An Improved Computational Approach for Salient Region Detection

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***Abstract*—Salient region detection in images is very useful for image processing applications like image compressing, image segmentation, object detection and recognition. In this paper, an improved approach to detect salient region is presented. The proposed method can generate a robust saliency map and extract salient regions with precise boundaries. In the proposed method, local saliency, global saliency and rarity saliency of three kinds of low-level feature contrast of intensity, color and orientation are used to compute the visual saliency. A new feature integration strategy is proposed in this paper. This method can select features and compute the weights of the features dynamically by analyzing the effect of different features on the saliency. Then a more robust saliency map is obtained. It has been tested on many images to evaluate the validity and effectiveness of the proposed method. We also compare our method with other salient region detection methods and our method outperforms other methods in detection results.**

***Index Terms*—salient region, saliency map, visual attention, image processing, feature integration**

I. Introduction

With the development of information technology, images become the main resource of information. How to analyze and process the huge image resources efficiently and effectively become the urgent problem. During the research, people find that most of the information often lies in some small key regions in the image. These key regions are so-called salient regions or regions of interest and so on. If we can extract these salient regions correctly and pay more attention to them, we can reduce the computational complexity and improve the speed of image processing significantly.

There have been some salient region detection methods. Most of them can successfully extract the salient regions in some circumstances but fail in some images. The most important step to detect salient regions is to compute the saliency of every part in the image. Most of the existing methods to compute saliency are based on feature integration theory that the saliency of every part in the image can be indicated by the difference of some feature values of it and its surroundings. Itti *et al.* have developed a biologically inspired computational model for computing visual saliency [1] [2]. They compute saliency maps using center-surround operation on features of intensity, color and orientation at different scales. Then an integrated saliency map is obtained by combining these feature saliency maps. But this method can only give the salient location and it cannot give the boundary of salient regions. They gave four combination strategies in [3]. The weights of different features were equal in the naive linear combination method. So the results were not satisfying. The method of linear combination with learned weights was better but it required a prior knowledge of the salient regions. The global non-linear normalization method and the iterative non-linear method both used a local competition strategy in one feature map. But those methods didn't analyze the effects of different features and just summed these normalized feature maps together.

Ma *et al.* proposed a computational method to detect salient regions by computing color contrast of every pixel in [4]. But they only use color feature. It is appropriate when the color feature is the most useful feature for the image. It can't give the right saliency result if the actual contrast resides in other features. The extracted salient regions using fuzzy growing often included the backgrounds or some wrong locations. Zhang *et al.* used the similar method to compute the feature contrast in [5]. They used multiple features like intensity, color and texture. But they didn't analyzing the different effect of each feature and just summed them up.

Hou *et al.* presented a spectra residual method to compute visual saliency in [6]. This method is simpler and more efficient than other existing method. But only intensity feature was used in the method. It could not get the right result if intensity was not the useful feature. And it could detect the right regions if the background was clustered and the salient region was flat [7].

Therefore, most of the existing methods have some shortcomings in saliency computing and feature integration strategy. Firstly, the saliency maps generated by those methods often provide some wrong salient locations which are not really salient. Otherwise, some regions are really salient but their saliency values are very

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low. Some methods have been presented to solve this problem [8] [9]. But these methods need image segmentation or learning and the complexity is high [10][11]. Secondly, different features have different effects on visual saliency. So it is necessary to give a strategy to decide what features are useful and integrate them with dynamic weight. Some combination strategies can be found in [12] [13]. But the results were not satisfying. Yiqun Hu *et al.* proposed a more integrated feature combination strategy in [14]. However, they used the size of a convex hull to approximate the area of salient points and a main feature map was referenced to evaluate other feature maps. These were not reasonable in some circumstances.

In this paper, an improved method for detecting salient regions is proposed. The proposed approach mainly includes two improvements. Firstly, the method to compute visual saliency is improved. A more robust saliency map can be generated using this method. Secondly, a novel feature integration strategy is presented. Different feature maps are analyzed and integrated together using dynamic weights.

