LAB 4

COLOR-BASED SEGMENTATION AND BLOB DETECTION

Marco Demutti

Matteo Dicenzi

1. Introduction

The aim of this experiment is to perform **color-based segmentation** and **blob detection** on different images.
Color-based segmentation allows to identify homogeneous regions in a colour image, that may represent objects or parts of objects in the scene. In order to do so, the goal of the segmentation technique is to classify each pixel, determining whether it has a color in a specified range or not. In this respect, *HSV color space* is used to represent the image, since in this case the color information is directly stored in the *Hue channel*. As for our specific case, color-based segmentation is used to segment two cars, with different colors, out of 6 different frames captured from a camera, and display the relative bounding box.
In the second part of the experiment, **blob detection** is carried out on a grayscale image to correctly identify two sunflowers of different dimensions. Indeed, this technique allows to extract regions (blobs) that differ in properties compared to surrounding regions, by convolving (and cross correlating) the image with a filter similar to the image patch to find (template matching).
For our purpose we are going to use LoG filters, that are circularly symmetric operators, of different scales and look for the maximum response (**characteristic scale**) for each one of the two selected sunflowers, in order to display the two corresponding blobs in the original image.

2. Procedure

In the first part of the experiment the 6 images are loaded and the RGB values of these images are converted to HSV values using MATLAB function *rgb2hsv*.
After splitting RGB and HSV channels, the dark car is selected in the first image (*area 368:413,557:644*), and then segmented in all 6 images by thresholding the Hue component in the range between $m - 0.4 * s$ and $m + 0.4 * s$, where m and s represent respectively the *mean value* and the *standard deviation* in the dark car area (computed using MATLAB functions *mean2* and *std2*). In order to carry out the segmentation, the function ***doSegmentation*** was written: given the Hue component of the image and the minimum and maximum thresholds as inputs, it outputs the binary segmented image, where each pixel appears white if the color belongs to the range $(minThr, \ maxThr)$, and black otherwise. Then, the relative *centroid* and *bounding box* is displayed both on the segmented image and on the color image by the custom function ***plotSegCentroidBoundaryBox***, which takes both images as inputs. In order to do so, MATLAB function *regionprops* is internally used to obtain the *Area*, the

Centroid and the *Bounding Box* of all the blobs; then the blob with the highest area is chosen and displayed on both images.
All the steps are then repeated for the red car in the first image (*area 352:429,678:784*), but in this case two different ranges are chosen to threshold the images: $(m-s,\ m+s)$ and $(0.97,\ 1)$, and the two different results are shown.
In the second part of the experiment, function ***computeScale*** is written to compute the laplacian response at different scales, with the following parameters: *starting standard deviation 1, number of scales 10, standard deviation increment sigma = 1.5*sigma*, and returns the **scale-space representation** (x, y, σ) of the image. To do so, MATLAB functions *fspecial* and *imfilter* are internally used.
Then, after selecting the two sunflowers in the areas *(386, 458)* and *(361, 166)*, the characteristic scale is computed as the scale that produces the peak of the Laplacian response. Finally, we compute an approximation of the radius of the two sunflowers using the formula

$$r = \sigma \sqrt{2}$$

and display the two corresponding circles.

3. Results

F*igure 3.1* shows the three channels of the RGB color space of the first image, along with the three HSV channels.
From *figure 3.1* we can notice that each channel encodes different informations.
Focusing for example on the red car (on the right of the image), we can see that the the overall color of the car is represented by different intensities of red, blue, and green (**additive primaries)** in the RGB channels. For this reason, the image corresponding to the R channel has bigger values of intensity in correspondence of the area, while the two other channels have lower values.
On the contrary, the Hue channel directly associates a value to each color. Specifically, on the area of the car, the value is around 1 (i.e. white in the gray colormap), that indeed represents the red color.
The components of all the other images are not provided, since the principle is the same as the one explained.

