Lab 6: Superpixels

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Abstract: In this laboratory, a segmentation function was created that is able to used four different clustering methods and six representation spaces,this function will be used in the BDSD500 database in the future.

Keywords: Segmentation, hierarchical, k-means, watershed, Gaussian.

1.. Introduction

Segmentation is one of the principal problems in artificial vision and image processing, the correct development of methods could one day allow us to develop bigger visual task in artificial vision like perceptual grouping and the understanding of instances seen by a computer.

In this practice, the objective is to create a function that is able to used four different clustering/segmentation methods such as k-means, GMM, watersheds and hierarchical segmentation in six color or representation spaces.Using a small database with annotations, the results of each method and color space will be tested in comparison to the human annotations.

2.. Methods and Materials

2.1.. Clustering Methods

2.1.1. K-means

Clustering method based in the random selection of k centroids in the representation space of the test data, each centroid represents a cluster and each data point is assign to a cluster, new centroids are selected iteratively until convergence. Is a simple method, but it depends in the initialization.

2.1.2. GMM

Method based in the assumption that the probabilistic density distribution of the data point, of the train data, is a mixture of Gaussian distributions. This is a troublesome assumption, but it can produces some good clustering results. It also uses soft-assignments and responsibility, that produces better results.

2.1.3. Watershed

Based in the topological term, is based in the 'flooding' of the topological representation of images to obtain the lines that separates regions. It can normally produce oversegmentation if the flooding is not limited, therefore markers that determine which regions will be imposed as the minimum regions are used. In this laboratory, hierarchical watershed was used to produce good automatic segmentations at different levels.

2.1.4. Hierarchical segmentation

In this method, a distance representation between cluster is used to produce a more rich clustering method, the distance is based in a similarity measure. This method can be implemented as a top-bottom or bottom-up algorithm, and it can produces multiple segmentation based in the distance one choses to generate the segmentation.

2.2.. Segmentation Parameters and Preprocessing

In order to reduce the computational time and memory problems some changes had to be done to the images, the first mayor change was the addition of the (x,y) coordinates of the pixels as channels in some segmentation, this could allow methods like k-means to take spatial information into account.

The second mayor change was in the watershed method, to obtain a "gray scale" image in every color space a weighted mean method was developed, if the image only had three channels the weight was the same for each channel, but if the image had 5 channels, the last two would have a minor weight(0.1) in comparison with the color channels. Additionally, if the watershed case for HSV images, their channels where multiply by 255 to allow the formation a better gradient.

In the GMM method, the shared covariance parameter had to be set to true, this allow that images that produces great covariances between its vectors couldn't stop the method.

In the hierarchical segmentation, especially with the linkage function, the image had to be rescale to half their size and only took into account their color canals. Additionally, the linkage parameter that saves the memory had to be set on true to allow the processing of the image.

2.3.. Evaluation

Two methods of evaluation were used in the small database, the first will segment the image, extract four clusters and compare to the four larger clusters from every annotation of the image, to obtain a numerical result, the Jaccard index was used to compare clusters.

The second method was similar, only that it took each annotation, find the number of clusters and produce a segmented image with the same number of clusters, compare the four larger clusters between the annotation and new segmentation and produce a Jaccard Index for every image with the different color spaces and clustering methods.

3.. Results and Discussions

3.1.. First evaluation: Four clusters vs four greatest clusters

In the figure 1, the statistics of each method are displayed, none of the methods achieved a larger mean Jaccard index than 0,2. This could be a result of the multiple clusters in some of the human annotations, the method extracted the four larger clusters to compare to the four clusters generated by the function, when comparing small clusters to larger ones the Jaccard Index could be small. The standard deviation in each method is small, which tells us that they are at least consistent.

3.2.. Second evaluation: Four greatest clusters vs four greatest clusters

In this method, the image was segmented with the same number of clusters as every corresponding human annotation, this was done in hopes that the four biggest segmentations will be more similar. As it can be appreciated in the second figure, the results were similar to the first evaluation with a small increase in the standard deviation, this only confirms that clusters in human annotations differ greatly form the function segmentations.

3.3.. Limitations

One important limitation while developing this function was the memory usage, methods like linkage for hierarchical segmentation will create immense arrays that surpass Matlab limits. To surpass this limitation, rescaling the images was necessary which is another limitation as in between values are eliminated for the subsampling of the images.

Other limitation was the number of clusters, four were selected to make a more general measurement of the precision and not consume much time. Taking into account a different number of cluster for each image could have improve greatly the result.

4.. Conclusions

The evaluation of the final function was not as successful as planned, one method did not take into account that the image could have more than our clusters, and the other method that did consider this fail.A better evaluation could show the real precision of this function, but a great limit for this function is the number of clusters parameter.

As is well know, the k-means method and GMM successful used is based in the k clusters the user determines, in this case also the watershed and hierarchical segmentation were limited to generate a minimum of k cluster. A function that can take into account other factors to generate a reasonable assumption of the number of cluster, or make the user decide upon watching each image, could produce better segmentations.

Images

Method	Mean Jaccard Index	Standart Desviation	Best Result
K-Means	0,13	0,01	0,28
Watershed	0,07	0,02	0,25
GMM	0,19	0,04	0,61
Hierarchical	0,13	0,03	0,32

Figure 1. Jaccard Indexes for the First Evaluation

Method	Mean Jaccard Index	Standart Desviation	Best Result
K-Means	0,09	0,04	0,22
Watershed	0,07	0,05	0,22
GMM	0,09	0,05	0,19
Hierarchical	0,16	0,12	0,43

Figure 2. Jaccard Indexes for the Second Evaluation

Figure 3. Example of segmentation in HSV space and k-means

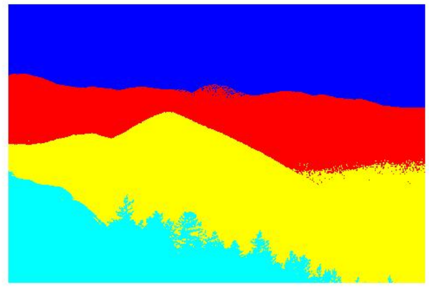

Figure 4. Example of segmentation in Lab space and Watershed

Figure 5. Example of segmentation in Rgb+xy space and K-means