The Method to Measure Saliency Values for Salient Region Detection from an Image

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***Abstract*— In this paper we introduce an improved method to measure saliency values of pixels from an image. The proposed saliency measure is formulated using local features of color and a statistical framework. In the preprocessing step, rough salient pixels are determined as the local contrast of an image region with respect to its neighborhood at various scales. Then, the saliency value of each pixel is calculated by Bayes' rule using rough salient pixels. The experiments show that our approach outperforms the current Bayes' rule based method.**

***Index Terms*— Salient region, Bayes' rule, Probability.**

I. INTRODUCTION

Several millions of amateur and professional images are shared and stored across various memory devices using digital cameras or smart phones, etc. Generally, images are very rich in content and convey a lot of information. All the information in a particular image is relevant for the further processing of the image. A particular image consists of foreground object regions and background regions. Foreground regions can be salient regions in the image. Salient regions in an image can be defined as the subset of the whole image which is considered relevant by the human visual system.

Detecting visually salient regions is useful in application such as object based image retrieval, adaptive content delivery[1,2], adaptive region-of-interest based image compression, and smart image resizing[3]. The most common approach to acquire salient regions is to detect moving objects against a static background[4,5]. These methods have been successful in many applications, but they cannot be used to detect salient regions in a single image. Supervised object detection methods are developed to find particular categories like persons, cars, etc[6,7]. These approaches have resulted in high performance, but the limitation is that the salient objects must reside in the predefined categories.

There are several general purpose saliency detectors. These techniques are suitable in situations where possible targets and imaging conditions are not known in advance. Most of the methods measure the local contrast of the image areas to their surroundings, which is done according to features like image intensity, color, and gradient orientation. The first general purpose saliency detector was introduced in Itti et al[8]. They use a center-surround difference operator on red-green and blue-yellow colors and orientation saliency map. Walther and Koch extended Itti's model[9]. Recently, Achanta et al. proposed more efficient methods to detect and segment salient regions from a single image[10]. In their methods, saliency is determined as the local contrast of an image region with respect to its neighborhood at various scales. The limitations are to determine the number of scales and the size of scales. According to these factors, the values of the last saliency map can be varied. Rahtu et al. introduced a new method to measure salient values using statistical framework and sliding window[11,12]. These methods can measure saliency values of pixels efficiently and rapidly. The accuracy of saliency values measured is relevant to the initial probability given within the sliding window. They used fixed initial probability.

In this paper, we proposed a method to measure saliency values of pixels which improves statistical framework. Within the sliding window, the initial probability is not fixed. The initial probability within the sliding window is calculated by the local contrast of an image region with respect to its neighborhood at various scales. The paper is organized as follows. The method to determine initial probability is described in Section2. Then, the proposed saliency measure method is described in Section 3. Experiment results are presented in Section 4. Finally, in Section 5 conclusions are presented.

II. INITIAL PROBABILITY

To calculate the initial probability of the image regions, rough saliency values of pixels must be determined. For this, we use the method which Achanta et al.[10] proposed. We use the CIELab color space to generate feature vectors for color and luminance because perceptual differences in CIELab color space are approximately Euclidean. Rough saliency values of pixels are determined as the local contrast of a pixel with respect to its neighborhood at various kernel sizes. Larger kernel sizes might highlight non-salient regions as salient, while

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smaller kernel sizes are basically edge detectors. In this paper, we use three different kernels to calculate rough saliency values. For an image of width w pixels and height h pixels(assuming w to be smaller than h), each kernel size is $w/2$, $w/4$, $w/8$ respectively. At a given kernel size, 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 feature vectors of the pixel and average feature vectors of the neighborhood pixels.

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

,where N is the number of neighborhood pixels, and v is the feature vector corresponding to a pixel. The distance D is a Euclidean distance.

Filtering is performed at three different kernel size according to Eq. 1 and the final rough saliency map is determined as a maximum of saliency values across the kernel sizes K.

$$m_{i,j} = \max_{K}(c_{i,j}) \tag{2}$$

,where $m_{i,j}$ is an element of the combined saliency map M obtained.

