DETECTION OF SALIENT REGION VIA HIGH DIMENSIONAL COLOR TRANSFORM AND LOCAL SPATIAL SUPPORT

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Abstract— An introduction of unique technique is proposed to automatically discover salient areas in an image. Our technique includes global and local functions to extract the features of a saliency map. The first key idea of work is to create a saliency map of a photograph via using a linear combination of colors in a excessive-dimensional color space. This is based on a statement that salient areas frequently have distinctive hues compared with backgrounds in human belief; however, human notion is complicated and especially nonlinear. By mapping the low-dimensional red, inexperienced, and blue coloration to a characteristic vector in a high-dimensional coloration area, to display and able to composite a correct saliency map by means of finding the most effective linear aggregate of color coefficients inside the excessive-dimensional shade space. To further improve the performance of our saliency estimation, our second key idea is to utilize relative region and color assessment among super pixels as functions and to resolve the saliency estimation from a tri-map to know-based totally set of rules. The extra nearby features and mastering-based set of rules complement the global estimation from the high-dimensional color transform-based algorithm. The experimental results on 3 benchmark datasets display that our technique is effective in contrast with the preceding trendy saliency estimation techniques.

Index Terms — Salient area detection, super pixel, tri-map, random forest, color channels, high-dimensional color space.

I. INTRODUCTION

In this paper, we propose a novel approach to automatically detect salient regions in an image so for that we have to generate tri-map initially. Our approach first estimates the approximate locations of salient regions by using a tree-based classifier. The tree-based classifier classifies each super pixel as foreground, background or unknown. The foreground and background are regions where the classifier classifies salient and non-salient regions with high confidence. The unknown regions are the regions with ambiguous features where the classifier classifies the regions with low confidence. The foreground, background and unknown regions form an initial tri-map, and our goal is to resolve the ambiguity in the unknown regions to estimate accurate saliency map. From the tri-map, we propose two different methods, [2] high-dimensional color transform method i.e., global salient estimation [5] and local learning based method to estimate [9] the saliency map. The results of these two methods will be combined together to form our final saliency map. The overview of our method is presented in fig.1. Our algorithm is performed in super pixel level in order to reduce computations.

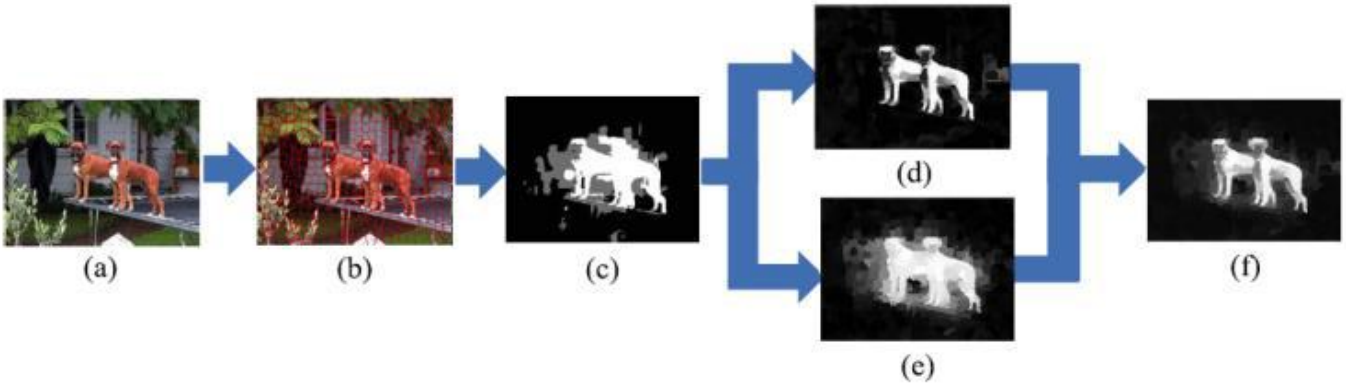

Fig. 1: Overview of our algorithm: (a) Input Image. (b) Over segmentation to superpixels. (c) Initial Salient Trimap. (d) Global Salient region via HDCT. (e) Local Salient region detection via random forest. (f) Our final saliency map

II. INITIAL SALIENCY TRIMAP GENERATION

Super pixel Saliency Features:

For an input image 1, we first perform over-segmentation to form super pixels X = {X1, . . . XN}. We use SLIC superpixel [1] because of its low computational cost. For saliency detection we first concatenate the super pixels' x- and y-locations into our feature vector. Then we concatenate the color features. Next we concatenate histogram features. The histogram feature of the super pixel DH is measured using the chi-square distance between other superpixels histograms. Where b is the number of histogram bins. In our work, we used eight bins for each histogram. For texture and shape features, we utilize the super pixel area, Histogram of gradient and singular value features [4].

$$D_H = \sum_{j=1}^{N}\sum_{k=1}^{b}[(h_{ik-}\ h_{jk})2\ /(h_{ik}+h_{jk})]$$

Initial Saliency Tri-map via Random Forest Classification:

After calculating the feature vectors for every super-pixel we use classification algorithm [5] to verify each region is salient or not. Here we use adaptive thresholding technique [10] .We decided whether each superpixel belongs to foreground candidate, background candidate, or unknown regions using the response value extracted from the classifier. If foreground= 1 and background = −1 then a superpixel's response value exceeds foreground ,then it belongs to the foreground region; however, if the value is lower than background, then it belongs to the background region; else, it is considered as unknown. From this classification we get initial saliency Tri-map which contains foreground background and unknown regions.

III. SALIENCY ESTIMATION FROM TRIMAP

In this work present global salient region detection via HDCT and learning based method. Pixels in the salient region have independent and identical color distribution. A linear combination of high dimensional color channels, separate salient regions and backgrounds. Color contrast of local feature can reduce the gap between an in autonomous and identical color distribution model implied by HDCT and true distributions of realistic images.

A. Global Saliency Estimation via HDCT

Colors are important cues in the human visual system [6]. Many previous studies have noted that the RGB color space does not fully correspond to the space in which the human brain processes colors. It is also inconvenient to process colors in the RGB space as illumination and colors are nested here. Therefore, many different color spaces have been introduced, including YUV, YIQ, CIELab, and HSV. Instead of picking a particular color space for processing, we introduce a HDCT that unifies the strength of many different color representations. Our goal is to find a linear combination of color coefficients in the HDCT space [2] such that the colors of salient regions and those of backgrounds can be distinctively separated.

B. Local Saliency Estimation via Regression

FSi j denotes the j th nearest foreground superpixel and BSi j denotes the j th nearest background superpixel from the ith superpixel. Although the HDCT color space based salient region detection provides a competitive result with a low false positive rate, this method has a limitation in that it is easily affected by the texture of the salient region, and therefore, it has a relatively high false negative rate. To overcome this limitation, we present a learning-based local salient region detection that is based on the spatial and color distance from neighboring superpixels along with HDCT color space representation. For saliency estimation, we used the superpixel wise random forest regression algorithm, which is effective for large high-dimensional data. It contains optimal linear combination of color values that results in per-pixel salient map .We extracted feature vectors using the initial tri-map. First, for each superpixel, we find the K-nearest foreground superpixels and K-nearest background superpixels . For each superpixel Xi, we find the K-nearest foreground superpixels fig.2 X FS = {XFS1, XFS2, … XFSK} and K-nearest background superpixels X BS ={XBS1, XBS2, . . ., XBSK}, and we use the Euclidean distance between a superpixel Xi and superpixels XFS or X BS as features. The Euclidean distance [8] to the K-nearest foreground (dFSi € RKX1) and background (dBSi €RKX1) features of the ith superpixel and then, we estimated the saliency degree for all superpixels.

$$d_{FS_i} = \begin{bmatrix} \left\|P_i - p_{FS_{i_1}}\right\|_2^2 \\ \left\|p_i - p_{FS_{i_2}}\right\|_2^2 \\ \vdots \\ \left\|p_i - p_{FS_{i_K}}\right\|_2^2 \end{bmatrix}, d_{BS_i} = \begin{bmatrix} \left\|p_i - p_{BS_{i_1}}\right\|_2^2 \\ \left\|p_i - p_{BS_{i_2}}\right\|_2^2 \\ \vdots \\ \left\|p_i - p_{BS_{i_K}}\right\|_2^2 \end{bmatrix}$$

