

## Study on Hill-Climbing Algorithm For Image Segmentation

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**Abstract**— In this paper, Image segmentation is a very important part of image processing. Detection of salient image regions is useful for applications like image segmentation, adaptive compression, and region-based image retrieval. This problem can be tackled by mapping the pixels into various feature spaces, which are subjected to various grouping algorithms. It presents a novel method to determine salient regions in images using low-level features of luminance and color. The method is fast, easy to implement and generates high quality saliency maps of the same size and resolution as the input image.

**Keywords**- Salient regions, low-level features, segmentation

### I. INTRODUCTION

Image segmentation is a fundamental task in Image Processing, and preprocessing step for salient region exploration. Salient regions are useful in applications such as object based image retrieval, adaptive content delivery, adaptive region-of interest based image compression, and smart image resizing. We identify salient regions as those regions of an image that are visually more conspicuous by virtue of their contrast with respect to surrounding regions[2]. Similar definitions of saliency exist in literature where saliency in images is referred to as local contrast.

Our method for finding salient regions uses a contrast determination filter that operates at various scales to generate saliency maps containing saliency values per pixel[1]. Combined, these individual maps result in our final saliency map. We demonstrate the use of the final saliency map in segmenting whole objects with the aid of a relatively simple segmentation technique. The novelty of our approach lies in finding high quality saliency maps of the same size and resolution as the input image and their use in segmenting whole objects. The method is effective on a wide range of images including those of paintings, video frames, and images containing noise.

The paper is organized as follows. The Detection of salient regions and its use in segmenting salient objects is explained in Section 2. Hill-climbing Algorithm are presented in Section 3. The experimental

results are given in Section 4. Finally, in Section 5 conclusions are presented.

### II. THEORY

This section presents details of our approach for saliency determination and its use in segmenting whole objects. An overview of the complete algorithm is presented in Figure 1. Using the saliency calculation method described later, saliency maps are created at different scales. These maps are added pixel-wise to get the final saliency maps. The input image is then over-segmented and the segments whose average saliency exceeds a certain threshold are chosen[6].

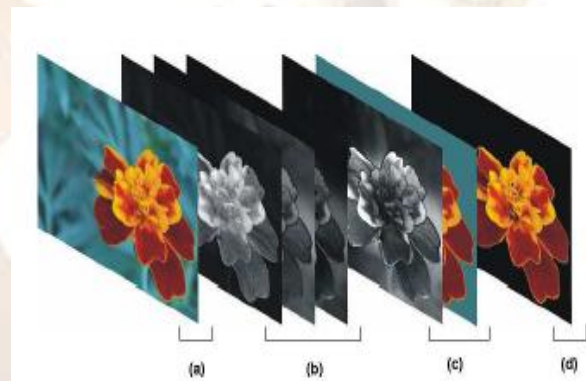


Fig. 1. Overview of the process of finding salient regions. (a) Input image. (b) Saliency maps at different scales are computed, added pixel-wise, and normalized to get the final saliency map. (c) The final saliency map and the segmented image. (d) The output image containing the salient object that is made of only those segments that have an average saliency value greater than the threshold  $T$  (given in Section A).

#### (A) Saliency calculation

Saliency is determined as the local contrast of an image region with respect to its neighborhood at various scales[4].

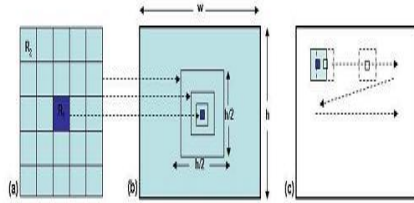


Fig. 2. (a) Contrast detection filter showing inner square region  $R1$  and outer square region  $R2$ . (b) The width of  $R1$  remains constant while that of  $R2$  ranges according to Equation 3 by halving it for each new scale. (c) Filtering the image at one of the scales in a raster scan fashion.

