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Color Image Segmentation based on Color Contrast and Improved Convex Hull

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Abstract: Since that it can enhance the Region Of Interest (ROI), saliency detection is important for imaging processing. Most saliency detection approaches are based on feature contrast to find the salient area. However, for the similar contrast between background and foreground, the traditional approaches always fail to differentiate these regions of the background from the foreground. To solve the similar contrast problem, this paper presents a novel method for color image segmentation based on improved convex hull and color contrast. Firstly, the method takes superpixel as the basic processing unit, and measures the contrast saliency map based on color contrast with uniqueness and spatial distribution. Secondly, it calculates convex hull using color boosted Harris corner points which was improved by FH algorithm. Based on the improved convex hull, the center saliency map is obtained. The final saliency map is constructed using the contrast saliency map and the center saliency map. Finally, the object is segmented out from the final saliency map using Otsu method. Compared with several state-of-the-art methods on MSRA 1000 and ECSSD dataset, the proposed method achieves better performances in visualization, precision and recall.

Keywords: Superpixel, color contrast, improved convex hull, saliency map, color image segmentation.

I. INTRODUCTION

Inspired by human visual system, an approach of visual saliency is used for image segmentation. Salience detection approaches enhance the contrast between the foreground and background in images, and thus the segmentations are achieved easily. Its applications are widely, including pattern recognition, computer vision, object detection, and so on. [1].

Most of existing saliency detection methods can be roughly classified into three categories: contrast-based, similarity-based and probability-based [3]. The similarity-based approaches are computed by the similarity between the object and its surroundings. For the probability-based methods, the uniqueness or rarity of the basic units are usually defined as the monotonic functions of the probability density. At present, most of the methods are contrast-based methods [4]. The contrast-based saliency can also be subdivided into global contrast, local contrast, and the combination of both. Local contrast methods assess the saliency of a specific image area based on immediate image neighborhoods, e.g., using histogram analysis [5] or variations at the pixel-level [6]. While such approaches may be more sensitive to image edges and noise. Global contrast methods take the complete image into account. Moreover, global contrast methods are usually based on color histogram [7], background subtraction [8], global energy [5] and so on. However, such methods have problems coping images with cluttered foreground and relatively high similarity between background and foreground regions.

Over all, the task of saliency methods is to highlight object boundaries and suppress the non-object parts of the image. While global contrast will highlight salient object uniformly, but the edge of object is not clear. Thus, researchers try to combine the two contrast-based methods. But when there is a high contrast area in the background of a color image, simply using a contrast-based approach will misjudge the region with high contrast in the background as a salient object. One typical failure case is shown in Figure 1. In this case, the center area of horse is background, violating our hypothesis. Furthermore, contrast-based method fails to obtain correct position due to their similar color with background region and nonuniform color appearance.

To address the above issues, we propose a color segmentation method which explicitly explores improved convex hull and color contrast. Firstly, we calculate the basic saliency map based on color contrast. Secondly, the convex hull is obtained using color boosted Harris corners which is improved with FH algorithm. Finally, we compute the center significant map for improving the convex hull and refine the segmentation result by fusing the above two saliency maps into a final saliency map, and use Otsu method to get the object.

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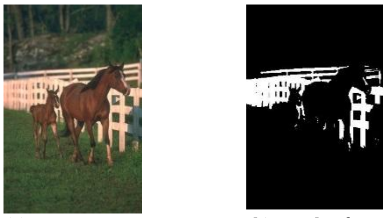

(a)Input image (b)Result of SF algorithm

Figure 1. Failure case based on contrast.

The paper is organized as follows. Details of the proposed method are presented and analyzed in Section Ⅱ, including the improvement of the convex hull and the computation of color contrast. Experimental results and discussions are presented in Section Ⅲ. Finally, conclusion is described in Section Ⅳ.

II. METHODOLOGY

Most of existing color image segmentation approaches are based on superpixel rather than single pixel [9]. Though superpixel-based features may bring additional computational cost, they are more suitable for complex visual images and can promise better distinguishability. Thus, we adopt superpixel as the basic computing unit. Research has shown that there are significant differences between salient and non-significant region in color images, and the distribution of object is compact rather than scattered throughout the image [10]. In this paper, over all, we first construct the saliency map based on color contrast through computing color uniqueness and color spatial distribution. Next, the saliency map can be improved by center saliency map based on improved convex hull. The framework of the proposed approach is shown in Figure 2. The whole process of the proposed approach mainly consists of five steps: superpixel abstraction, improved convex hull, saliency map computation based on color contrast, central saliency map computation based on the improved convex hull, and final saliency map generation and image segmentation.