We also use the color distance features between superpixels. The feature vector of color distances from the i th superpixel to the K-nearest foreground and background superpixels is defined as follows

$$d_{CF_i} = \begin{bmatrix} d(c_i, c_{FS_1}) \\ d(c_i, c_{FS_2}) \\ \vdots \\ d(c_i, c_{FS_K}) \end{bmatrix}, d_{CB_i} = \begin{bmatrix} d\left(c_i, c_{BS_{i_1}}\right) \\ d\left(c_i, c_{BS_{i_2}}\right) \\ \vdots \\ d\left(c_i, c_{BS_{i_K}}\right) \end{bmatrix}$$

Final Saliency Map Generation

After we generated the global and the local saliency maps, we combined them to generate our final saliency map shown in fig.2, therefore it shows comparison of precision recall curve of each step on MSRA dataset The examples show that the HDCT-based saliency map tends to catch the object precisely; however, the false negative rate is relatively high to textures or noise. In contrast, the learning-based saliency map is less affected by noise, and therefore, it has a low false negative rate but a high false positive rate. Therefore, combining the two maps is a significant step in our algorithm. Borji et al. [7] proposed two approaches to combine the two saliency maps. The first approach is to perform the pixelwise multiplication of the two maps, as shown below:

$$S_{mult} = \frac{1}{Z}\left(p(S_G) \times p(S_L)\right)$$

The second approach is to combine the two maps using a summation:

$$S_{sum} = \frac{1}{Z}\left(p(S_G) + p(S_L)\right)$$

In our study, we combine the two maps more adaptively to maximize our performance. Based on summation we adopt p(x) = exp(x) as a combination function to give greater weightage to the highly salient regions than multiplication of the two maps.

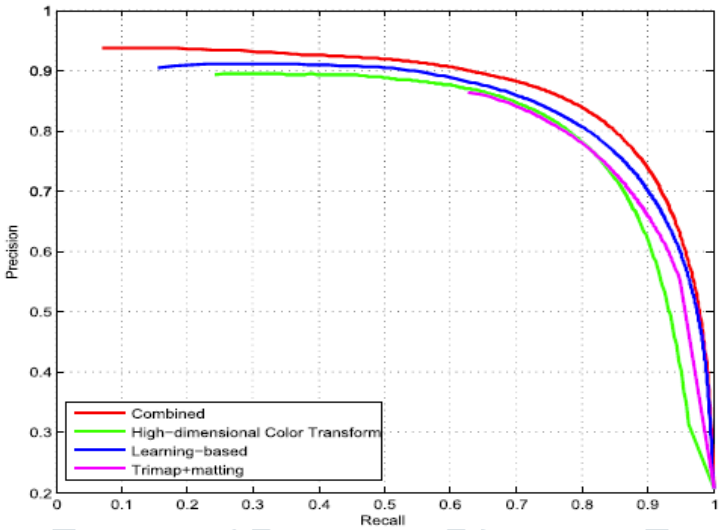

Fig.2 comparison of precision recall curve of each step on MSRA dataset

IV. BENCH MARK DATA SETS

1) MSRA-B Dataset: The MSRA-B salient object dataset contains many images with the pixel-wise ground truth used by the authors provided by Jiang et al. This dataset mostly contains comparatively salient objects in which the colors are definitely different from the background, and therefore, it is considered a less challenging dataset for salient object. For the original input image from Fig.3 we can observe color transform image, final segmented tri-map and also we get final extracted salient map for MSRA-B Dataset.

