Practice 6: Segmentation

Nicolás Morales Velandia
Universidad de los Andes
Carrera 1 # 19-27
n.morales10@uniandes.edu.co

Oscar Francisco Trujillo Puentes
Universidad de los Andes
Carrera 1 # 19-27
of.trujillo10@uniandes.edu.co

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, gmm, hierachical and watershed. The segmentation database BSDS500 of the University of Berkley will be used.

1. Introduction

The processing of images made by the human being has the ability, just by observing a few seconds an image, to be able to interpret and categorize semantic information. In this way, in the field of computer vision, the segmentation of an image is quite important. The process of segmentation of an image is defined as the process of dividing a digital image into multiple segments, with the aim of simplifying and changing the representation of an image in something that is more meaningful and easier to analyze. In this way the objective of this laboratory practice is to use the BSD500 segmentation database of Berkeley University, to create a function that can segment the different regions within the image. [1]

2. Methodology

For this laboratory the segmentation database was used BSDS 500 (Berkeley Segmentation Dataset and Benchmark) 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. For this experiment, was used a subset composed by 24 images. Each image has the annotation of the segmentation of 5 people.

Figure 1: Examples of BSDSTiny

From this, we propose to use the following parameters of the image to apply them in the segmentation function, such as, color space, clustering method and cluster number for each images. The input arguments of the function is a color image, in the rgb channel, and the return argument is an array, the same size as the 2-dimensional image, where pixels belonging to the same group have the same positive response integer.

In this practice, four methods of segmentation were used. The first, 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.

Finally, the principle of watersheds, where the minimums are points where the water accumulates and the maximums are edges, in this way the maximums are obtained as the edges and the minimums as the regions. On ther hand, hierarchy segmentation is type of nested segmentations, partitions at higher levels are unions of regions based on low levels. For this reason, the watersheds using the minimum markers produce a hierarchy segmentation, in this extended regional minimum at the contrast obtained by merging together the regional minimum that can be connected by a path of height

For this case, it is necessary to re-scale down the values of the channels, this in order to reduce the processing scales since they can take very high scales. Therefore, a faster convergence is reached. On the other hand, it was necessary to re-scale the images, this in order to reduce processing times as the main problem and memory uses. Additionally, this allows an easier organization of the obtained information, as it is the case of the application of filters. However, this generates the loss of relevant information as a form and makes comparison with annotations difficult.

To select the cluster number we did not apply any special method, as you know this is random or user's consideration, in our case we apply between 5 and 8 clusters where they resemble the annotations, with the idea of generating the same amount of regions. However, there are methods like the Elbow Method

Generally segmentation problems are evaluated using the Jaccard index, where the intersection of the areas on the junction is compared. However, the segmentation is not a perfect problem and everyone understands the objects in different ways, in this way, the coverage and presicion curves must be generated, the segmentation must be evaluated correctly in the specified region or if this extends. It is evaluated as a detection problem.

To evaluate the function developed, no method was applied, this is because the information was not similar and could not be compared. In addition, the methods were not as accurate as expected.

Finally, for the solution of the problem, a matlab code was developed since it has segmentation tools that are easier to use. However, when using python methods you could see better results. Additionally, the code was run over a group of 24 images with a 3 clusters 3,5 and 8 .

	k means	GGM	watershed	hierarchical
RGB	0.2036	0.2149	0.2171	0.1507
Lab	0.2863	0.2712	0.2372	0
HSV	0.2942	0.2247	0.2338	0
RGB+xy	0.2697	0.2646	0.2332	0
Lab+xy	0.2415	0.2475	0.242	0
HSV+xy	0.2127	0.2906	0.2323	0

Table 1: Mean Jaccard indice with 3 clusters

	k means	GGM	watershed	hierarchical
RGB	0.2046	0.2064	0.2171	0.1388
Lab	0.1997	0.1705	0.2372	0
HSV	0.2398	0.257	0.2338	0
RGB+xy	0.2526	0.2233	0.2332	0
Lab+xy	0.2097	0.2603	0.242	0
HSV+xy	0.272	0.3109	0.2323	0

Table 2: Mean Jaccard indice with 5 clusters

	k means	GGM	watershed	hierarchical
RGB	0.1583	0.2101	0.2171	0.1212
Lab	0.1382	0.1723	0.2372	0
HSV	0.2349	0.2052	0.2338	0
RGB+xy	0.1963	0.2385	0.2332	0
Lab+xy	0.248	0.1785	0.242	0
HSV+xy	0.1845	0.1884	0.2323	0

Table 3: Mean Jaccard indice with 8 clusters

	k means	GGM	watershed	hierarchical
RGB	0.991	0.8774	0.5558	0.6125
Lab	0.9254	0.8354	0.6056	0
HSV	0.9717	0.9697	0.6505	0
RGB+xy	0.9798	0.8068	0.6328	0
Lab+xy	0.7131	0.9843	0.6048	0
HSV+xy	0.9899	0.9537	0.6490	0

Table 4: Maximum Jaccard indice 3 clusters

3. Results

4. Discussion

By reviewing the method, it can be verified that using different color spaces allows for better results, especially if linear distances can be used. In this case, the one that yields the best results is that of lab + xy, using k-means, the safest thing is that it is due to the use of the Uklidean distance and that the selected color channel is linear, in addition the imposition is not necessary of minimus. The methods are limited mainly in the allocation of clusters, it is an iterative method, that in some images you can get to see better results according to the color channel and the clustering method that is used.

On the other hand, there is no special channel for the op-

	k means	GGM	watershed	hierarchical
RGB	0.9081	0.934	0.5558	0.6125
Lab	0.9368	0.9254	0.6056	0
HSV	0.9685	0.9797	0.6505	0
RGB+xy	0.9563	0.9668	0.6328	0
Lab+xy	0.8031	0.9753	0.6048	0
HSV+xy	0.9420	0.9673	0.6490	0

Table 5: Maximum Jaccard indice 5 clusters

	k means	GGM	watershed	hierarchical
RGB	0.6682	0.898	0.5558	0.6598
Lab	0.4809	0.6444	0.6056	0
HSV	0.9502	0.8216	0.6505	0
RGB+xy	0.7723	0.9229	0.6328	0
Lab+xy	0.7964	0.8427	0.6048	0
HSV+xy	0.9952	0.8053	0.6490	0

Table 6: Maximum Jaccard indice 8 clusters

eration, everything depends on the information you want to obtain. Since, the methods fail to require a number of specific clusters, they are iterative and the image needs a lot of processing before its proper development. In addition, the evaluation strategy could be improved by applying the purchase on each region, the image and making the coverage and precision curves. Finally, a method could be used to establish the Ks automatically, in the same way better segmentation methods could be applied, as is the case of a more adequate way to implement minimums in the use of wathersheds.

5. Conclusions

References

[1] 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.