

# Segmentation with Clustering methods

Luisa Fernanda Borbón R.  
Universidad de los Andes  
Departamento de Ingeniería Biomédica  
lf.borbon@uniandes.edu.co

## Abstract

*Segmentation is an image processing technique that divides an image into different relevant parts or objects. In this sense, throughout this work the problem of segmenting images from a subset of the BSDS500 dataset was approached by using different clustering algorithms and color spaces.*

*Keywords: clustering, segmentation, color spaces.*

## 1. Introduction

Image Segmentation is an important and challenging technique of image processing, basis of recognition problems resolution and image semantic characterization. This technique is used to break down an image into its meaningful parts, by dividing it according to similar local characteristics or properties [2]. Before approaching segmentation as a supervised problem, the task was solved following a bottom-up approximation. This involves taking into account small details of the image such as pixels or reduced region characteristics in order to build up the large scale representation. For this task, clustering algorithms such as K-means and Gaussian Mixture Models have been used, specially when there is no previous knowledge of the desired objects to segment [1].

As mentioned before, the unsupervised approximation to segmentation depends highly on the local information of the image. Because of this, a main issue in this topic is finding the image representation that maximizes the similarities within an object and its differences with others, to segment it. In this sense, the problem could be addressed by changing the feature representation of the image, varying for example color or texture, in order to discriminate easily the object of interest. For instance, finding the optimal color representation can be a good first insight to approach the problem. Image data is commonly presented with the RGB color space, but there are other spaces that may be able to present different but valuable information, like the perceptually uniform spaces: *Lab* and *HSV* [3].

In this work, the problem of segmenting an image was approached by using different clustering algorithms and color spaces. For this objective the segmenting function created was applied over a subset of the BSDS500 segmentation database, which included annotations to evaluate the performance of the algorithm developed. In this case, the comparison between taking or not into account the closeness of the pixels position was also made. This article presents the methodology in section 2, including the image preprocessing, clustering algorithm and evaluation methods. used in this article is described on section 2, while results and discussion can be found on sections 3 and 4, respectively.

## 2. Materials and Methods

In order to make the image segmentation, a python function with four possible inputs was created. The first input was the image path name, which corresponded to one of the BSDS500-Small dataset colored images. The second input was to the color space and had the options: 'rgb', 'lab', 'hsv', 'rgb+xy', 'lab+xy' and 'hsv+xy'. The change between color spaces was done with the module *skimage* and the '+xy' suffix was added when taking into account the spatial closeness of the pixels to group. The third input was the clustering method to apply in order to segment the image, which included: 'kmeans', 'gmm', 'hierarchical' and 'watersheds'. Finally, the last input parameter was the number of clusters or categories to divide the image in the method.

The steps followed in the methodology were: Image configuration, cluster algorithm and evaluation.

### 2.1. Database and Image Preprocessing

As mentioned before, the database used for this work was a subsample of the BSDS500 Segmentation Dataset. This collection contained 60 training and 28 testing images, with annotations corresponding to 5 different subjects. Some examples of the images with their corresponding annotations are shown in figure 1



Figure 1. Examples of the images and annotations that can be found in the BSDS500 dataset.

In order to tune the segmentation parameters and configure the clustering methods, the values were changed manually and evaluated until a better segmentation was obtained. When making the color spaces that took into account the pixel position, these channels had to be scaled down because these channels passed the color limits (255). On the other hand, in order to decrease the computing time and difficulty, the images were re-scaled when making the hierarchical clustering.

All the clustering methods used need as input the number of clusters or regions to discriminate with the algorithm. This parameter is going to be key in obtaining good results and needs to be chosen manually. Probably the best way to do so is by looking at the interesting images and making an estimation of the desired objects or regions to obtain. When having a large dataset, this task can be hard but needs to be done in order to develop the clustering.

## 2.2. Clustering Algorithms

### 2.2.1 K-means

The first method implemented was the K-Means algorithm [1]. This method approaches clustering as an optimization problem, which starts by selecting  $k$  randomly located centroids and optimizes their positions. The algorithm ends when the centroids stabilize (no relevant change in their position) or a previously defined number of iterations is achieved. This method was applied using the scikit-learn module, and changing the number of centroids to the corresponding image.

### 2.2.2 Gaussian Mixture Model

The second method was the Gaussian Mixture Model, which fits the image as a Gaussian mixture distribution with  $k$  components. An important aspect of this algorithm is that it follows a soft assignment, giving each pixel a probability of fitting into a category or not.

### 2.2.3 Hierarchical Clustering

The third method used was Hierarchical clustering, that implements an agglomerating tree distribution by setting the

branches according to the images similarities. This kind of approach tends to over-adjust the model but it works well when having a high number of clusters.

