# EXTRACTION OF SIGNIFICANT REGIONS IN COLOR IMAGES FOR LANDMARK IDENTIFICATION

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Abstract: In this paper, we address the problem of natural landmark characterization in outdoor environments. Our approach assumes that the image has been previously processed in order to detect the most color-salient areas of the image, which are considered as possible candidates to contain a landmark. We take each of these selected areas and perform a color segmentation of them involving only the most relevant regions, which will be used to characterize a possible landmark contained in this area. The re-identification of the same landmarks in successive views should be done in a posterior step by comparing their descriptions, which consist in the color and first and second order moments of each segmented region. The main contribution of this paper is the algorithm for the segmentation of the relevant regions of an image.

## 1 INTRODUCTION

To make vision-based robot navigation possible in outdoor environments, a robot must be able to detect and characterize relevant landmarks found in the environment so that they can be recognized later on. In order to make this task feasible it is necessary to restrict the search for landmark candidates to the most promising areas of the scene. In our approach, we assume that a number of salient areas have already been selected for further processing. The procedure to find the salient areas of an image is not the subject of this paper, but a description of some methods that could be applied can be found in (Celaya and Jimenez, 2003) or (Itti, 1998).

This paper focuses on the characterization of the selected areas to allow the identification of the same landmarks in different views. Techniques for landmark characterization based on grey level gradients, like the SIFT algorithm (Lowe, 2004), have had a great success, but they are too dependent on the point of view, which may change a lot during the navigation process. A more robust landmark characterization can be obtained using color information. The approach we follow consists in a color-based segmentation with the particularity that not all pixels in the image are necessarily assigned to a region: only those parts of the image that constitute a relevant feature are obtained as the result of the segmentation. The candidate landmark is then characterized by the color content and the spatial moments of its relevant regions, and matched against other landmarks found in subsequent images.

Many color-based image segmentation techniques can be found in the literature. Pixel-based techniques, such as histogram thresholding (Littmann, 1997) or color clustering methods (Uchiyama, 1994), work exclusively in the color space and extract regions with excellent color homogeneity, but with no spatial continuity. Region based techniques, such as split-and-merge (Celenk, 1990) or region growing methods (Themeau, 1997), are a better option as they assure both color homogeneity and spatial continuity, but their results depend too much on the order in which pixels are processed. Other techniques such as contour based methods (Macaire, 1996) make use of gradient or Laplacian operators which make them too sensitive to noise. Finally, physics based methods, such as the dichromatic reflection model (Shafer, 1985), avoid effects of reflections and shading by modelling how light interacts with each object, but they can only be used when the reflection properties of objects are known, something unfeasible in previously unknown outdoor environments.

In this paper we present our approach to the segmentation and extraction of significant regions of an image that combines region growing and histogram thresholding. It can be seen as an "incomplete" image segmentation, in the sense that not all pixels need to be classified in some region, but only those defining significant regions. With significant region we mean that it presents sufficient color homogeneity, is sufficiently different from its surroundings, and its size is not too small. Ideally, a useful landmark should be characterized with a small number of significant regions. Thus we designed our algorithm so that only the most significant regions are obtained.

In the next Section we define the color similarity test used by the segmentation algorithm, which is described in Sec. 3. Some experiments and results obtained with this approach are presented in Sec. 4.

## 2 COLOR SIMILARITY TEST

Our segmentation algorithm uses a color similarity test to determine if a pixel should be included in a region or not. For this, instead of computing a complex distance defined in a 3-dimensional color space, our test uses three one-dimensional distances, one for each color component. The test succeeds only if all three distances stay below their respective fixed thresholds. Clearly, the results of the test will depend on the color space we use. A major requirement for any outdoor vision system is robustness in front of varying illumination. In these conditions, the HSI color space (hue, saturation, intensity) is preferable to RGB, since it provides more robustness to changes in light intensity and other effects. However, a well known drawback of the HSI color space is that the hue value is not reliable for low values of saturation or intensity, and similarly, the saturation value is not reliable for low intensity values. According to this, we compute the distance between HSI components using two correction factors $K_g$ and $K_d$ to take into account the above mentioned indeterminacies associated with greyness and darkness, respectively:

$$(1)\quad dist_H(h_1,h_2) = \min\left(K_g, K_d\right) * \left|h_2 - h_1\right|$$