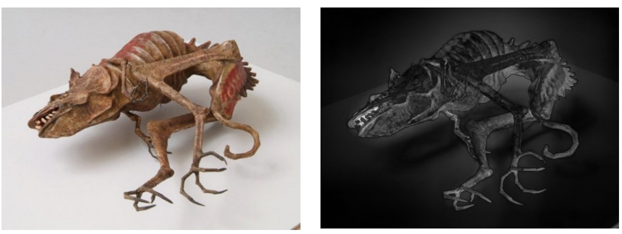

Fig. 1. Original and rough saliency map image

Fig. 1 shows an original image and the corresponding rough saliency map image. In the right image of Fig. 1, all of the pixels have values between 0 and 1 and pixels closer to white color have higher saliency values.

For initial probability, all of the pixels must have a value 0(nor salient) or 1(salient), the equation is as follows:

$$p_{i,j} = \begin{cases} 0 & if\ m_{i,j} \le \mu + \sigma \\ 1 & otherwise \end{cases}$$
$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{h} \sum_{j=1}^{w} (m_{i,j} - \mu)^2} \tag{3}$$
$$\mu = \frac{1}{N} \sum_{i=1}^{h} \sum_{j=1}^{w} m_{i,j}$$

,where N is the number of pixels in the image and μ, σ is the average saliency value and corresponding standard deviation respectively.

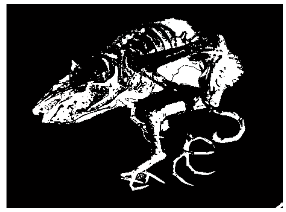

Fig. 2. Binary saliency map

Fig. 2 shows the binary saliency map image that is calculated by applying Eq. 3 to the rough saliency map. With this binary saliency map, the initial salient probability of any region of the image can be generated.

III. SALIENCY MEASURE

To measure saliency values, we use the statistical framework proposed by Rahtu et al.[11,12]. Basically an image is divided into overlapped windows. Each window W is again divided into a inner kernel K and outer border B. Let x be a pixel inside W and $F(x)$ be some feature value computed at x. In this paper, we use CIELab color values as features F.

Define two hypotheses, H_0: point x is nor salient, and H_1: point x is salient, and denote the corresponding a priori probabilities as $P(H_0)$ and $P(H_1)$. It is assumed that H_1 is valid for pixels inside K and H_0 is valid for pixels in B. According to Bayes' theorem, $P(H_1 \mid F(x))$ is as follows:

$$P(H_1 \mid F(x)) = \frac{p(F(x) \mid H_1)P(H_1)}{P(F(x))} \tag{4}$$

Recalling that

$$P(F(x)) = p(F(x) \mid H_0)P(H_0) + p(F(x) \mid H_1)P(H_1) \tag{5}$$

We can further write

$$P(H_1 \mid F(x)) = \frac{p(F(x) \mid H_1)P(H_1)}{p(F(x) \mid H_0)P(H_0) + p(F(x) \mid H_1)P(H_1)} \tag{6}$$

Using the estimated $P(H_1 \mid F(x))$, we can compute the probability of H_1 for each pixel in K and saliency measure is defined as follows:

$$S(x) = P(H_1 \mid F(x)) \tag{7}$$

The saliency value of a pixel can be computed several times due to overlapped windows and we define the final saliency value of a pixel to be the maximum.

$$S(x) = \max_j \{S_j(x) \mid x \in W(j)\} \quad (8)$$

To measure saliency values using the described algorithm, we need the initial probability for $P(H_1)$ and $P(H_0) = 1 - P(H_1)$. For this, Rahtu et al.[11,12] used a fixed probability $P(H_1) = 0.25$ in all windows. In this paper, we use the different initial probability for each window using the binary saliency map computed in Section 2. With the our modified algorithm, higher salient regions can have higher initial probability. Therefore we can acquire better final saliency map.

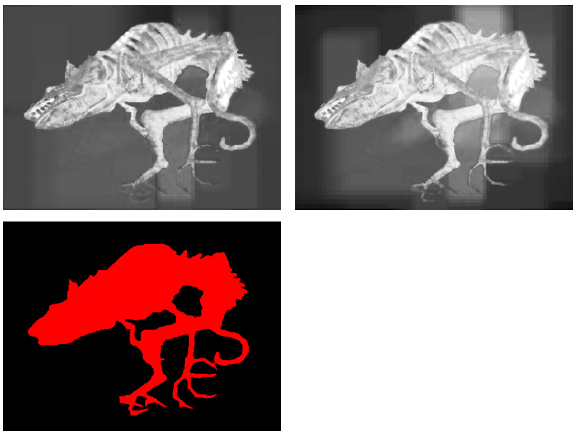

Fig. 3. A Rahtu et al.'s result(left top), our result(right top), and ground truth(left bottom)

Fig. 3 shows the Rahtu et al.'s result and our result with respect to the same image. Two results are visually very similar, but saliency values of pixels are different. In Fig. 3, the left bottom image is ground truth. With the two results and ground truth image, we can acquire the average saliency value within salient region and not salient region. In case of Rahtu et al.'s result, the average saliency value of 0.612224 and 0.357206 is computed within each region respectively. In case of out result, the average saliency value of 0.681398 and 0.361298 is also computed. Therefore, we can know that out modified algorithm can better discriminate between salient region and not salient region.

