposed to make a function to segment an image. This function has the objective of cluster pixels with similar characteristics. The algorithms that will be used to clustering the pixels are kmeans and gmm over yhe segmentation database BSDS500 of the University of Berkley will be used. In the same way, the results of the segmentation between the two methods and the UCM method are compared. All were compared with the presicion and coverage curves, with the results obtained, it was observed that the UCM method obtained the best results in F max and the area under the curve.

1. Introduction

The image's segmentation is the process that divide an image in different regions. One of the regions represent an object in the image or instance with different characteristics. For the study of segmentation, there are different methods based on parameters such as color, texture, shape, luminance, among others. So, the goal of this practice is to evaluate and compare the methods of segmentation by Clustering, from Kmeans and GMM's models, applicated in a color's space (Lab). Moreover, the results will be compare with UCM (ulta contorn maps) and to propose which of three is better on the consolidation of images presented in the BSDS500 database. Additionally, it is sought to compare the results obtained through the segmentation with these methods with ultra-metric contour map (UCM), .

2. Methodology

2.1. Materials - BSDS500 Database

This base data is composed by 500 images with their annotations. The data are divided in three subsets: training, validation and testing. For the development of this laboratory, the segmentation process was carried out on each of the images in the testing section. That images was natural images, the annotations made by humans for each image.

Figure 1: Examples of BSDSTiny

2.2. Materials - Benchmarks folder

the benchmarks folder had the codes that evaluated the results for the segmentation methods. The function All bench fast allowed to compare the annotations with the segmentations to different Clusters. The plot eval function allowed to graphic the curves with precision and coverage. This activity helped to compare between the inputs

2.3. Methods

For the developed of different experiments were used two segmentation methods, K-means and GMM (Gaussian Mixture Model). K-means is a type of iterative clustering method using in unsupervised learning, the aim in this method is generate n number groups based in the number of k assigned and the centroid that is the means, each data was assigned to the with the nearest means as formed the different clusters. These clusters have a circular form and with these results was generated a partitioning in different data space know as Voronoi cells.

On the other hand, Mixture Model is a probabilistic model for represent in different clusters or "subpopulations" of overall data, it corresponds to the mixture of distribution that represents the probability distribution of all. In this way, the Gaussian mixture models is a unsupervised method of clustering where created k number of clustering that have a gaussian distributions where the data are assigned in the nearest mean according to the covariance that the same cluster has, which allows the cluster to take an elliptical form in different directions and the data have a better fit. This method does not converge in all the images, especially when the cluster number increases, in this way the SharedCovariance parameter was changed, in true, in this way it was guaranteed to obtain results on each image.

These methods were selected for the following reasons. First, they are easy methods to implement and implement in MATLAB, they do not generate an overshoot or super pixels, as in the case of watersheds, since extended minimums are not imposed. On the other hand, in the case of implementing the hierarchical method, it is necessary a high number of h with which to join the extended regional minimums and generate regions that are better assimilated to the expected results. Additionally, using the jaccard index, results greater than 0.7 are obtained using k-means in the HSV + XY color space and GMM in the color space LAB + XY.

In these methods, the most relevant hyperparameter are the number of clusters (k), this define in how many groups or partition the data is divided and must be a positive integer. The values taken for the development of this practice were from 3 to 15 clusters, these were selected from the response of images previously segmented and evaluated with the index of jaccard, where values higher than 0.4 are obtained; in addition, it is carried out from the amount of regions present in the annotations of the training images, where they are always greater than 3 and less than 15 in order to avoid oversegmentation. The other parameters of the functions were left in default defined values such as Squared Euclidean distance to define the distance between the center and the other data in the method of k means.

The precision is a measure of positive predict values and the recall is a measure of how successful are the positive results. Thus, the precision-recall curve shows the tradeoff o relationship between precision and recall for different number of clusters or thresholds. The most relevant features in precision and recall curve is a high area under the curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate.

In this way, the ideal result is area under the curve equal to 1, where the value of precision is 1 and recall 1, moreover, the curve should have rectangular form, two lines with an angle of 90 grades than show the figure 1. On other hand, the groundtruth shows than the human annotation match in 0.79, which says that the human is 79 % correct with respect to the annotations; for this reason, the method is efficient if the area under the curve is more than 0.79.

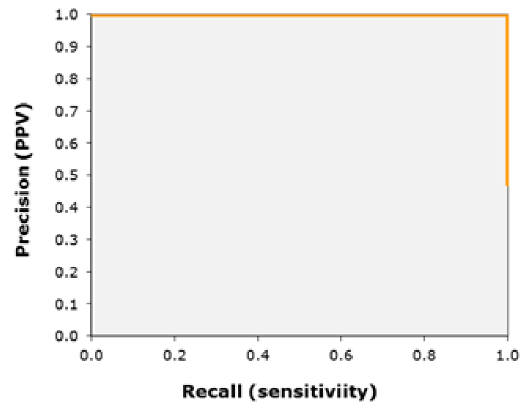

Figure 2: Expected results

3. Results

Next, the graphs of presicion - Recall.