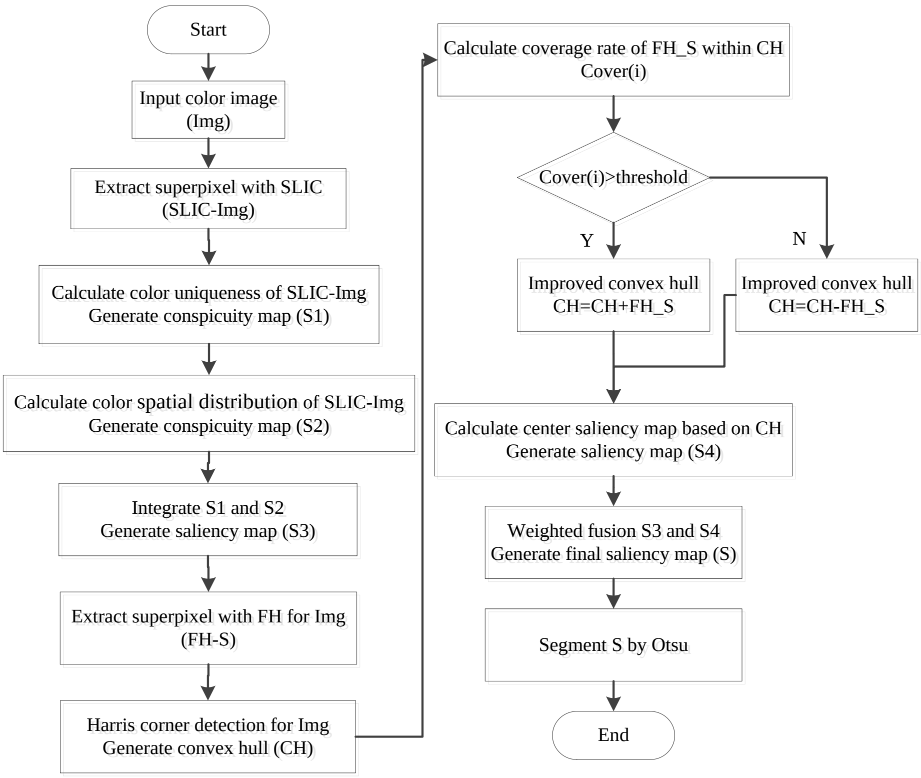

Figure 2. The framework of the proposed approach.

A. *Image block abstraction*

As the basic computing unit, the visual saliency detection algorithm with a single pixel has huge computational cost and is sensitive to noise and other factors [11]. Similar to [9, 10, 13], we adopt the SLIC (Simple Linear Iterative Cluster) algorithm [10] to generate superpixels for color contrast. Specifically, each element should locally abstract the

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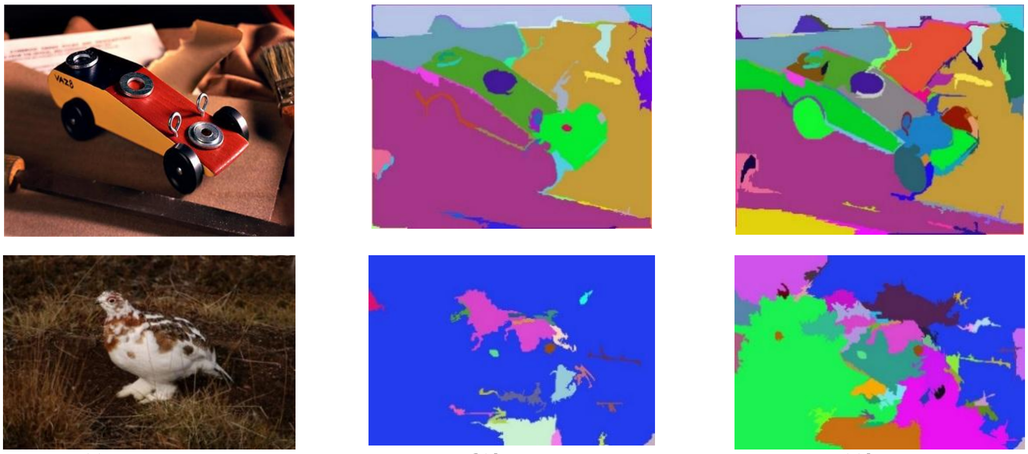
image by clustering pixels with similar attributes (such as color) into homogeneous area (as shown in Figure 3(b)). This method not only helps decrease high computational cost but also makes the proposed approach more discriminative. As shown in Figure 3, all superpixel blocks represent a unique part. Then, saliency detection between whole image areas can be evaluated using those elements. Furthermore, as shown in Figure 3(c), we get position P_i and mean color C_i of superpixel i.