This paper is organized as follows. Section II describes the outline and details of the proposed salient regions detection method. Section III gives some experimental results and discussion. Section IV presents our conclusions and prospects.

II. IMPROVED APPROACH FOR SALIENT REGION DETECTION

Fig. 1 shows the framework of our proposed approach for salient region detection. Firstly, low-level visual features like intensity, color and orientation are extracted. Then visual saliency of each feature map is computed to get some feature saliency maps. These feature saliency maps are integrated to get an integrated saliency map using dynamic weights according to their different effects on saliency. Then, the integrated saliency map is simply segmented using a threshold and a binary image is generated. Finally according to the binary image, the salient regions are extracted.

A. Visual Feature Extraction

Early vision features have significant effects on saliency of the regions in the image. If the region has intensity information that is different from its surrounding intensity information, the region is remarkable in the intensity feature. If the region has different color information from its surrounding color information, the region is salient in the color feature map. In addition, edge, shape and orientation also have effects on the visual saliency. Since the retina cells can extract intensity, color and orientation information from natural scenes, we use these factors as the basic features of the saliency map [1].

Because HSI (Hue, Saturation and Intensity) color space is consistent with human color perception system and is better than RGB color space, the input image is transformed from RGB space to HSI space using (1).

Then we use I channel in (1) to represent intensity feature of the input image. H (hue) channel and S (saturation) channel are used to describe the color feature of the image. Four orientation feature maps can be obtained by filtering the intensity feature map using four Gabor filters with orientation 0°, 45°, 90°, 135° respectively.

$$\begin{cases} H = \frac{1}{360}[90 - Arc\tan(\frac{F}{\sqrt{3}}) + \{0, G > B; 180, G < B\}] \\ S = 1 - [\frac{\min(R,G,B)}{I}] \\ I = \frac{(R+G+B)}{3} \\ F = \frac{2R - G - B}{G - B} \end{cases} . \quad (1)$$

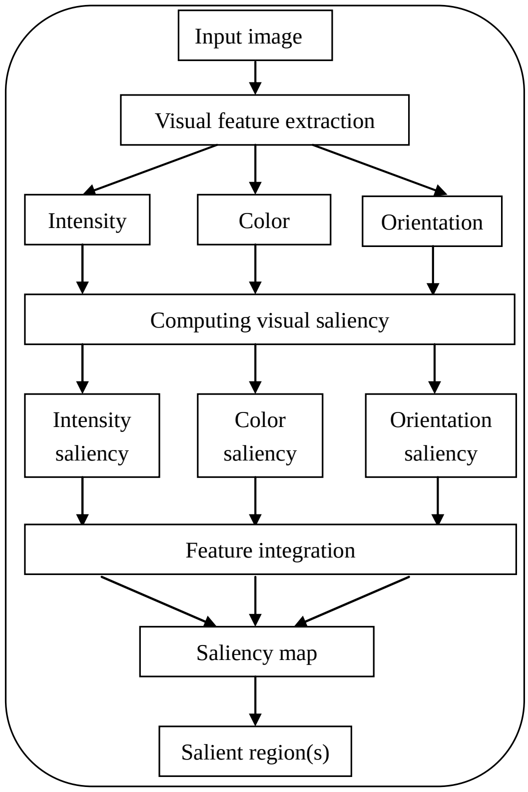

Figure 1. Block diagram of salient regions detection

B. Computing Visual Saliency

After extracting low-level visual features, visual saliency of every part in each feature map is required to compute. Existing methods to compute saliency always generate some wrong saliency results. For example, the computed salient areas often locate on the boundaries between salient object and background where feature value changes sharply. This can be seen in the top row of Fig. 2. In addition, the saliency value of a clustered background is high but the saliency value of a flat foreground area is low in some circumstances which are shown in the bottom row of Fig. 2. The first column shows the input images. The second column shows the saliency maps generated by Itti's method based on center-surround operation [1]. The saliency maps computed by Hou's method based on spectra residual are shown in the third column [6] and Achanta's results based on global feature contrast are shown in the fourth column [13].