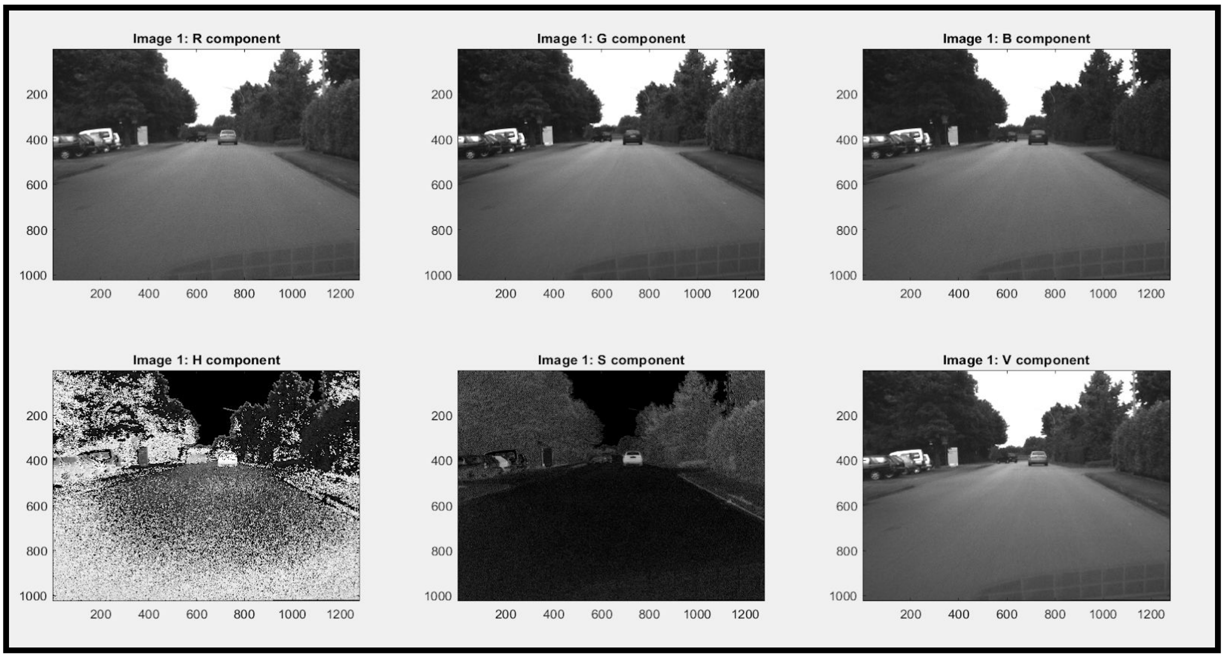

Figure 3.1: RGB and HSV components of image 1

In *figure 3.2* we can see the Hue component of the dark car selected from the first image; we used the information encoded in this area (i.e. standard deviation and mean value) to identify the dark car in each one of the provided images. This was possible because the dark car is always present and the corresponding *standard deviation* and *mean value* of the Hue component are approximately always the same in every image. Therefore we were able to identify the car and display the *centroid* and *bounding box* on the segmented image, as shown in *figure 3.3 (left)*.
Finally, in *figure 3.3 (right)* we overlapped the *centroid* and the *bounding box* to the original RGB image.
The same procedure was repeated for the 5 other images, obtaining similar and correct results. Among these, only the ones regarding the sixth image are shown (*figure 3.4)*, while the others are omitted.