(a)Input image (b)Rendering of SLIC (c)Replace the superpixel with mean color

Figure 3. The result of SLIC algorithm.

To extract foreground better, convex hull is used. Existing methods based on convex hull usually generated with interest points. The convex hull is used to compute the approximate location of salient object. The convex hull still contains a large number of background areas, so the FH method is used to improve the convex hull. Felzenszwalb and Huttenlocher [12] proposed a segmentation method based on the idea of minimum spanning tree. The algorithm generates superpixels of different scales, where k is used to determine the size of the region, and the larger the k is, the larger the region generated by the algorithm, as shown in Figure 4. Empirically, k is set to 500.



(a)Input images (b)k=1000 (c)k=500

Figure 4. The result of SLIC algorithm.

B. *Saliency map computation based on color contrast*

In most cases, a color feature, which is conspicuous from other features in certain aspects, captures much attention with human vision system [13]. Therefore, it should be more meaningful to the visual saliency calculation with color contrast. We propose color contrast analysis for extracting saliency map based on the following hypotheses: on the one hand, the rare color is more outstanding in the whole image. On the other hand, the wider a color is distributed in the whole image, the less possible a prominent object contains this color.

The rare color has visually priority to catch attention in the human vision system. We measure the color uniqueness saliency for each superpixel of the image by

$$S_U(i) = \sum_{j=1}^{N} \| c_i - c_j \|^2 \cdot w\left(p_i, p_j\right) \tag{1}$$

where N is the number of all superpixels in the image, c_i is the average color of superpixel i in CIELab, and p_i denotes the position of superpixel i. A local function w yields a local contrast term, which tends to evaluate the distance between two segments:

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$$w\left(p_i, p_j\right) = \frac{1}{Z_i}\exp\left(-\frac{1}{2\sigma^2}\| p_i - p_j \|^2\right) \tag{2}$$

where Z_i is the normalization factor in order to ensure $\sum w\left(p_i, p_j\right) = 1$. As can be seen from the uniqueness of color, the greater difference in color between a region and the surrounding area has, the more notable the area is. Saliency represents uniqueness. Therefore, it is necessary to see whether the element is distributed to a unique location. We define the color spatial distribution in a given image as:

$$S_D(i) = \sum_{j=1}^{N} w\left(c_i, c_j\right)\cdot\left\| p_j - \mu_i \right\|^2 \tag{3}$$

$$\mu_i = \sum_{j=1}^{N} w\left(c_i, c_j\right)\cdot p_j \tag{4}$$

where μ_i defines the weighted mean position of color c_i, and $w\left(c_i, c_j\right)$ evaluates the similarity of color c_i and c_j. It is significant for the superpixels, which have a large different and distances with other superpixels in the image. The saliency value based on color contrast can be calculated by:

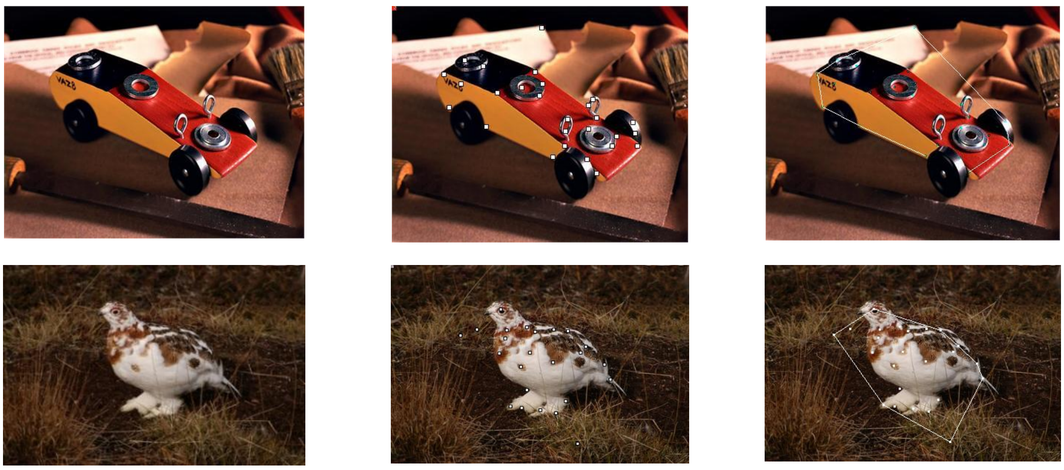
$$S_C(i) = S_U\left(i\right)\cdot\exp\left(-k\cdot S_D\left(i\right)\right) \tag{5}$$