Therefore, to get a more robust saliency map our proposed method considers three kinds of saliency which are local saliency, global saliency and rarity saliency.

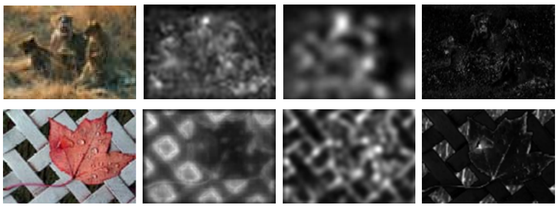

Figure 2. Example of incorrect saliency map.

1) Local saliency: Whether a region is salient in the image or not depends on the distinctness between itself and its environment [4]. Here we use local saliency to represent the difference between a region and its surroundings. Different from other methods which compute saliency in spatial domain, we analyze the local saliency in frequency domain.

In frequency domain, an image can be decomposed into magnitude spectrum and phase spectrum. It has been discussed in [15] [16] that phase spectrum is very important in image reconstruction. If we reconstruct the image with phase spectrum only or with a random changed magnitude spectrum, the reconstructed image can reserve the structure information and less distort the original image [15]. But if we reconstruct the image with a random changed phase spectrum, the reconstructed image severely distort the original image. It is indicated that phase spectrum represents the information of value changing at each position whereas magnitude spectrum represents the particular value at each position. Because we only care the change of feature value, we reconstruct the image with phase only to eliminate the influence of magnitude spectrum and get the local saliency. The process is described as follows.

a) Discrete Fourier transform: Transform the input image from spatial domain into frequency domain using (2).

$$\begin{aligned} F(u,v) &= \sum_{x=1}^{M}\sum_{y=1}^{m} f(x,y) e^{\frac{-j2\pi ux}{M}} e^{\frac{-j2\pi vy}{N}} \\ &= R(u,v) + jI(u,v) \end{aligned} \quad . \quad (2)$$

Where *f(x,y)* means the feature map with dimension *M*N*. The values *F(u,v)* are the DFT coefficients of *f(x,y)*.

b) Extract phase spectrum: Compute the phase spectrum using (3).

$$P(u,v) = \arctan\left(\frac{I(u,v)}{R(u,v)}\right). \quad (3)$$

c) Compute local saliency: Reconstruct the image with phase spectrum only using (4) and get the local saliency map.

$$S_{local}(x,y) = \frac{1}{M*N}\sum_{u=1}^{M}\sum_{v=1}^{N} I(u,v) e^{\frac{-j2\pi ux}{M}} e^{\frac{-j2\pi vy}{N}} . \quad (4)$$

Some examples are shown in Fig. 3. The images in the top row are original images and their intensity feature maps are shown in the middle row. The local saliency maps of the intensity feature maps are shown in the bottom row.

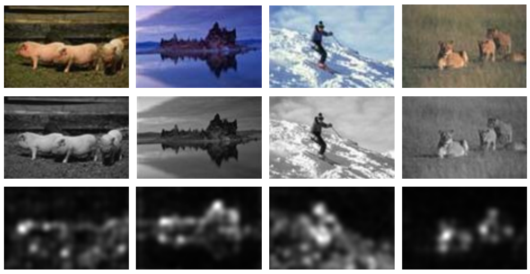

Figure 3. Example of local saliency map

2) Global saliency: Fig. 3 shows that local saliency can indicate the places where feature values change and give them high saliency value. But only considering local saliency is not enough because high local saliency values often lie in boundaries between salient areas and the background. The saliency values inside the salient object are low. This can be seen from Fig. 3. So we use global saliency as well.

Global saliency map of a feature map can be computed using (5).

$$\begin{cases} S_{Global}(x,y) = e^{\frac{|f(x,y) - f_{avg}(x,y)|}{f_{avg}(x,y)}} \\ f_{avg}(x,y) = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y) \end{cases} . \quad (5)$$

Fig. 4 shows some global saliency maps. The images in the top row are original images and their intensity feature maps are shown in the middle row. The global saliency maps of the intensity feature maps are shown in the bottom row.