This is evaluated as the distance between the average feature vector of the pixels of an image sub-region with the average feature vector of the pixels of its neighborhood. This allows obtaining a combined feature map at a given scale by using feature vectors for each pixel, instead of combining separate saliency maps for scalar values of each feature. At a given scale, the contrast based saliency value  $c_{i,j}$  for a pixel at position  $(i, j)$  in the image is determined as the distance  $D$  between the average vectors of pixel features of the inner region  $R1$  and that of the outer region  $R2$  (Figure 2) as:

$$c_{i,j} = D \left[ \left( \frac{1}{N_1} \sum_{p=1}^{N_1} v_p \right), \left( \frac{1}{N_2} \sum_{q=1}^{N_2} v_q \right) \right]$$

where  $N1$  and  $N2$  are the number of pixels in  $R1$  and  $R2$  respectively, and  $v$  is the vector of feature elements corresponding to a pixel. The distance  $D$  is a Euclidean distance if  $v$  is a vector of uncorrelated feature elements, and it is a Mahalanobis distance (or any other suitable distance measure) if the elements of the vector are correlated. In this work, we use the *CIELab* color space, assuming sRGB images, to generate feature vectors for color and luminance. Since perceptual differences in *CIELab* color space are approximately Euclidian,  $D$  in Equation 1 is:

$$c_{i,j} = \|v1 - v2\|$$

where  $v1 = [L1; a1; b1]^T$  and  $v2 = [L2; a2; b2]^T$  are the average vectors for regions  $R1$  and  $R2$ , respectively. Since only average feature vector values of  $R1$  and  $R2$  need to be found, we use the integral image approach as used in for computational efficiency. A change in scale is affected by scaling the region  $R2$  instead of scaling the image. Scaling the filter instead of the image allows the generation of saliency maps of the same size and resolution as the input image. Region  $R1$  is usually chosen to be one pixel. If the image is noisy (for instance if high ISO values are used when capturing images, as can often be determined with the help of Exif data (Exchangeable File Information Format)) then  $R1$  can be a small region of  $N \times N$  pixels

For an image of width  $w$  pixels and height  $h$  pixels, the width of region  $R2$ , namely  $w_{R2}$  is varied as:

$$\frac{w}{2} \geq (w_{R2}) \geq \frac{w}{8}$$

Assuming  $w$  to be smaller than  $h$  (else we choose  $h$  to decide the dimensions of  $R2$ ). This is based on the observation that the largest size of  $R2$  and the smaller ones (smaller than  $w=8$ ) are of less use in finding salient regions (see Figure 3). The former might highlight non-salient regions as salient, while the latter are basically edge detectors. So for each image, filtering is performed at three different scales (according to Eq. ) and the final saliency map is determined as a sum of saliency values across the scales  $S$ :

$$m_{i,j} = \sum_S c_{i,j}$$

$\forall i \in [1, w], j \in [1, h]$  where  $m_{i,j}$  is an element of the combined saliency map  $M$  obtained by point-wise summation of saliency values across the scales.

#### (B) Whole Object Segmentation using Saliency Maps

The image is over-segmented using a simple *K-means* algorithm. The  $K$  seeds for the *K-means* segmentation are automatically determined using the hill-climbing algorithm [7] in the three-dimensional *CIELab* histogram of the image.

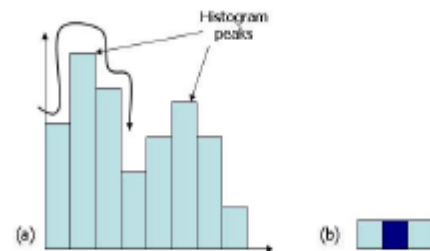


Fig. 3. (a) Finding peaks in a histogram using a search window like (b) for a one dimensional histogram.

The hill-climbing algorithm can be seen as a search window being run across the space of the  $d$ -dimensional histogram to find the largest bin within that window.

Figure 3 explains the algorithm for a one-dimensional case. Since the *CIELab* feature space is three-dimensional, each bin in the color histogram has  $3^d - 1 = 26$  neighbors where  $d$  is the number of dimensions of the feature space. The number of peaks obtained indicates the value of  $K$ , and the values of these bins form the initial seeds.