### 2.2.4 Watersheds

The last method applied was Watersheds. This algorithm is considered an efficient segmentation technique that is based on mathematical morphology, which allows to extract the borders of the regions present in an image. Watersheds classify the pixels based on the following parameters: the homogeneity of their textures, the gradient in a gray scale and according to their spatial proximity, that is, how far the pixels are from each other.

## 2.3. Evaluation

The proposed evaluation methodology was based on comparing the number of pixels in the resulting segmentation with its corresponding annotation. Due to the fact that the annotations have different labels and number of categories, the groundtruth annotation was taken as a template to extract the associated segment on the created image and compare their sizes. The value of accuracy was obtained by dividing the number of pixels on the segmented region over the number of pixels of the annotations.

## 3. Results

As the dataset presents various images, one of them was selected in order to analyze the function results on it. This train image was '22090.jpg', which contains a natural scenery with a boat, bridge, and nature in different colors. For each clustering algorithm and color space representation, the metric value was obtained as shown in the following figures.



Figure 2. Second groundtruth annotation of the train image '22090.jpg'.

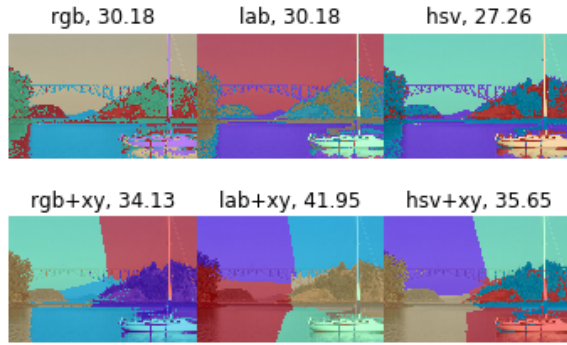


Figure 3. K-Means Clustering algorithm applied with  $k=5$ . The color space used and the metric number evaluation is shown on top of each result.

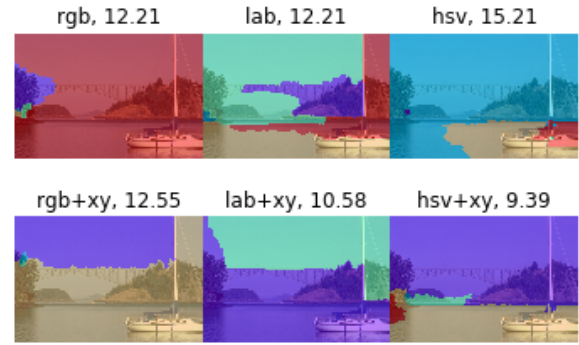


Figure 6. Watershed Clustering algorithm applied with  $k=5$ . The color space used and the metric number evaluation is shown on top of each result.

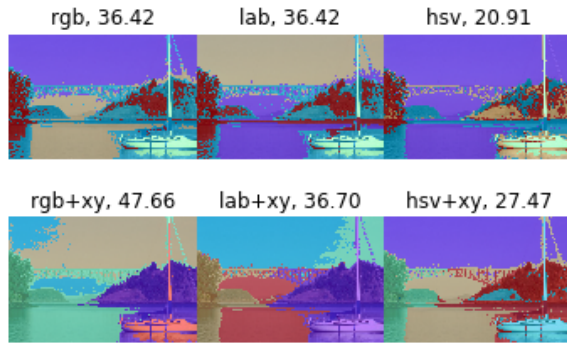


Figure 4. Gaussian Mixed Model Clustering algorithm applied with  $k=5$ . The color space used and the metric number evaluation is shown on top of each result.

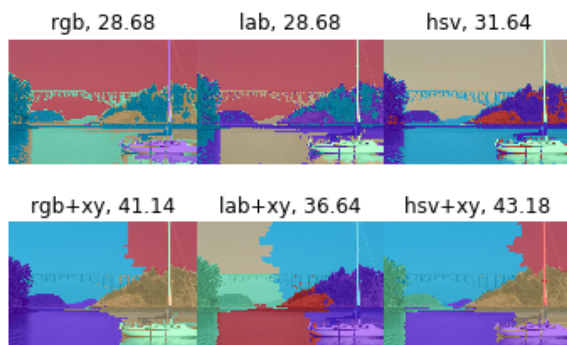


Figure 5. Hierarchical Clustering algorithm applied with  $k=5$ . The color space used and the metric number evaluation is shown on top of each result.

According to this results, the best method was the Gaussian Mixed Model with the space color RGB+XY.

## 4. Conclusions

## References

- [1] P. Arbelaz. Lecture 5: Clustering, computer vision, 2019. Universidad de los Andes.
- [2] K. Dilpreet. Various image segmentation techniques: A review. International Journal of Computer Science and Mobile Computing, Vol. 3, Issue. 5, May 2014, pg.809 to 814.
- [3] G. Paschos. Perceptually uniform color spaces for color texture analysis: An empirical evaluation. IEEE Transactions on image processing, Vol. 10, No. 6, June 2001.

## 5. Images