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Novel Approach for Salient Region Detection

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Abstract: Salient region detection in image is useful for applications like adaptive compression, image segmentation and region-based image retrieval. Many of existing saliency detection techniques do not pay much attention to the noise problem. In this paper the proposed model uses L0 smoothing filter to reduce the effect of noise and achieve a better performance. The important role in our framework is played by the L0 smoothing filter. The L0 filter is extremely helpful in characterizing fundamental image constituents, i.e. salient edges and can simultaneously reduce insignificant details, thus producing more accurate boundary information for background merging. The saliency maps in this paper are extracted by three features: the color spatial variance, border measurement, and region contrast. The color spatial variance is utilized to calculate the degree of color distribution. Based on the observation that salient objects are less likely to be connected with the borders of an image, the boundary information of each segment is used to determine the salient region. Last but not least, a region contrast method is used for extracting global contrast used to achieve full resolution map with well defined boundaries. Thus this method will give more accurate results as compared to other methods.

Keywords: Image segmentation, L_0 smoothing filter, Region contrast,Sailent region detection

I. INTRODUCTION

Visual saliency is a broad term referring to the “meaningful” region of an image. This is the perceived quality used for evaluating whether an object attracts viewers attention. Whether a region is salient or not may depend on its uniqueness, unpredictability, or rarity, and is highly related to the color, gradient, edge, and boundaries, which are the main sources of visual stimuli. It is known that two stages of visual processing are involved: bottom-up and top-down. Bottom-up factors highlight image regions that are different from their surroundings. We focus on bottom-up data driven saliency detection in this paper. Any algorithm which is designed to detect the salient region should have the following characteristics

- Uniformly highlight whole salient regions.
- Emphasize the large salient object
- Establish well-defined boundaries of salient objects.
- Efficiently output full resolution saliency maps
- Disregard high frequencies arising from texture, noise and blocking artifacts.

Methods of saliency detection are broadly classified in two schemes local contrast methods, global contrast methods. These methods are supposed to produce saliency map as shown in fig1

(a) (b)

Fig1. (a): Original image. (b) : Saliency maps [1]

Local contrast method determines a salient feature of an image region with respect to small local neighbourhood. Limitation of such scheme is these methods highlight the object boundary instead of the entire object. These methods obtain low resolution saliency maps. Global Contrast methods evaluate saliency of an image region using its contrast with respect to entire image. Advantage of global contrast method is obtain full resolution saliency maps, uniformly highlight entire objects, accuracy in terms of precision and recall is better compared to local contrast based methods.

The saliency maps in this paper are extracted by three features: the color spatial variance, border measurement, and global contrast. The color spatial variance is utilized to calculate the degree of color distribution. When a color is extensively distributed in an image, it may be the background color. Based on the observation that salient objects are less likely to be connected with the borders of an image, the boundary information of each segment is used to determine the salient region Last but not least, a region contrast method is used for extracting global contrast used to achieve full resolution map with well defined boundaries.

The rest of the paper is structured as follows. Section 2 describes related work. Section 3 gives programmer’s design in which proposed framework for saliency detection is described. Section 4 includes the results and .Section 5 concludes the paper

II. LITERATURE SURVEY

Extracted saliency maps are widely used in many computer vision applications including object of interest image segmentation, object recognition, adaptive compression of images, image editing and image retrievalThe major difficulty associated to the wind energy sources is that in general they don’t take part in the services system (adjustment of the voltage, of the frequency, possibility of operation in patrolling the block)

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whose flow is not easily foreseeable and very fluctuating. Ma and Zhang.[8] used a fuzzy growth model to generate saliency maps. Harel *et al*. combined the saliency maps of Itti *et al*. with other feature maps to highlight the distinctive regions of an image. Hou and Zhang [9] constructed a saliency map by extracting the spectral residual of an image in the spectral domain. This method outputs low resolution saliency maps of size 64 × 64 pixels for any input image size Achanta *et al*.[10] determined the salient regions in images using low-level luminance and color features. This method produces saliency map of the same size as the input image and better highlights the smaller salient region than the larger ones Recently, Goferman *et al*.[11] considered both local and global features to highlight the salient objects enhanced by means of visual organization. Disadvantage of this method is that computational complexity is high; such methods using local contrast tend to produce higher saliency values near edges instead of uniformly highlighting salient objects.