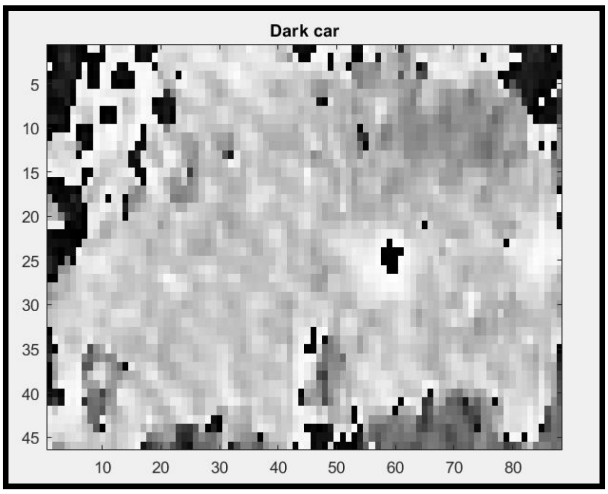

Figure 3.2: Hue component of dark car

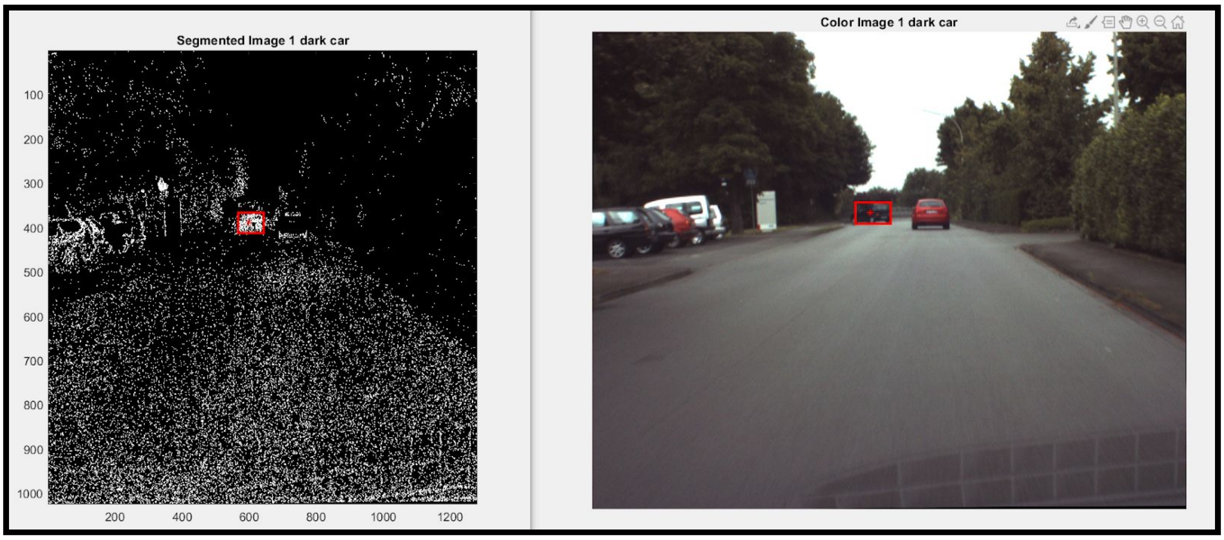

Figure 3.3: Segmented image 1 (left), color image 1 with dark car correctly identified (right)

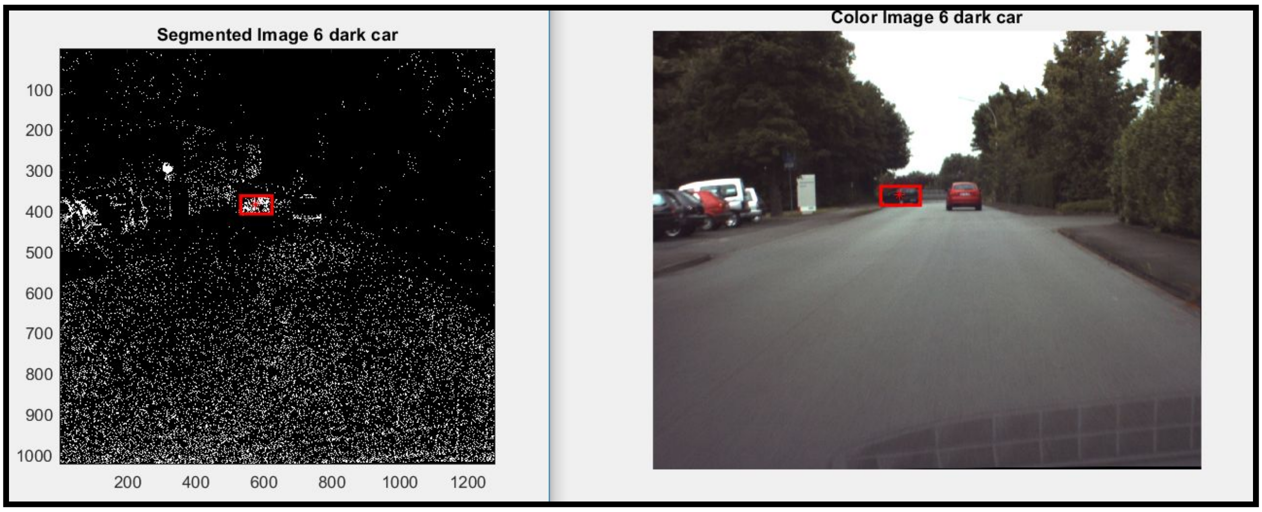

Figure 3.4: Segmented image 6 (left), color image 6 with dark car correctly identified (right)

Figure 3.5 shows the Hue component of the red car selected from the first image; once again, in this area we computed *mean value* and *standard deviation*, in order to identify the red car in each one of the images. This led us to the results displayed in the *figure 3.6*. This is clearly not a good result. The reason for this failure is to be found in the information we used to identify the red car: since the region of pixels in which it is located is not completely red, the mean value will be lower than expected, having the consequence of taking into account more colors than the expected ones. Specifically, we can observe that the colors in the background correspond to very different values of the Hue components with respect to red color of the car: this is also confirmed by the fact that the standard deviation is large, suggesting a great variety of colors in the car region.