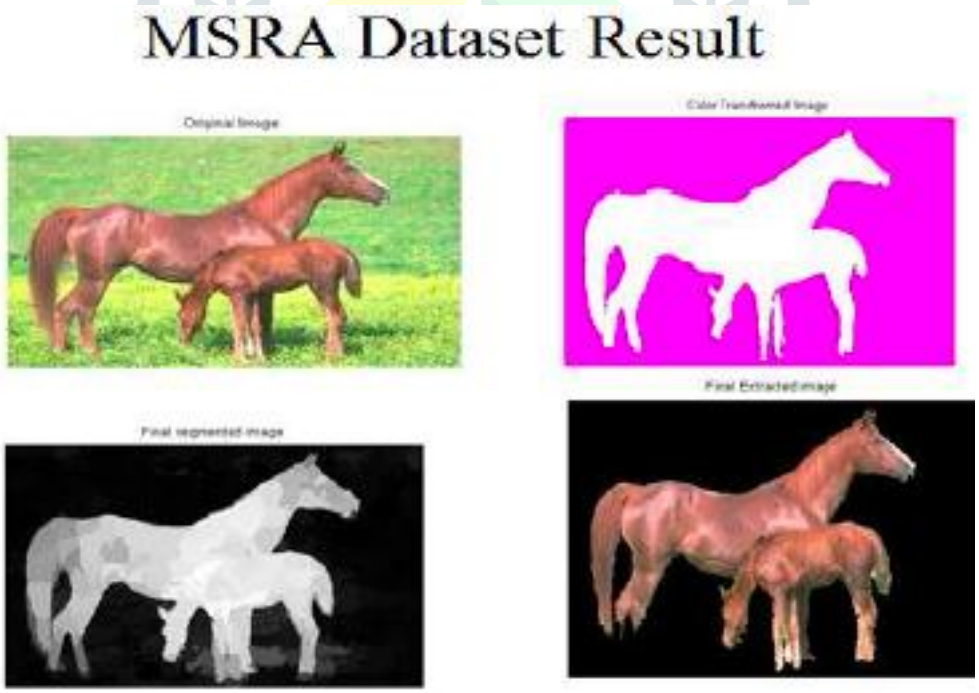

Fig. 3 MSRA dataset result

2) ECSSD Dataset: The ECSSD dataset contains many images that include multiple salient objects[3] with structurally complex backgrounds that make the detection task much more challenging, such as a green apple on a tree or a yellow butterfly on yellow flowers. In addition, many images contain a single salient object with multiple colors, making it harder to detect the salient object entirely. . For the original input image from Fig. 4 we can observe color transform image, final segmented tri-map and also we get final extracted salient map for ECSSD Dataset.

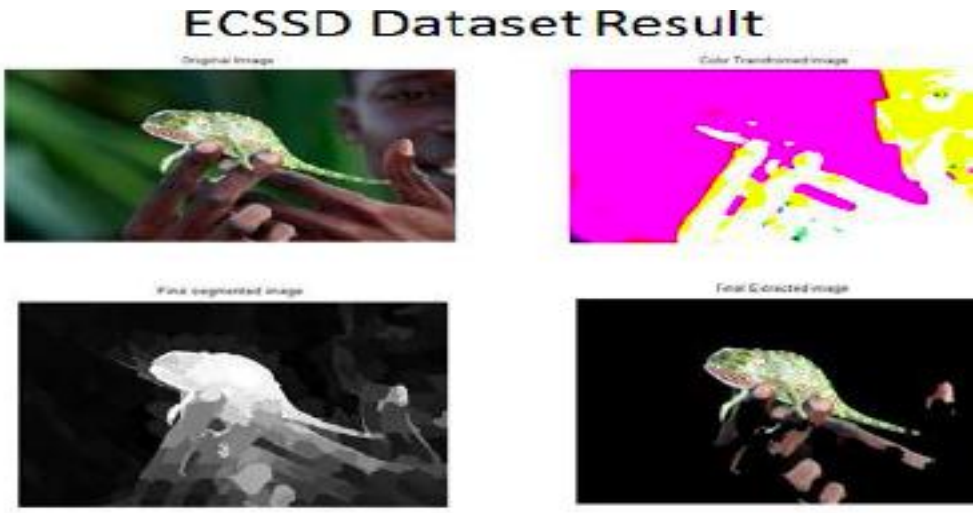

Fig. 4 ECSSD Dataset Result

3) PASCAL-S Dataset: The PASCAL-S dataset contains many images with multiple objects in a single image with pixel-wise ground-truth annotations. This dataset [3] provides both fixations and salient object annotations. However, this dataset is challenging as it contains many test images with very large or very small salient objects that are relatively difficult to detect entirely. . For the original input image from Fig. 5 we can observe color transform image, final segmented tri-map and also we get final extracted salient map for PASCAL Dataset.