Global contrast based methods evaluate saliency of an image region using its contrast with respect to the entire image. Moreover, Achanta *et al*. [3] proposed a frequency tuned method that defines the pixel saliency based on a frequency-domain analysis and the differences in color from the average image color. The elegant approach, however, only considers first order average color, which can be insufficient to analyze complex variations common in natural images. Zhai and Shah [4] defined the pixel level saliency by constructing spatial and temporal attention models. However, for efficiency they use only luminance information, thus ignoring distinctiveness clues in other channels. In 2011, Cheng *et al*.[2] used histogram- and region based contrasts to compute salient maps with high precision and recall rates. Disadvantage of this method is that if there are some noisy regions these methods may not detect the right region accurately. Recently, Po-Hung Wu and Chien-Chi[1] proposed a method calculate the saliency map based on three features i.e. color spatial variance, border measurement, and PCA-CA method.

III. FRAMEWORK

The block diagram of salient region detection is shown in fig.2 It. consist of three modules first module consist of Gaussian Mixture Model (GMM) and a color spatial variance (CSV); second module is image segmentation and border measurement (BM); and third module is global contrast based method

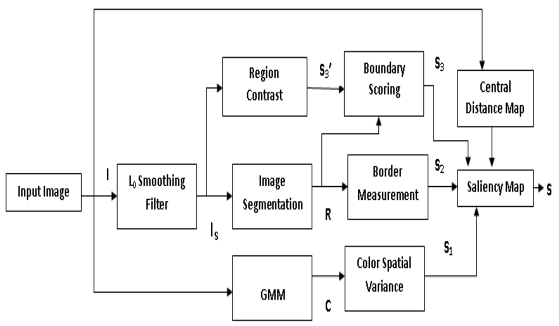

Fig2: Block Diagram

The efficiencies of the second components are greatly enhanced by the L0 smoothing filter. In the first module, a GMM is used for clustering the color values in the L*a*b color space into n classes and the color spatial variance is calculated. For the second module a dynamic region segmentation algorithm is utilized to extract the high-level information and achieve full-resolution saliency maps. It is known that segmentation algorithm is mainly responsible for efficiency of segmentation results mostly depends on the and the context of images. This relationship is relaxed with the benefit of the L0 smoothing filter due to robust boundary preservation. As observed that salient objects are less likely to connect to the image border, the number of pixels in each segment that overlap the image border is counted to determine the saliency. For the third component segmented results of smoothened image obtained from the second component are taken and compute the saliency value based on the color contrast computation and define the saliency for each region as the weighted sum of region contrast to all regions in the image to obtain better precision and recall. Finally results obtained from the three modules are combined to obtain the final saliency map which is then multiplied by center distance map.

A. Color Spatial Variance

GMM based Color spatial variance method, which is one of the most statistically efficient methods for clustering, is a widely used global feature that matches the human visual system. If a color is extensively distributed within an image, it may be the background color. In other words, a specific color with a smaller spatial variance will attract greater attention, and is more likely to be part of the salient object.

Traditionally, each pixel in the GMM can be represented as

$$P(c \mid I(x,y)) = \frac{\omega_c N(I_{(x,y)}|\mu c,\Sigma_c}{\Sigma_c\, \omega_c N(I_{(x,y)}|\mu c,\Sigma_c} \quad (1)$$

Where w_c , μc, Σ_c and are the weight, mean, and covariance of the cth component, $N(\cdot)$ is the Gaussian model, and I(x,y) is the pixel at the coordinate (x, y).