Figure 4. Example of global saliency map

3) Rarity saliency: Rarity saliency means the less a feature value occurs the more possible it belongs to a salient area.

The areas that have novel and rare feature values often attract people’s attention and become salient areas in the image. The easiest method to measure the rarity of a feature value is to count the number it occurs in the image. The higher the number is, the lower the saliency is. The histogram of an image is an adequate statistical tool to count the number of each pixel feature value occurs. So the rarity saliency can be computed using (6).

$$S_{Rarity}(x,y) = \frac{1}{hist(f(x,y))}. \quad (6)$$

Where *f(x,y)* is the feature value of pixel *(x,y)* in the feature map and *hist(•)* is the histogram of the feature map.

Fig. 5 shows some rarity saliency maps. The images in the top row are original images and their intensity feature maps are shown in the middle row. The rarity saliency maps of the intensity feature maps are shown in the bottom row.

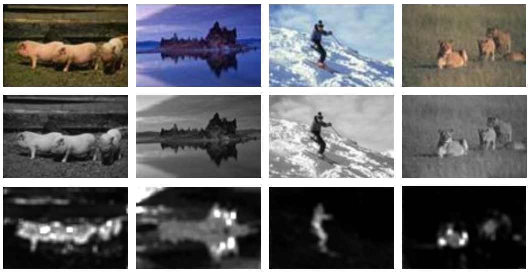

Figure 5. Example of rarity saliency map

4) Feature saliency map: Finally, local saliency map, global saliency map and rarity saliency map need to be combined into a feature conspicuity map. Different weights need to be applied to each saliency result. To compute the weight of each saliency result, the variance Vi of each saliency result is calculated first. The higher the variance is, the more important the saliency result is [17]. Then the feature conspicuity map can be generated using (7).

$$\begin{cases} V = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left| f(x,y - \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} f(x,y)\right| \\ w_i = \frac{V_i}{\sum_{i=1}^{3} V_i} \\ C_F = w_1 * S_{Local} + w_2 * S_{Global} + w_3 * S_{Rarity} \end{cases} .(7)$$

The process of generating intensity conspicuity map is shown in Fig. 6. Firstly, the intensity feature of the input image is extracted. Then local saliency, global saliency and rarity saliency of the intensity map are calculated. Then these three kinds of saliency results are combined into an intensity conspicuity map.

C. Feature Integration

Using the method described in the above section, conspicuity maps of intensity feature, color feature and orientation feature of input image are generated. Then we need to integrate these feature conspicuity maps into an integrated saliency map. In this paper, a novel and reasonable feature integration strategy is used to combine these feature conspicuity maps into a final saliency map. The strategy and process of feature integration are described as follows. We use salient area, salient point location and salient point distribution to measure the importance of the feature conspicuity maps and compute their weights.

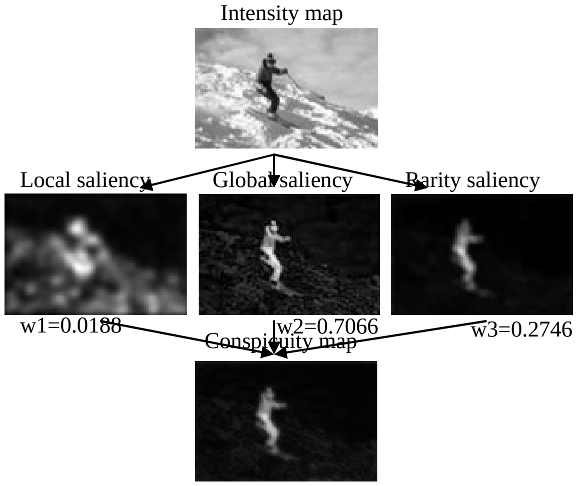

Figure 6. Example of feature conspicuity map

1) Salient points extraction: Before combining feature conspicuity maps into an integrated saliency map, we should extract salient points [14]. Simply threshold these feature saliency maps using a threshold T which can be computed using (8) [18].

$$T = \arg\max_t \left(-\sum_{i=1}^{t} p_i * \log_2 p_i - \sum_{i=t+1}^{L} p_i * \log_2 p_i\right). \quad (8)$$

Where, T is the threshold. L is the total gray level of the feature conspicuity map and p_i is the frequency that the gray value i occurs in the feature saliency map. The pixels whose values are bigger than the threshold are considered as salient points.