Since *K-means* algorithm clusters pixels in the *CIELab* feature space, an 8-neighbor connected-components algorithm is run to connect pixels of each cluster spatially. Once the segmented regions  $r_k$  for  $k = 1; 2:::K$  are found, the average saliency value  $V$  per segmented region is calculated by adding up values in

the final saliency map M corresponding to pixels in the segmented image:

$$V_k = \frac{1}{|r_k|} \sum_{i,j \in r_k} m_{i,j}$$

$|r_k|$  is the size of the segmented region in pixels. A simple threshold based method can be used wherein the segments having average saliency value greater than a certain threshold  $T$  are retained while the rest are discarded. This results in an output containing only those segments that constitute the salient object.

### III. Hill-Climbing Algorithm

The segmentation method should be nonparametric[5] and should take the local and global feature distribution into consideration the hill-climbing based segmentation is a simple and fast nonparametric algorithm that detects the peaks of Clusters in the global three dimensional color histogram of an image[8]. The histogram bins rather than the pixels themselves to find the peaks of clusters; thus, the algorithm can find the peaks efficiently. Then, the algorithm associates the pixels of a detected cluster based on the local structure of the cluster. The hill-climbing based segmentation algorithm[6] is outlined below.

Algorithm: Hill climbing based segmentation

Input: an image

Output: a set of visually coherent segments

- 1 Compute the color histogram (one-dimensional) of the image.
- 2 Start at a non-zero bin of the color histogram and make uphill moves until reaching a peak as follows:
  - 2.1 Compare the number of pixels of the current histogram bin with the number of pixels of the neighboring (left and right) bins.
  - 2.2 If the neighboring bins have different numbers of pixels, the algorithm makes an uphill move towards the neighboring bin with larger number of pixels.
  - 2.3 If the immediate neighboring bins have the same numbers of pixels, the algorithm checks the next neighboring bins, and so on, until two neighboring bins with different numbers of pixels are found. Then, an uphill move is made towards the bin with larger number of pixels.
  - 2.4 The uphill climbing is continued (repeat steps 2.1-2.3) until reaching a bin from where there is no possible uphill movement. That is the case when the neighboring bins have smaller numbers of pixels than the current bin. Hence, the current bin is identified as a peak (local maximum).

Select another unclimbed bin as a starting bin and perform step 2 to find another peak. This step is continued until all non-zero bins of the color histogram are climbed (associated with a peak).

The identified peaks represent the initial number of clusters of the input image; thus these peaks are saved.

2.5 If no uphill move is done, the stopping bin is identified as a peak of a hill, and all bins leading to this peak are associated with it.

3. Select another unclimbed bin as a starting bin and perform step 2 to find another peak. This step is continued until all non-zero bins of the histogram are climbed (associated with a peak).

4. The identified peaks represent the initial number of clusters of the input image; thus these peaks are saved.

5. Neighboring pixels that lead to the same peak are grouped together. Although, we used a global color histogram to find the peaks, step 5 takes into account the spatial information of the pixels when forming the segments, i.e. only spatially close (neighboring) pixels that lead to the same peak are grouped into one segment

Finally, neighboring pixels that lead to the same peak are grouped together, that is associating every pixel with one of the identified peaks. Thus, forming the clusters of the input image.

Although, used a global color histogram to find the peaks, step 5 takes into account the spatial information of the pixels when forming the segments, i.e. only spatially close (neighboring) pixels that lead to the same peak are grouped into one segment.

### IV. EXPERIMENTAL RESULT

The proposed Modified Hill-climbing algorithm is implemented using MATLAB and tested on real images to explore the segmentation accuracy of the proposed approach.

## V .CONCLUSION

We presented a novel method of finding salient regions in images, using low level features of color and luminance, which is easy to implement, noise tolerant, and fast enough to be useful for real time applications. It generates saliency maps at the same resolution as the input image. We demonstrated the effectiveness of the method in detecting and segmenting salient regions in a wide range of images. The approach is at least five times as fast as a prominent approach to finding saliency maps and generates high-resolution saliency maps that allow better salient object segmentation.



Fig4.left side original image and rightside segmented image

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