In our framework, the maximum likelihood is used instead of probability models

$$c^*_{I(x,y)} = \arg\max_{c \in C} p(c|I_{(x,y)}) \quad (2)$$

Where C is the set of all components. The horizontal and vertical spatial positions, v_h (c*) and v_v (c*), of each color component can then be further simplified as

$$v_h (c^*) = \frac{1}{N}\sum_{I(x,y)\epsilon\, c^*} |x - \mu_x (c^*)|^2 \quad (3)$$

$$v_v (c^*) = \frac{1}{N}\sum_{I(x,y\epsilon\, c^*)} |y - \mu_y (c^*)|^2 \quad (4)$$

Where μ_x μ_y are the means of the x and y coordinates, respectively, and N is the number of pixels with a maximum likelihood of c*. The color spatial variance of the c*th component can then be defined as being the maximum of the x- and y-coordinate variances:

$$V (c^*) = \max (v_h (c^*), v_v (c^*)) \quad (5)$$

Note that the color spatial variances of all of the components are normalized to the range of [0, 1]. Finally, the global feature map is determined from

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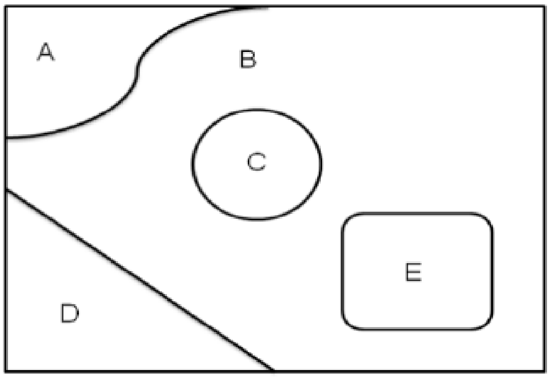
$$(I_{(x,y)}) = V(c^*_{I(x,y)}) \quad (6)$$

B. Image Segmentation and Border Measurement

Firstly, the input image is pre-processed using the L0 smoothing filter[5]. Then, it is segmented using method in [6]. Using the L0 smoothing filter before segmentation can prevent over-segmentation. Based on our observation that salient objects rarely connect with image borders, an adaptive region-merging method and border measurement is designed to exploit this idea. There is no "best" segmentation algorithm for every kind of images or for every purpose. Therefore, the region-merging algorithm serves as a post-process for improving the image segmentation results, and attempts to merge non-salient regions as much as possible.

For example, in Fig. 3, according to the assumption, the probability of regions C and E (class 1) being salient objects is higher than that of regions A, B, and D (class 0), as the boundaries of the latter regions greatly overlap the image border.



We therefore apply an adaptive threshold. If the Euclidean distance of two regions is smaller than the threshold, they are merged together. Here the value of q is initialized as 70

$$\text{Thr(i,j)} = \begin{cases} q & \text{Where class}(i) = \text{class}(j) \\ w(i,j) * q & \text{Where class}(i) \neq \text{class}(j) \end{cases} \quad (7)$$

$$\omega(i,j) = 1 - \max\left(\frac{r_i}{R_i}, \frac{r_j}{R_j}\right) \quad (8)$$

After merging the regions, boundary information is used to evaluate the region saliency. The boundary weight of region i can be defined as

$$b\omega(i) = \frac{\text{length (i)}}{2(h+w)} \quad (9)$$

Where length (i) is the length of the overlapping part of the image border and the boundary of region i, and h and w are the height and width of the image, respectively. Note that the boundary weight is normalized in the range of [0, 1]. Finally, the border feature map can be determined from

$$S_2(I_{(x,y)}) = \exp\left(\frac{-b\omega(i)}{\sigma^2}\right) \text{ for } I_{(x,y)} \in \text{region i} \quad (10)$$

Where σ is 0.5 The exponential function is used for visual enhancement. The boundary information helps to decide the adaptive threshold for region merging and then the new boundary information about overlapping the image border is used to construct the border feature map defined in (10).