2) Salient area calculation: Based on the rarity principle, the more the salient points in a feature saliency map are, the less useful the feature saliency map is. That means if there are so many salient points in a feature saliency map, these salient points are not really salient. Unlike [14] in which the size of a convex hull is considered as salient point area, we compute the number of salient points as the salient point area using (9). The experiment results show that this method is simpler and more effective than the method of [14].

$$W_{area} = N. \quad (9)$$

Where, W_{area} means the weight of salient point area and N represents the number of salient points. If the area of salient points is larger than 70% of the area of the whole image, the weight of the feature saliency map is set to zero. This means it is not included when in feature integration.

3) Salient location calculation: People often pay more attention to the region near image center that means the region near the image center are more likely to be a salient region. So we consider the salient point location as a criterion. Compute the average distance between the salient points and the image center as the location criterion using (10).

$$W_{location} = \frac{1}{N}\sum_{i=1}^{N} Dist(sp_i, center). \quad (10)$$

Where, $W_{location}$ is the weight of salient point location. N is the number of salient points. sp_i means each salient point and *center* means the center of the image. *Dist* means the distance between two points.

4) Salient points distribution: If the salient points don’t cluster together but distribute separately in the feature saliency map, the feature saliency map is not very useful. So we compute the spatial distribution of salient points using (11) as another criterion.

$$W_{distribution} = \frac{1}{N}\sum_{i=1}^{N} Dist(sp_i, centroid). \quad (11)$$

Where, $W_{distributio}n$ is the weight of salient point spatial distribution. *centroid* means the center of the salient points.

5) Feature integration strategy: The weight of each feature map can be computed dynamically using (12).

$$\begin{cases} W_i = \dfrac{\dfrac{1}{W_{fi}}}{\sum_{i=1}^{m}\dfrac{1}{W_{fi}}} \\ W_{fi} = W_{area}^{i} + W_{location}^{i} + W_{distribution}^{i} \end{cases}. \quad (12)$$

Where, W_i means the weight of each feature conspicuity map and m is the number of feature conspicuity maps.

Then the final integration saliency map can be generated using (13).

$$SM = \sum_{i=1}^{m} W_i * C_F^i. \quad (13)$$

Where, SM is the integration saliency map and CF_i means each feature saliency map. Fig. 7 shows an example of feature integration.

D. Salient Region Detection

After generating the integration saliency map, we should threshold it to get a binary image BM using (14). Here the value of the threshold T can be computed using (8).

$$BM(x,y) = \begin{cases} 1 & SM(x,y) \geq T \\ 0 & SM(x,y) < T \end{cases}. \quad (14)$$

There are some defects in the binary image, so we use some morphological operations to improve the binary image.

Firstly, if the binary image contains some undesired or isolated white pixels whose eight neighbors are all black pixels, the morphological operation is done to removes these isolated pixels from the resulting binary image.

Secondly, erosion operation and dilation operation are done to fill small gaps within the white region.