we set $k = 6$ in our experiment. The proposed algorithm can achieve better results when foreground and background regions have highly contrast.

C. *Central saliency map computation based on improved convex hull*

The convex hull can be obtained by image feature points. Currently, the algorithms used for calculating feature points include Harris, SURF, SIFT descriptors and so on. The Harris descriptor is often used for the detection of ROI, for its small calculation cost and stable result. Harris operator may produce some useless corner points. The proposed model overcomes this drawback using color boosted Harris descriptor [14].

The corner points are detected using color boosted Harris algorithm in a color image. In such cases, if the corner points at the boundary are not take away then the convex hull may enclose the entire image. We eliminate those near the image boundary, and calculate a convex hull to enclose all the remaining corner points. Some results of the convex hull are shown in Figure 5. So, the minimum convex hull is formed by the remaining points. Now we make a decision that the region outside the convex hull is the background area, while the area within the convex hull is the outstanding area. Figure 5 shows the minimum convex hull containing background areas. Therefore, we use the FH algorithm to improve the minimum convex hull so as to obtain a more accurate convex hull.



(a)Input Images (b)Corner points (c)Convex Hull

Figure 5. The Harris corner points and the convex hull.

As shown in Figure 4, the superpixel generated by FH algorithm has a good fitting effect on the edge of the image target. Therefore, the improved convex hull obtained by this method has a good fitting result to the target edge. Here, we improve the convex hull based on the coverage of each superpixel and original convex hull. If most of the pixels in a superpixel within the convex hull, we assume that all the pixels within the superpixel should be in the convex hull. On the contrary, we consider it should be a part of background. The coverage of each superpixel with the original convex hull is defined as:

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$$P_S = \frac{|S \cap C|}{|S|} \tag{6}$$

where S is the superpixel generated by FH approach, and C represents the convex hull. $|S|$ denotes the number of elements within region S. We improved the original convex hull as

$$\begin{cases} C = C + S, & P_S \ge t; \\ C = C - S, & P_S < t. \end{cases} \tag{7}$$

where the threshold t was set to 0.65. A superpixel S should belongs to foreground area if the coverage P_S of the superpixel S within the original convex hull C is greater than or equal to t, and then the convex hull C was improved as $C = C + S$. Otherwise the convex hull C was improved as $C = C - S$. Some examples of the improved convex hull are shown as Figure 6.


(a)


(b)

Figure 6. The improved convex hull.

A convex hull is a convex polygon consisting of a series of corner points. But the real edges of an object in a natural image are usually curves rather than straight lines. Consequently, it is hard to enclose salient object appropriately with the original convex hull. The improved convex hull which improved using superpixel is composed of superpixel edges and partial convex hull lines. As can be seen from Figure 6, the improved convex hull is not strictly convex hull. Compared with the original convex hull, the improved convex hull can enclose salient object more appropriately. Therefore, the saliency computed by the improved convex hull is more accurate. In addition, we assume that the area outside the improved convex hull is the background.

The Euclidean distance between the superpixel and the central point of the improved convex hull was calculated. Thus, the nearer a region approximates to the central point, the higher values it gets. To make our approach uniform, we calculate the central saliency of the improved convex hull as

$$\begin{cases} S_{CH}(i) = \exp\left(-\frac{\|x_i - x_0\|^2}{2\sigma_{x^2}^2} - \frac{\|y_i - y_0\|^2}{2\sigma_{y^2}^2}\right), & i \in CH \\ S_{CH}(i) = 0, & i \notin CH \end{cases} \tag{8}$$

where S_{CH} is the central saliency map, x_0 and y_0 are respectively the horizontal and vertical coordinates of the central point, σ_x and σ_y respectively denotes the horizontal and vertical variances, and (x_i, y_i) is the coordinate of the superpixel.