$$(2)\quad dist_S(s_1,s_2) = K_d * \left|s_2 - s_1\right|$$

$$(3)\quad dist_I(i_1,i_2) = \left|i_2 - i_1\right|$$

where

$$(4)\quad K_g(s_1,s_2) = \frac{1}{1+e^{-(\min(s_1,s_2)-s_{grey})}}$$

$$(5)\quad K_d(i_1,i_2) = \frac{1}{1+e^{-(\min(i_1,i_2)-i_{dark})}}$$

$K_g$ makes the hue distance vanish as one of the compared saturations falls below the grey saturation threshold $s_{grey}$, empirically set to 10% of the saturation range. On the other side, $K_d$ makes both the hue and the saturation distances vanish as one of the compared intensities falls below the dark intensity threshold $i_{dark}$, set as 10% of the intensity range. These two correction factors take the form of sigmoid functions to guarantee a continuous gradual correction when values are near both thresholds.

Two colors are considered similar by the test if:

$$(6)\quad \max\left(\frac{dist_H}{thresh_H}, \frac{dist_S}{thresh_S}, \frac{dist_I}{thresh_I}\right) \le 1$$

## 3 SEGMENTATION METHOD

Our segmentation algorithm is based on the combination of two complementary methods: region growing and histogram thresholding.

### 3.1 Random Seeds & Region Growing

The segmentation method consists in a series of region growing processes initiated at seed pixels selected at random. This is done to avoid a complete examination of all image pixels, since our goal is not a classification of all pixels, but the identification of the most significant regions composing the image. Since too small regions are not considered significant for landmark characterization, it is appropriate to use a random exploration, which gives more probability to find large regions than small ones. Instead of using a fixed number of random seeds, we define a minimum percentage of the image to be segmented and let the process continue until this percentage is reached. However, this percentage may be hard to reach in the case of textured images that give rise to a large number of small regions. To tackle these situations, an alternative stop condition occurs when the number of segmented regions goes beyond a limit.

The process of region growing from a seed pixel is done using a mask of the image to hold the pixels included in the region, and a list of pixels to be expanded, both of them initialized with the selected seed. The region is characterized by a specific color, initially taken as that of the seed pixel.

The expansion of a pixel consists in checking its eight neighbours for color similarity with its region. Pixels considered similar are included in the mask and added at the end of the expansion list. The process stops when all pixels in the expansion list have been processed. Repeated checking of the same pixels is avoided by keeping track of the already examined pixels. Also, if a seed pixel is contained in a segmented region, it is not expanded again.

## 3.2 Defining a Region Color

To decide if a pixel is included in a region, we perform a similarity test between the color of the pixel and the color that characterizes the region. Initially, the region is characterized by the color of the seed pixel and, as new pixels are included, the region color evolves to better represent the region.

To determine the current region color, two approaches have been tested: taking the color average of the included pixels, and taking the peak value of the current histogram. In both cases, since the region color evolves, the inclusion of a pixel in a region depends on the precise time at which the test is performed. To solve this, an iterative process of relaxation can be done in the following way: once a growing process is completed, the region color is fixed and all the included pixels are incorporated in the expansion list. Then the region growing process is repeated as before, except that the region color is not updated during the process. The pixels in the resulting region are used to compute the new region color that will be used in the next iteration of the relaxation process. Successive relaxation steps can be repeated until convergence to a stable region.

Tests performed in a number of images show that, when using the color average, convergence is reached in about five steps in most cases. However, if the histogram peak is used, convergence is faster, and is reached after just one or two steps. In both cases, the segmentation is robust to the random selection of seeds, always providing equivalent results in different executions.

Therefore, we adopted the histogram peak to represent the region color. Moreover, since results do not vary significantly with relaxation, we perform a single step in order to improve computing time.

## 3.3 Merging Regions

The region growing processes are independent, in the sense that a pixel may be included in a region no matter if it was already included in another one or not. This mitigates the well known problem of region growing techniques, whose outcome often depends on the order in which seeds are expanded. Thus, in our approach regions may overlap, indicating that they are relatively similar. For this reason, after the growing processes overlapping regions are merged provided they pass a test of color similarity, though with a larger tolerance than in the case of pixels.

Since we allow regions to overlap, in some cases highly overlapped regions, only differing in a few pixels, may be obtained from different seeds. This affects efficiency since the same tests are repeated unnecessarily. To avoid this, the expansion of a region into an already existing one is limited only to region borders: pixels already included in another region are added to the region mask, but not to the expansion list.

An additional merge process is also done to join similar regions that don’t overlap, but that are close enough to each other.

In the final output of the segmentation process, regions below a predetermined size are filtered off. The remaining regions are then characterized by their representing color and their spatial moments up to order 2, which will be used later on for landmark identification.