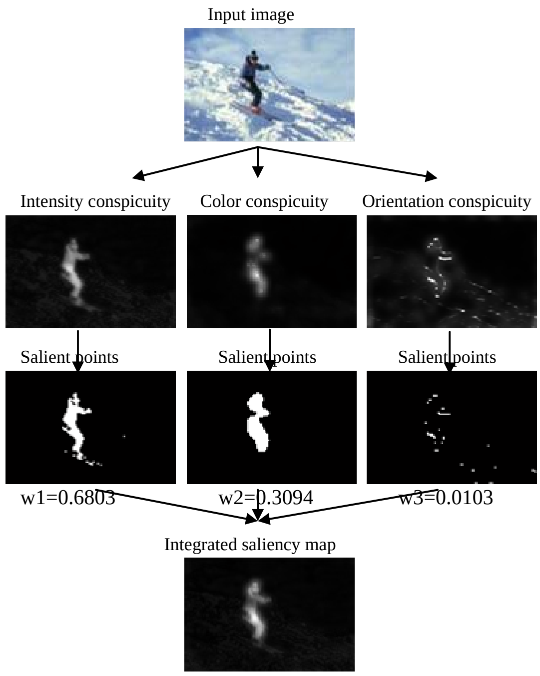

Figure 7. Example of feature integration

Finally, if the salient region is not small and very smooth, the white region in the generated binary image will only center on the boundary of the region and the inner of the region is black region in the binary image. So we fill the enclosed black regions to get a whole white region which represents a whole salient region in the input image.

Then salient regions can be extracted by adding the binary image to the original image. Fig. 8 shows the process of detecting salient region.

III. EXPERIMENT RESULTS

The proposed approach was extensively tested with many natural images to ensure proper functioning. We have collected many image sources from image search engines and selected more than 100 images each of which contains at least a salient region to test our approach. This section presents experimental results and analysis of the proposed salient region detection approach.

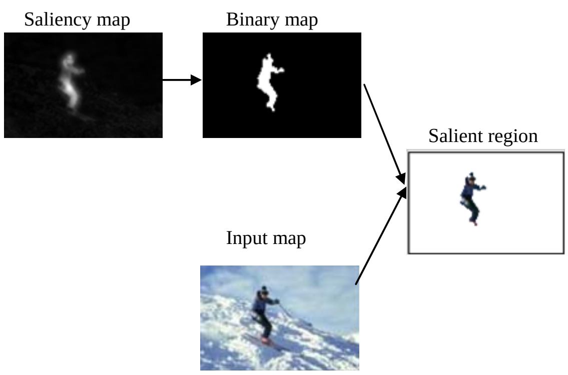

Figure 8. Example of salient region detection

A. *Results*

The proposed salient region detection method has been tested on the computer with Intel Pentium 1.8 Ghz and 512M memory using more than 100 natural scene images. Fig. 9 shows the simulation results of the proposed method. Primary images are shown in column 1, saliency maps are shown at column 2, binary images are presented at column 3 and the salient regions are shown at column 4.

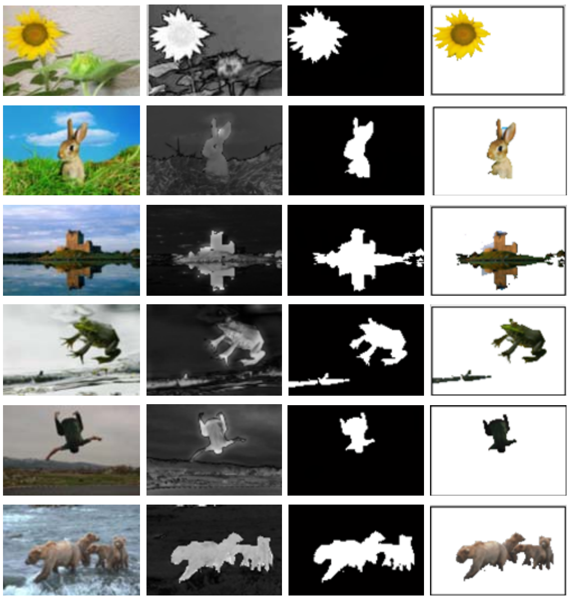

Figure 9. Results of our proposed method

B. *Comparison*

The detection results of salient regions from our proposed approach are compared with results from Itti's method [1], Hou's spectral residual method [6] and Achanta's results [13] for the same input images. The comparison results are shown in Fig. 10. The input images are shown in column 1. The saliency maps generated by Itti's method are shown in column 2. Images in column 3 and column 4 are results of Hou's method and Achanta's method respectively. Our saliency maps are shown in column 5. The saliency maps of Itti's model are generated using saliency toolbox which is downloaded from http://www.saliencytoolbox.net. Saliency maps of Hou's are generated using his program from http://bcmi.sjtu.edu.cn/~houxiaodi.Achanta's global saliency maps are generated using the program from http://ivrg.epfl.ch/supplementary_material/RK_CVPR09/SourceCode/.