C. Region Contrast and Boundary Scoring

Humans pay more attention to those image regions that contrast strongly with their surroundings. Besides contrast, spatial relationships play an important role in human attention. High contrast to its surrounding regions is usually stronger evidence for saliency of a region than high contrast to far-away regions. Since directly introducing spatial relationships when computing pixel-level contrast is computationally expensive, we introduce a contrast analysis method, region contrast (RC), so as to integrate spatial relationships into region-level contrast computation. In RC, First segment the input image into regions, then compute color contrast at the region level, and define the saliency for each region as the weighted sum of the region's contrasts to all other regions in the image. The weights are set according to the spatial distances with farther regions being assigned smaller weights.

The color distance between two regions r1 and r2 is defined as,

$$D_r(r_1, r_2) = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} f(c_1, i) f(c_2, j)\ D(c_1, i, c_2, j) \quad (11)$$

where $f(c_k, i)$ is the probability of the ith color c_k, i among all nk colors in the k-th region r_k, k = {1,2} Note that we use the probability of a color in the probability density function (i.e. normalized color histogram) of the region as the weight for this color to emphasize more the color differences between dominant colors. Storing and calculating the regular matrix format histogram for each region is inefficient since each region typically contains a small number of colors in the color histogram of the whole image. Instead, we use a sparse histogram representation for efficient storage and computation we further incorporate spatial information by introducing a spatial weighting term in Equation 5 to increase the effects of closer regions and decrease the effects of farther regions.

Specifically, for any region rk, the spatially weighted region contrast based saliency is defined as:

$$S(r_k) = \sum_{r_k \neq r_i} [\![\exp\left(-\frac{D_s(r_k, r_i)}{\sigma_s^2}\right)]\!] \omega(r_i) D_r(r_k, r_i) \quad (12)$$

Where $D_s(r_k, r_i)$ is the spatial distance between regions r_k, and r_i and σ_s controls the strength of spatial weighting. Larger values of σ_s reduce the effect of spatial weighting so that contrast to farther regions would contribute more to the saliency of the current region. The spatial distance between two regions is defined as the Euclidean distance between their centroids.where $\sigma_s^2 = 0.4$

Finally boundary scoring method is used to obtain the well defined boundary of the object. This method converts the segmented image of second component to logical image which is compared with the resulting map to obtain the final saliency map

D. Saliency Computation with center distance map

Finally, the saliency map is defined as being the average of the three feature maps multiplied by the center distance map:

$$S = \frac{1}{3}(S_1 + S_2 + S_3) \times D \quad (13)$$

$$D\left(I_{(x,y)}\right) = \frac{e^{-\left(\left(x-\frac{\omega}{2}\right)^2+\left(y-\frac{h}{2}\right)^2\right)}}{2\times \mathrm{dig}} \quad (14)$$

Where dig is the diagonal length of the image. The center distance is used to emphasize the habit of capturing salient objects in the middle of images. Because three feature maps are combined, our proposed algorithm is more robust than other methods and has similar saliency values in the entire salient regions.

IV. RESULT

The saliency map of the proposed work is as shown below

(a) (b)

Fig 4: (a) Input Image (b) Saliency map using our method

To evaluate the performance of saliency detection methods, the precision-recall rate and F-measures are utilized to reliably compare the extracted saliency maps. Precision-recall rate for a given saliency map with a gray value within [0, 255], the binary masks are extracted by thresholding the saliency maps at each threshold value in the range of [0, 255] and the precision and recall of each binary mask are computed

V. CONCLUSION

This paper proposed a novel framework for salient region detection using an L0 smoothing filter. They can reduce noise and other redundant information and increase both the accuracy and efficiency of saliency detection. Furthermore the color spatial variance, border information, and global contrast were utilized to construct the full resolution saliency maps having well defined boundaries.

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