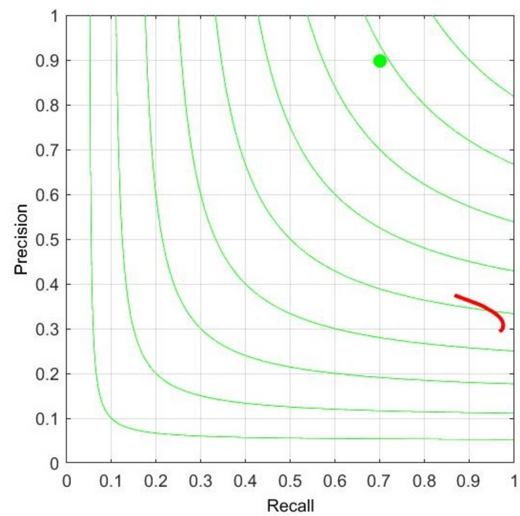

Figure 3: Results using K means

K means Boundary ODS: F(0.87, 0.37) = 0.52 [th = 1.00] OIS: F(0.92, 0.38) = 0.54 Area_PR = 0.04

Region GT covering: ODS = 0.35 [th = 1.00]. OIS = 0.36. Best = 0.38 Rand Index: ODS = 0.71 [th = 13.00]. OIS = 0.73. Var. Info.: ODS = 2.95 [th = 1.00]. OIS = 2.94. Elapsed time is 4.296596 seconds.

GMM Boundary ODS: F(0.78, 0.48) = 0.59 [th = 4.00] OIS: F(0.84, 0.54) = 0.66 Area_PR = 0.15

Region GT covering: ODS = 0.43 [th = 3.00]. OIS = 0.51. Best = 0.59 Rand Index: ODS = 0.76 [th = 7.00]. OIS = 0.79. Var. Info.: ODS = 2.41 [th = 2.00]. OIS = 2.14. Elapsed time is 1.946577 seconds.

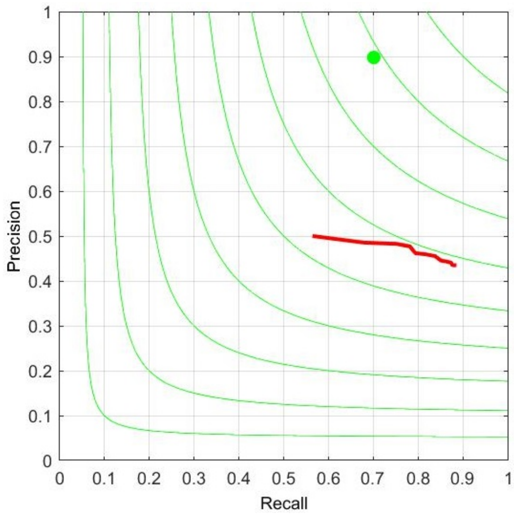

Figure 4: Results using gmm

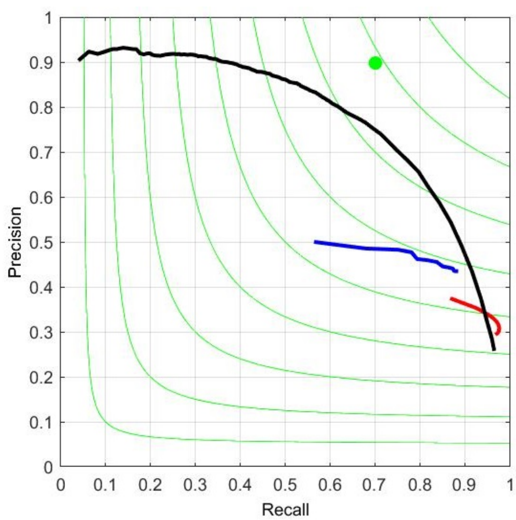

Figure 5: Three Results

UCM Boundary ODS: F(0.73, 0.73) = 0.73 [th = 0.13] OIS: F(0.77, 0.75) = 0.76 Area_PR = 0.73

Region GT covering: ODS = 0.59 [th = 0.20]. OIS = 0.65. Best = 0.74 Rand Index: ODS = 0.83 [th = 0.12]. OIS = 0.86. Var. Info.: ODS = 1.69 [th = 0.29]. OIS = 1.48.

4. Discussion

When comparing the results of the methods, it was not possible to overcome the results obtained by the UCM method, developed by Professor Pablo Arbelaez. This it can be shown in the data obtained for the F maximum measure. The measure of area under the curve is not taken into account, this is due to the fact that the results obtained by the UCM2 method take into account a large number of K,

Additionally, it should be noted that the main limitations of the methods of segmentation by clustering studied, k means and GMM, are the aterations to the great dependence on the initialization and the previous selection of the number of clusters. In addition, the results obtained with these methods are not the best because they use only the information related to the color in each image.

It is considered that the most appropriate way to improve the developed segmentation algorithms is through a more precise representation space, that is, to have as much information as possible about each point. or each window. It may be useful to include information about the texture, since it is an important part of what the difference between objects represents. The use of space or spatial coordinates is not considered,

5. Conclusions

It was observed that the clustering methods are not very effective at the time of segmentation due to lack of labels, processing times and, in addition, they are very difficult to evaluate.

The segmentation method by clustering GMM presents better results in the BSDS500 database than the method k means.

The segmentation based only on the color information is insufficient to achieve an optimal separation of the objects or instances present in an image. This explains why the UCM method exhibits much better results than those obtained with the clustering methods studied.

The selection of the parameter k is very important for obtaining better results in the segmentation algorithms by means of clustering k means and GMM. With the highest values of k, a greater coverage is obtained, however, the values of the F maximum measure are lower than those obtained with values lower k.

References