From Fig. 10 we can see that Itti's saliency maps can only give the rough location of salient regions and they cannot generate correct boundaries of salient regions (the second column). In some cases, Hou's and Achanta's methods can get the outline of salient regions. But in some images, the salient results computed by their methods are incorrect. The edges between objects and background which have high feature contrast will have high saliency value but the true salient areas which are flat will have low saliency value. This can be seen especially in the first row and the third row. Because our proposed method takes local saliency, global saliency and rarity saliency into account, the defects mentioned above can be eliminated effectively. Using the saliency maps generated by our methods, the whole salient regions with correct boundaries can be detected.

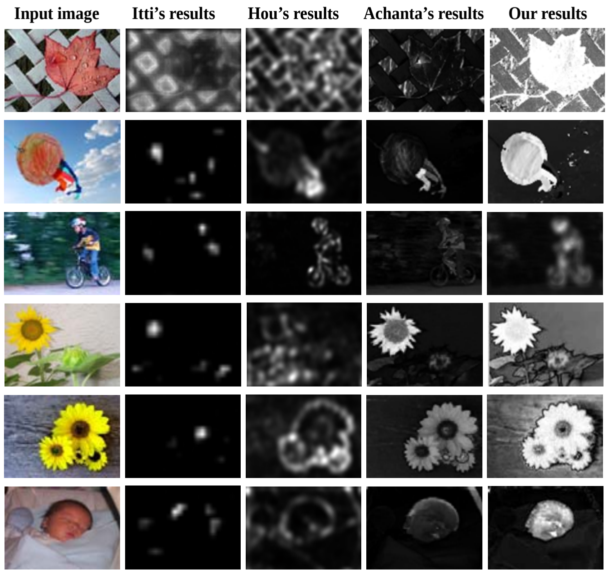

Figure 10. Results of comparison

C. *Evaluation*

In order to obtain an objective evaluation, we also compare our detection results with ground truth images. A huge ground-truth image database based on bounding boxes has been established in [10]. But such bounding-box-based ground truth is far from accurate. Two accurate contour-based ground truth databases have been generated manually in [7] and [13]. In this paper, we choose the object-contour-based ground truth image database which has 1000 binary images from [13]. Fig. 11 shows some examples of comparison between our segmented binary images and ground truth images. The first column shows input images and the second column shows saliency maps generated by our methods. Binary images by segmenting saliency maps are shown in column 3. Ground truth images are shown in column 4.

In order to give a quantitative evaluation, we use two measurements: hit rate and false alarm rate. Hit rate means the percentage of correct salient points which are considered salient both by the proposed method and ground truth. False alarm rate means the percentage of false salient points which are considered salient by the proposed method but refused by ground truth.

The hit rate is defined as

$$\textit{hit rate} = \frac{\sum_x G(x) * BM(x)}{\sum_x G(x)}. \tag{15}$$

Where, G is the ground truth image, BM is the segmented binary image by the proposed method.

The false alarm rate is defined as

$$false\ alarm\ rate = \frac{\sum_x (1-G(x)) * BM(x)}{\sum_x (1-G(x))}. \quad (16)$$

Where, G is the ground truth image, BM is the segmented binary image by the proposed method.