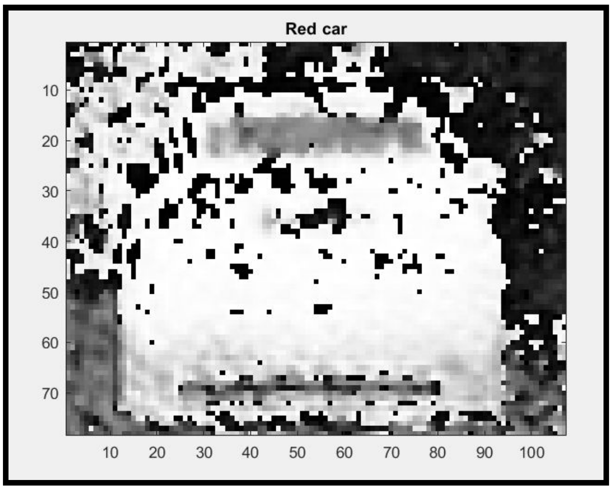

Figure 3.5: Hue component of red car

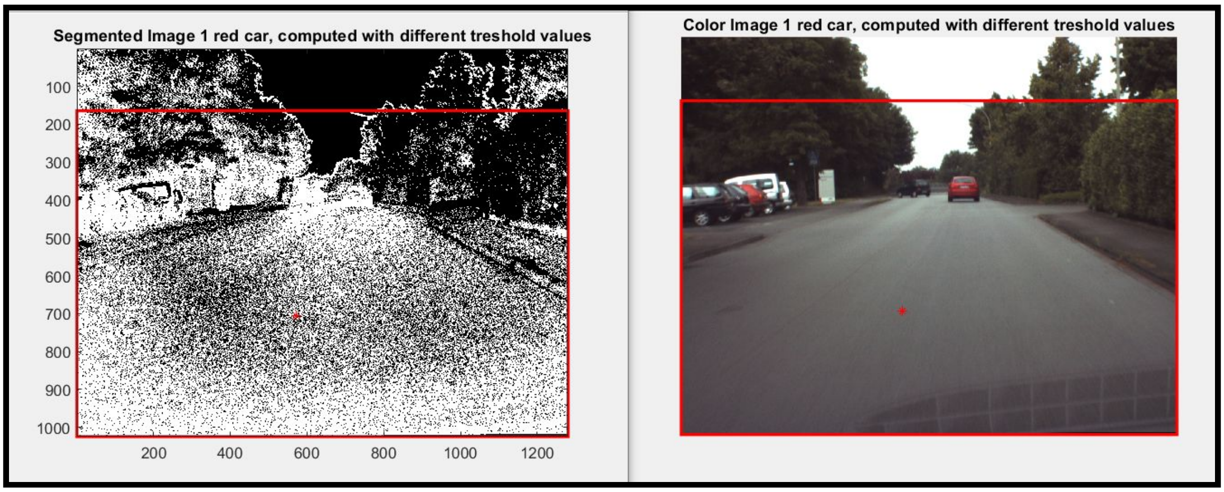

Figure 3.6: Segmented image 1 (left), color image 1 with wrong identification of red car (right)

The results can then be strongly improved by segmenting the image with a specific threshold in the range *(0.97, 1)*, where '1' identifies the Red color in the Hue component. The final result is shown in *figure 3.7*.
As for the case of the dark car, the same procedure was correctly applied to all the 5 other images but the resulting images are omitted.