D. *Saliency map fusion*

We start by normalizing both saliency map based on color contrast and saliency map based on improved convex hull to the range [0…1]. Hence, we combine these maps as follows to compute a final saliency map:

$$S_i = \alpha S_C(i) + (1-\alpha) S_{CH}(i) \tag{9}$$

where α and $(1-\alpha)$ represent the weight of the saliency map based on color contrast and of the improved convex hull, respectively. When $\alpha = 0.45$, the best results can be achieved.

E. *Thresholding*

After the final saliency map obtained, the Otsu thresholding method was used for object segmentation:

$$BM(i) = \begin{cases} 1, & S(i) \ge T; \\ 0, & S(i) < T. \end{cases} \tag{10}$$

$$T = graythresh(S(i)). \tag{11}$$

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where *T* is the threshold obtained by Otsu approach, and *BM* is the final binary image containing the objects that are most salient in the original color image.

III. RESULTS AND DISCUSSION

To demonstrate the effectiveness of our method, we use MATLAB R2016 to implement the proposed algorithm which run on a computer with Intel Core i3 CPU and 4GB memory. We evaluate the performance of the proposed algorithm with measuring its precision rate, recall rate, F-Measure and visualization.

1) Algorithm performance evaluation: In this section, we compare the proposed method with the state-of-the-art approaches: SF [10], RC [7], SR [15], ITTI [6], AC [16] and BYS [9]. We evaluate its performance on MSRA 1000 and ECSSD dataset which are often used in salient object segmentation. Here, we use the most popular criteria (precision, recall rate and F-Measure) to evaluate the performance of the proposed approach in saliency detection. Precision rate represents the percentage of salient pixels correctly assigned, while recall rate represents the percentage of detected salient pixels compared to the ground truth number of salient pixels. We also take the F-Measure into account, which jointly considers precision and recall rate. The precision, recall and F-Measure curves on MSRA 1000 and ECSSD dataset are shown in Figure 7 and Figure 8 respectively.

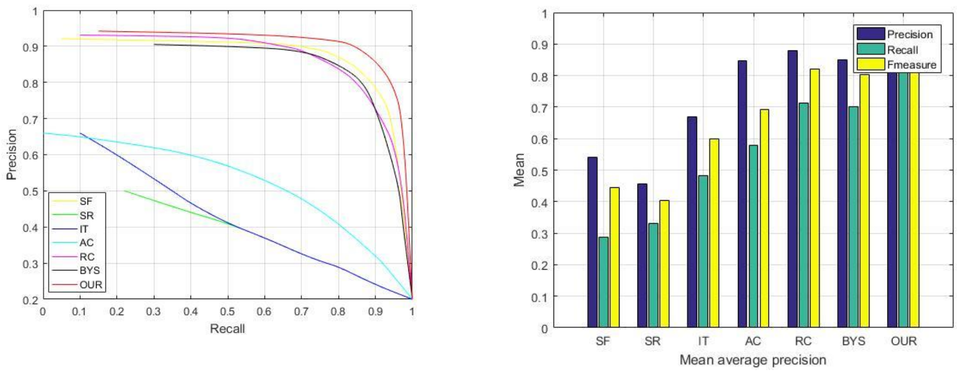

Figure 7. The comparison of various methods on MSRA 1000 dataset.

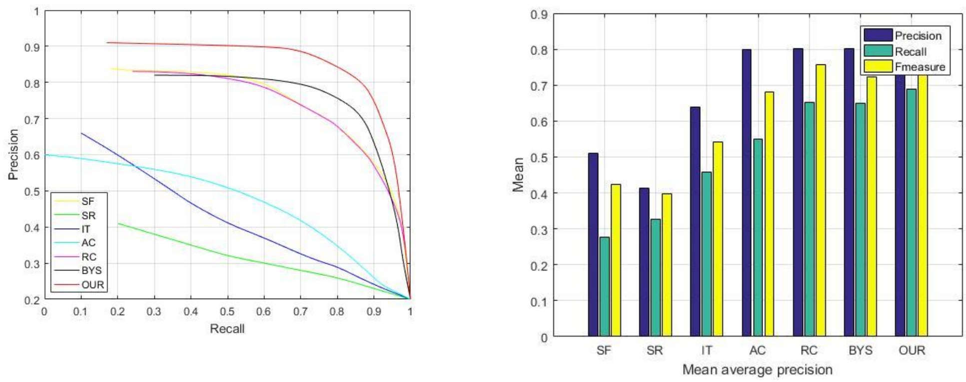

Figure 8. Comparison of various methods on ECSSD dataset.

