# Segmentation

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## Abstract

*The segmentation of objects within an image is an open challenge that has been studies among the last years. Some of the methods used for this purpose is the clustering. For this study it was used four different clustering methods in order to compare them. The results showed that the clustering can actually work as a segmentation method, but its performance will depend on the hyperparametrization of the functions in order to achieve good results.*

## 1. Introduction

Automatic object segmentation in images is one of the actual challenges in computer vision. The geometry perception grouping and the perceptual organization of an image, is one of the tasks that researchers have been study the last few decades. [1] The human perception allows the observer to identify different regions on an object, even if there are not clear complete edges of it, because the brain is in charge of the visual function and is able to interpret an image from the information from the environment. [2] Because of this, there are some strategies implemented in order to identify objects in images using unsupervised segmentation algorithms performed by clustering methods. On this study, some segmentation algorithms were tested to determine the performance of the segmentation comparing different clustering methods. Techniques such as k-means, watershed, hierarchical and Gaussian mixture model were used to segment images from the BSDS data base. [3]

### Clustering methods

K-means method uses the Lloyd's algorithm in which the data is partitioned assigning $n$ observations or points to an specific $k$ cluster. Each cluster is defined by its centroid, which position is changed in every iteration by the average of the observations. At the end, there are defined clusters that characterize a different region in the image. [4]

In respect to the Gaussian mixture models, the $k$ multivariate normal density distribution components compose this method. The components that describe the procedure consider a $d$-dimensional mean, a covariance characterized by a $d$-by-$d$ matrix and a mixing proportion. The method computes different probabilities for the component membership, that contain the relation of probability for each observation. The separation of the clusters is associated to the estimation of the component means, covariance matrices and the mixing proportions. [5]

On the other hand, the clustering by the agglomerative hierarchical method generates nested clusters by merging them. This hierarchy is represented as a tree, in which the root of the tree is a single cluster that contains the all the observations and the leaves comprise only one sample. The ward method, which is the used for this case, considers the sum of the squared differences to minimize this result for all the clusters. The intuition of this method is based on the k-means procedure, but is implemented using a hierarchy. [6]

Finally, the watershed algorithm consists in the division of the image by segments in which it is located a local minimum. The followed idea is that the limits of the regions are the maximum, which at the same time separate a minimum of another. Where one of these maxima is found, a partition is built that does not allow the passage of "water" from one minimum to another. At the end, there is a complete map of the image with local minimums that represents the segmentation regions. [7]

## 2. Materials and Methods

### 2.1. Segmentation methods implementation

The images were downloaded from the provided data base. Either the images, the segmentations and the boundaries information were stored in variables for further processing. The entire data set available for this study was down-sampled and rescaled to a minor size to achieve several segmentation results. In general, the proposed methods to perform the segmentations require a high machine capacity to be successful. Due to the dataset, having more than one image to process, it was necessary to reduce the total size of the images. Also, the used software for the development of this work was *Python*.

It was developed an algorithm in which a function was created to segment images using different clustering methods. The implementation of the function, first considered the different space colours that can be selected for the analysis of the onset image. For this, the options consisted in the *RGB*, *Lab* and *HSV* space colours. Furthermore, there was an extra parameter taken into account which included the $x$ and $y$ position of each pixel from the onset image. This last parameter gave the spacial information of the pixels to have a better approximation adding this to the clustering phase.

For the k-means method, it was considered a random selection of the initial centroids from the data. Also, the maximum number of iterations per run, was settled at 300. Regarding the Gaussian mixture method (GMM), the parameters mainly comprised the own general covariance matrix for each component, and a random initialization of either the weights, the means and the precisions. This was made to have a different distribution of the data in comparison to the k-means method. Besides, for the hierarchical segmentation method it was selected the default parameters of the function which consists on an euclidean affinity as the metric to determine the linkage, and a *ward* linkage criterion to compute the used distance for between the sets of samples. As well, the watershed method used the negative values of the maximum local peaks, selected with the amount of clusters that enter as a parameter. Former functions were used to implement the final algorithm. [8]

## 3. Results and Discussion

There were 5 different ground truth segmentations for each, so it was selected one of the images in order to reduce the problem of ambiguity that is given by the number of people who are engaged in segmenting the same image. In addition, the maximum number of clusters in the ground truth data for the segmentation was used to perform the necessary clusters and thus compare the proposed method with the annotations.

The images were clustered using the different possible combinations of the parameters. Some of the results are presented in the following figures. The obtained segmentations are presented in the right side of the image, while the left side corresponds to the ground truth. For instance, figure 1 represents the automatic segmentation using the k-means method in a RGB space colour. As it is possible to see in figures 3 and 4 the differences between the spaces colours and the actual information of the onset image, can change the performance of the method. In figure 3 the segmentation is partially and contains a lot of errors, while the figure 4 presents the exact same clustering method, varying the space colour and taken into account the spatial information of each pixel.

One of the main limitations of the current methods is the right selection of the hyperparameters because, per each

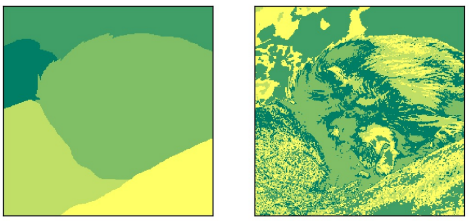

Figure 1: Image segmentation by k-means method using RGB space colour.

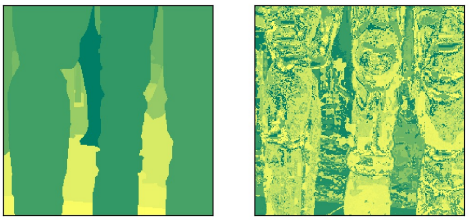

Figure 2: Image segmentation by k-means method using Lab space colour.

method there are at least 5 different parameters that can me modified and optimized according to the used clustering method. According to the results, the space colour and the information of the location of the pixels inside an object matters. With this, it was proven that the used method is sensible to the position of the pixel either spatially and in the colour space where is described. The best result is presented in the figure 4. This may be possible because of the information that the channels bring to the clustering. This is, the channel information plays an important role when the clustering is being performed.

## 4. Conclusions

As it is possible to see from the results, the clustering method to segment objects in images is viable. Nevertheless, the quality of the segmentation will be closely related

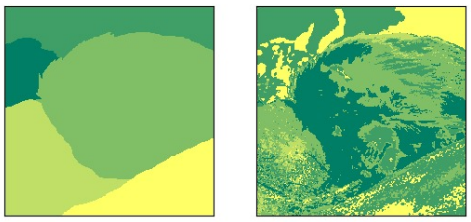

Figure 3: Image segmentation by GMM method using RGB space colour.

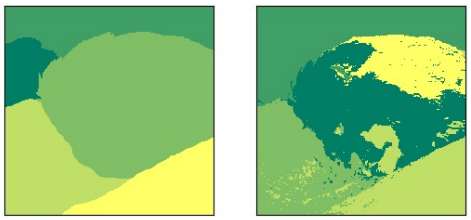

Figure 4: Image segmentation by GMM method using Lab space colour and xy spatial information.

to the choice of clustering method and the hyperparameterization that is chosen for each of the cases.

## References


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