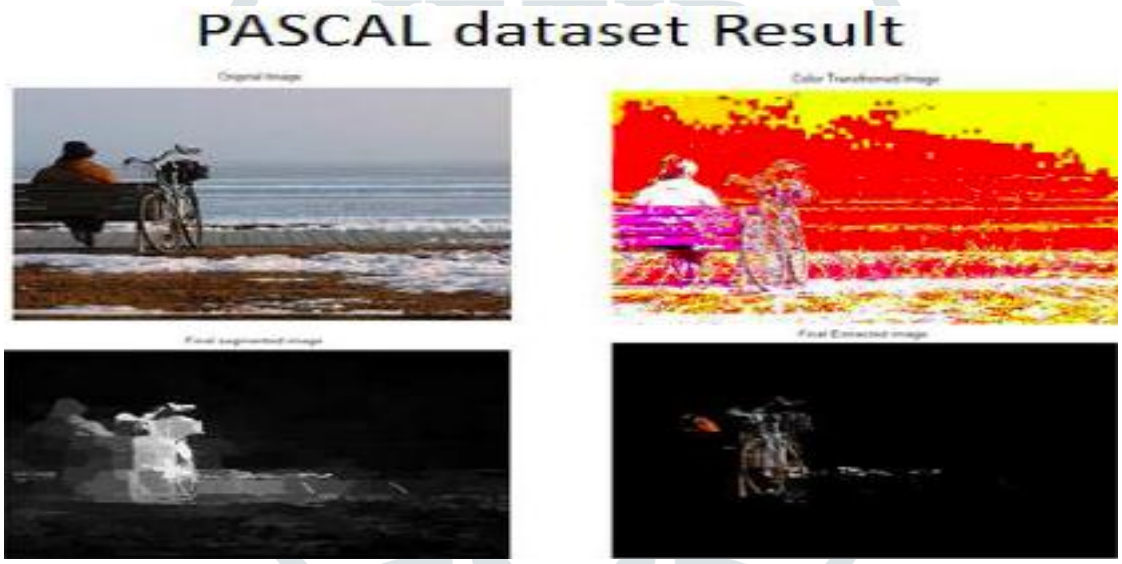

Fig.5 PASCAL-S Dataset Result

V. EXPERIMENTS

A. Benchmark Datasets for Salient Region Detection

1) MSRA-B Dataset

5,000 images are in the MSRA-B dataset with the pixel-wise ground truth. Color of saliency region different from the background region. Same training set used, including 2,500 images and the test set including 2,000 images.

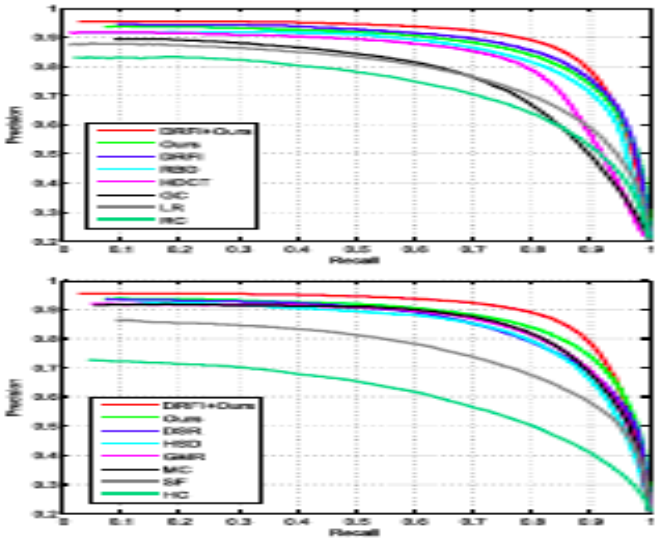

Fig.6 F-measure curve with 12 state-of-the-art algorithms on MSRA-B dataset

F-measure curve with state-of-the-art algorithm on MSRA-B dataset

B. Performance Evaluation

Use two standard criteria for calculate salient region detection algorithm: precision-recall rate and F-measure rate.

1) Precision-Recall Evaluation

The precision is also called the positive predictive value, and it is defined as the ratio of the number of ground-truth pixels retrieved as a salient region to the total number of pixels retrieved as the salient region.

VI. CONCLUSION

We have presented a novel salient region detection method that estimates the foreground regions from a trimap using two different methods: global saliency estimation via HDCT and local saliency estimation via regression. The trimap-based robust estimation overcomes the limitations of inaccurate initial saliency classification. As a result, our method achieves good performance and is computationally efficient in comparison to the state-of-the art methods. We also showed that our proposed method can further improve DRFI, which is the best performing method for salient region detection. The goal to extend the features for the initial trimap to further improves our algorithm's performance.

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