IV. EXPERIMENTS

In this section, we will show the several experiment results. Fig. 4 shows the original images and ground truth images used for experiment. Two result images generated with each image are visually very similar, but the average saliency values within salient region and not salient region given are not similar. Larger difference of average saliency values between salient region and not salient region can make better segmentation. To compare with Rahtu et al.'s method, we use MATLAB code which they provide. The ground truth images are generated using photoshop.

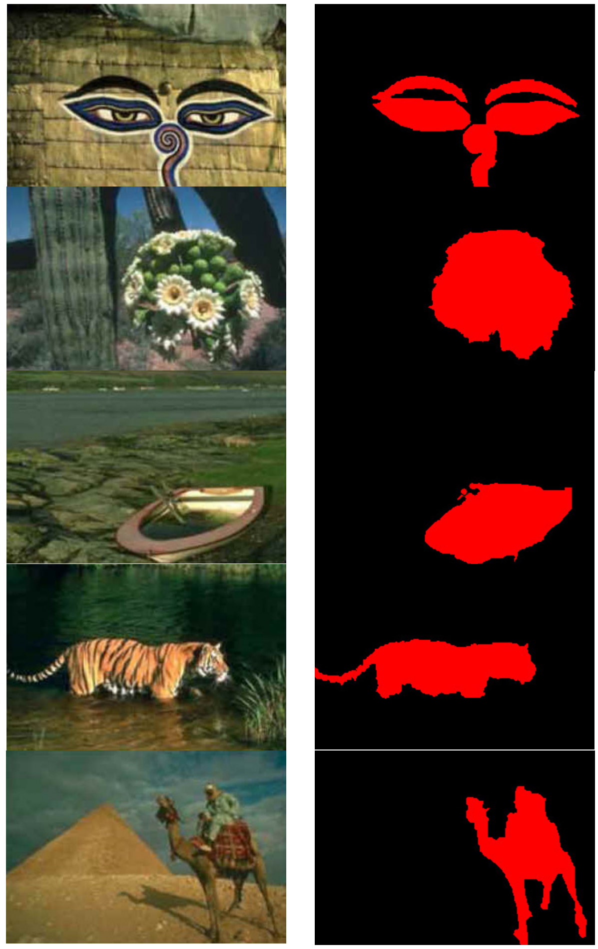

Fig. 4. Test images: left images are original images and right images are ground truth images.

TABLE I.
COMPARISON OF AVERAGE SALIENCY VALUE

		salient	not salient	difference
Test1	Rahtu et al.	0.542846	0.301538	0.2413080
	Our result	0.706489	0.341139	0.365350
Test2	Rahtu et al.	0.442939	0.355732	0.087207
	Our result	0.610288	0.403561	0.206727
Test3	Rahtu et al.	0.393375	0.305291	0.088084
	Our result	0.557618	0.286963	0.270655
Test4	Rahtu et al.	0.592279	0.380788	0.211491
	Our result	0.737021	0.427248	0.309773
Test5	Rahtu et al.	0.392143	0.315067	0.077063
	Our result	0.602441	0.337863	0.264578

Table 1 shows the comparison results between Rahtu et al.'s method and our method. In table 1, the third column is average saliency value of salient region, the fourth column is average saliency value of not salient region, and the last column is difference between two average saliency values. Table 1 shows that our modified algorithm can make better result than Rahtu et al.'s original algorithm.

IV. CONCLUSIONS

In this paper, we proposed a modified algorithm of Rahtu et al.'s algorithm to measure saliency values of pixels. While the original algorithm used fixed probability as initial probability, we applied the different initial probability for each kernel window. For this, binary saliency map is generated from rough saliency map as preprocessing step. Consequentially, our method could measure better saliency values than original method.

In this paper, only saliency values of pixels are determined. From this saliency values, detecting salient regions is important research area. Also, the improvement of our method is a future study to acquire better accurate saliency values.

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