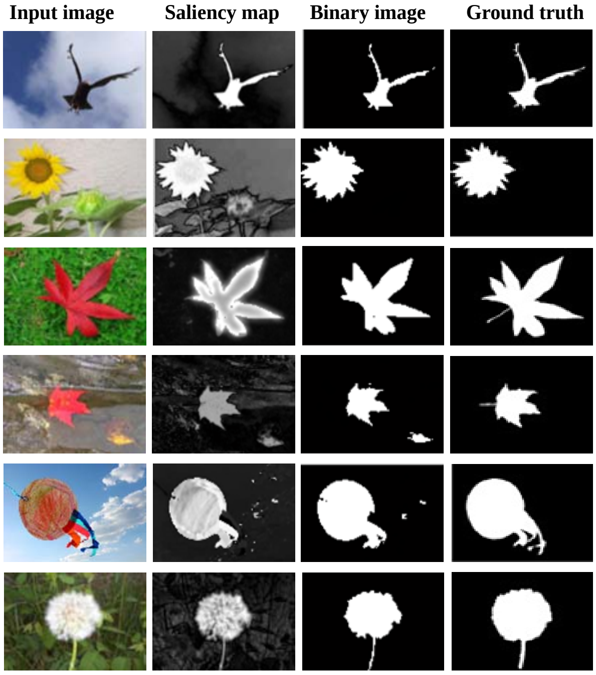

Figure 11. Comparison results with ground truth

Tab.1 shows comparison of average hit rate and average false alarm rate between our method and other methods.

From Tab. 1 we can see that Itti's method have the lowest false alarm rate but its hit rate is the lowest too. Because it saliency map can only generate the center location of salient regions. Hou's method and Achanta's method both have higher hit rate and false alarm rate than Itti's method. And they can detect salient regions with rough borders. But in some images the detected salient regions includes some wrong areas and background and this increase the false alarm rate. False alarm rate of our method is lower than Hou's and Achanta's and similar with Itti's. The hit rate of our method is highest.

TABLE I. EVALUATION RESULT OF DIFFERENT METHODS

Method	Average hit rate	Average false alarm rate
Itti's	0.4197	0.1281
Hou's	0.7891	0.2302
Achanta's	0.8793	0.1582
Ours	0.9104	0.1325

D. Discussion

If the input image is very complex and clustered or there is no very salient region in the image, our proposed method will fail to extract salient regions. Therefore, only those images which at least have one salient region are chosen in our experiments. The proposed experiment results have shown that our proposed method has performed well in most cases. More than 85% results have successfully extracted salient regions from the background and matched the ground truth images. However, our method has some limitations including two categories:

- Not the whole salient regions can be detected in some images. Some parts of the true salient regions are neglected. This leads to low hit rate.
- Parts of the clustered background are extracted as salient regions. This leads to high false alarm rate.

There are two reasons that are likely to lead to above defects. One reason is the generated saliency map. Although our method has solved some problems of current other methods, the generated saliency maps are not very well in some images which have very clustered background or low-contrast foreground. This need to be further researched.

The other reason is the threshold to binary saliency maps. The threshold directly affects the segmentation results. If the threshold is too high not all the pixels of salient regions will be extracted. This will result in low hit rate. Contrarily, a low threshold will lead to too many pixels be extracted. This will result in high false alarm rate. We can make a balance between high hit rate and low false alarm rate to select the threshold.

IV. CONCLUSION

A new method for salient region detection is proposed in this paper. Multiple features like intensity, color and orientation are analyzed. It computes local saliency, global saliency and rarity saliency to construct the saliency map and according to the saliency map to extract salient regions. The process is entirely unsupervised. It does not need user intervention. The proposed model is not domain-specific and does not impose limits on the variety of images. It can be used for all kind of images provided that there is at least one meaningful salient region.

Some experiment results and quantitative and qualitative analysis have been presented in this paper. The limitations of the proposed method are related to the only bottom-up visual attention saliency map and the threshold to get the binary image. The research on top-down visual attention to improve the saliency map will be included in future work.

Early vision features are also important to construct the saliency map. A simple feature can not entirely represent the character of the salient region. Therefore, multiple features analysis is used in the proposed method. In this paper, we consider colors, intensity and orientations as the features of the image. However, it is very likely that there are some other features such as edge and symmetry feature which also should be considered. What feature and how many features should be extracted according to the target will also be included in future work.

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