# 4 EXPERIMENTS AND RESULTS

In figures 1 to 3 a mountain environment image is segmented. The result of the region growing process is shown in figure 2, where an oversegmentation is present with more than 30 regions. Each extracted region is represented by its color and an ellipse representing its spatial moments. The result after the merge process is shown in figure 3, resulting in 8 final regions. The image size is 640x480 and 85% of it was segmented, taking about 500 ms in a 2.40GHz processor.

In figures 4 to 6 a field road environment image is segmented. A strong oversegmentation is present after the region growing process with more than 70 regions, as shown in figure 5. But, after the merge process the final result is 13 regions, as shown in figure 6. The image size is 240x240 and only 60% of it was segmented, taking about 150 ms in the same processor.

For real-time navigation we need shorter processing times and therefore the integration with a previous salient region detection module would be useful to reduce the fraction of the image to be segmented.

The output of the saliency module is an ellipse indicating the approximate position, orientation and size of a salient color region in the image together with its color range. This information is used to separate the salient region from its background. Then, its convex hull is obtained and the enclosing area is considered a candidate landmark, in which the segmentation takes place.

Figure 1: Image of a mountain environment.

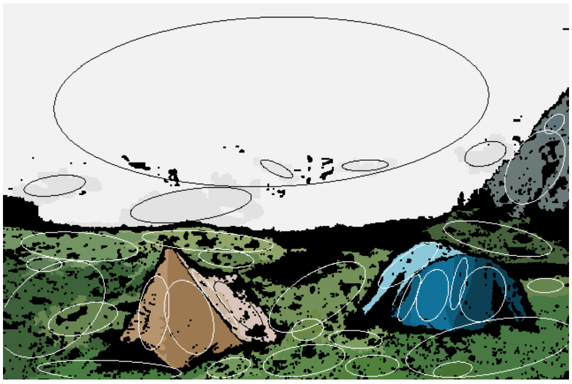

Figure 2: +30 extracted homogeneous regions after the growing process. The image is oversegmented.

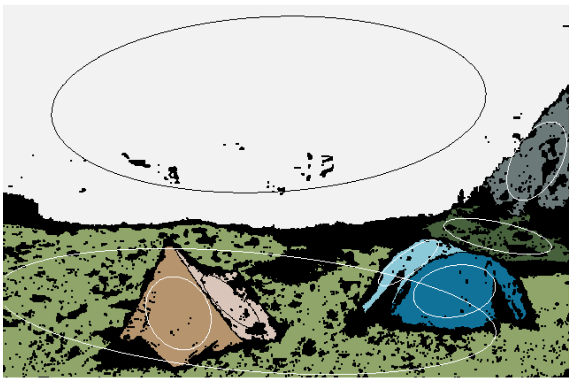

Figure 3: 8 final regions after the merge of the similar overlapped and neighbour regions.

Figure 4: Image of a field road environment.

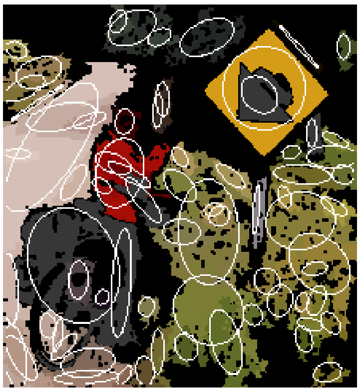

Figure 5: +70 extracted regions after the growing process. The image is oversegmented.

Figure 6: 13 final regions after the merge of the similar overlapped and neighbour regions.

Figures 7 and 8 show two experiments where the integration of the saliency and segmentation modules has been tested. In each upper image, the saliency ellipse indicates the presence of one salient area, red lighthouse and blue tent, respectively. Then, the extracted salient area, its convex hull, and the result obtained after segmentation are shown below.

In the first experiment, figure 7, the image size is 600x570 and only 1% of the image was segmented (73% of the landmark) with 50 ms of total processing time for the three steps process. The second experiment, figure 8, took a total of 80 ms to segment a 6% of the 640x430 image (77% of the landmark).

Figure 7: The red lighthouse is given as salient area. It is separated from the background and its convex hull is segmented in a 11 regions landmark.

Figure 8: The blue tent is given as salient area in the image. It is separated from the background and its convex hull segmented in a 7 regions landmark.

## 5 CONCLUSIONS

The results of our experiments show that the implemented segmentation algorithm can be used in a landmark detection system for robot navigation. Our next step will consist in testing a matching algorithm to identify landmarks in different views.


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