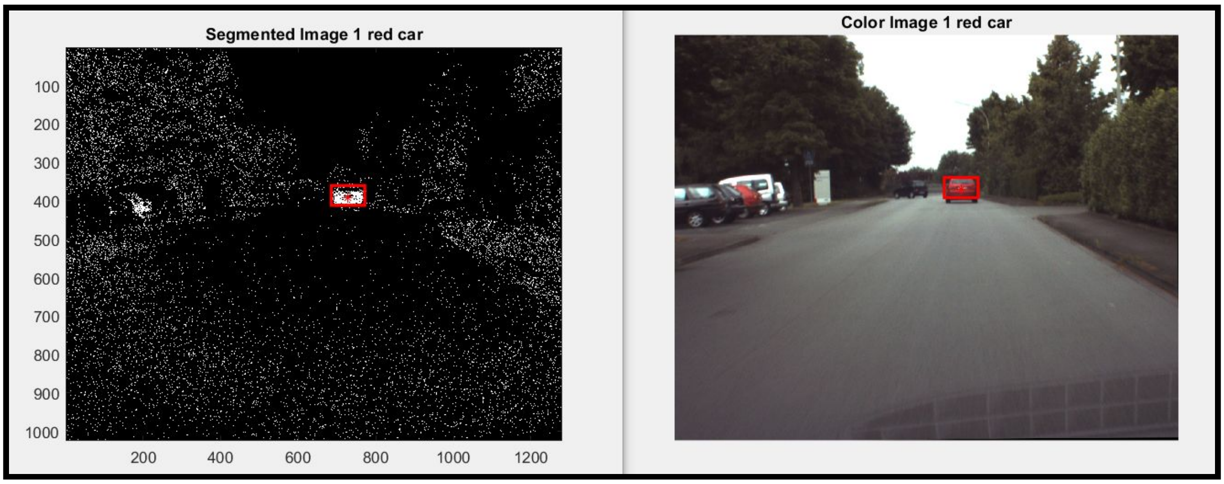

Figure 3.7: Segmented image 1 (left), color image 1 with red car correctly identified (right)

As regards the second part of the experiment, *figure 3.8* shows the Laplacian responses for the two selected sunflowers as functions of the scales. In particular, we can notice that the Laplacian response of the bigger sunflower achieves a maximum for $\sigma = 8$, while in the case of the smaller one it is achieved for $\sigma = 6$. This corresponds to the **characteristic scale** of the two sunflowers.

Finally, *Figure 3.9* shows the circles along the two sunflowers, of different radii corresponding to the different characteristic scales.

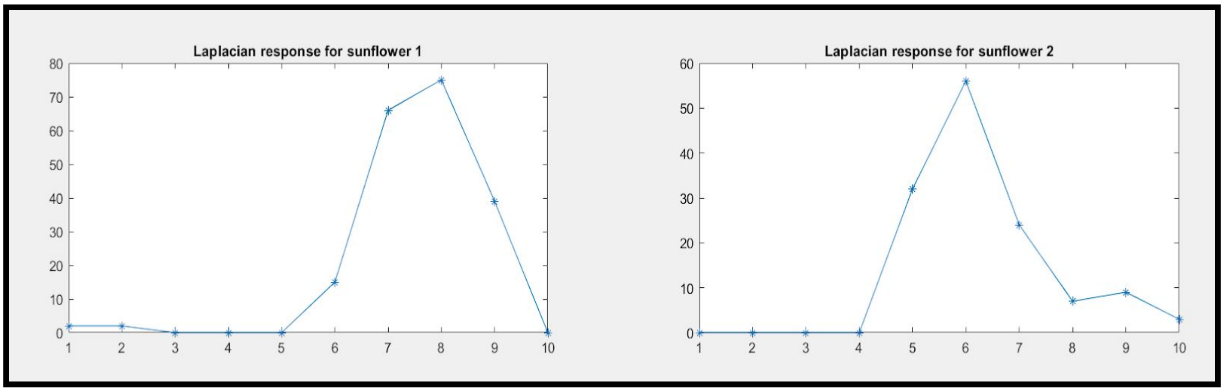

Figure 3.8: Laplacian responses for the two highlighted sunflowers

Figure 3.9: evidenced sunflowers (the right image is zoomed)

4. Conclusions

The results in the first part of the experiment were coherent with the ones we expected: using some properties like the *mean value* and *standard deviation* in order to compute a threshold, we were able to properly identify the dark car in each one of the images.
However, during the experiment we noticed that the correctness of the results is always deeply related to the selection of the area of the dark car, if we decide to compute the mean and the standard deviation and use their values for the threshold.
This is also confirmed in the case of the red car, in which we had to force the threshold to a fixed range (in a neighbourhood of the Hue values for the red color).
Therefore we can conclude that the procedure is not very robust.
As regards the last part of the experiment, we obtained a satisfactory result, proving that it is possible to identify regions related to objects in arbitrary images, by using **blob detection**. In our specific case, i.e. the two objects being two sunflowers, this also allowed to correctly compute the radius of the circle containing each one of them.