2) Visualization evaluation: We provide a detailed comparison of our method with the above-mentioned algorithms on datasets with binary ground truth. As shown in Figure 9, our algorithm consistently produces result maps close to ground truth and has a better capability of solving the complex background. Moreover, with the help of improved convex hull, our method can uniformly locate salient object areas. The results of our approach have a significant improvement compared with previous saliency models. The result maps generated by the proposed approach also have better visualization compared with recently saliency methods. On some examples of the ECCSD dataset, our method gets poor result when the background has no obvious difference with the foreground or is much cluttered as shown in Figure 9.

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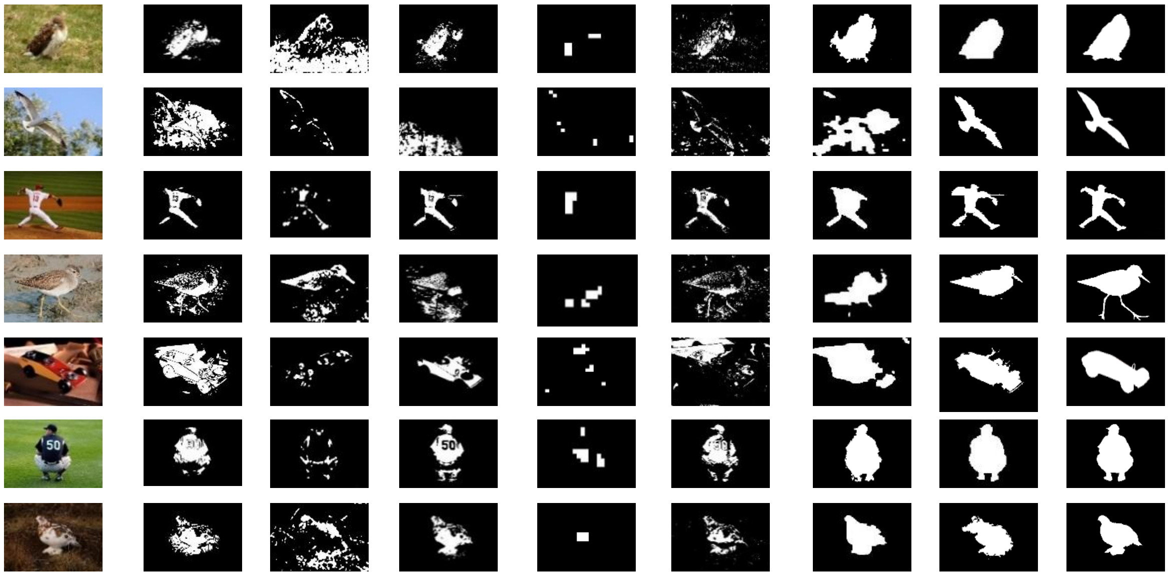

(a)Input images (b)RC (c)SR (d)SF (e)ITTI (f)AC (g)BYS (h)Our (i)GT

Figure 9. Visualization evaluation.

IV. CONCLUSION

This paper proposed a new method for color image segmentation using improved convex hull and color contrast. Firstly, the basic saliency map based on color contrast with the color uniqueness and the spatial distribution was calculated. Secondly, the central saliency map based on the improved convex hull was obtained. Then, the two saliency maps, i.e. basic saliency map and central saliency map, were fused into a final saliency map. Finally, the salient objects were segmented out from the final saliency map using Otsu method. Experimental results indicate that the proposed method has higher accurate rate and recall rate than the state-of-the-art saliency detection methods on the MSRA 1000 and ECSSD dataset. Furthermore, by explicitly combining color contrast and improved convex hull, the proposed method is more suitable for processing images with cluttered foreground compared to background.

Experimental results on images which contain multiple targets indicate that the proposed method got poor results. Moreover, when background has little difference with foreground in a color image, the proposed method could not find the object correctly. In future works, multi-target segmentation will be studied. More powerful image features for saliency detection will be considered.

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