Elliptical region of interest based saliency detection

Anmol Maharana
Dept. Of Electrical Engg.
NIT, Rourkela
Rourkela, India
anurkl16@gmail.com

Dr. Smita Pradhan
School of Biomedical Engg.
IIT, BHU
Varanasi, India
ssmita.pradhan@gmail.com

Dr. Dipti Patra
Dept. of Electrical Engg.
NIT, RKL
Rourkela, India
dpatra@nitrkl.ac.in

***Abstract*—The two main tasks of computer vision problems are extraction of image descriptors and their subsiquent matching. The choice of type and level of description is task dependent, which is a low-level approach for solving computer vision problems. Saliency detection is a basic task in perceptual organization. Without any prior assumption, automatic estimation of salient object regions in an image enhances the computer vision applications. In this paper, we proposed a novel saliency detection algorithm, which evaluates the local saliencies over random elliptical regions of interests. Though the proposed algorithm is multi-scale approach, it is simple, efficient, and gives high-quality saliency maps with higher resolution as compared to other existing methods. The qualitative and quantitative results of the proposed saliency deaction algorithm consistently outperforms other state-of-the atrs realizing higher precision with better recall rates and F-measure value.**

***Index Terms*—Saliency, circular region and region of interest**

I. Introduction

Human vision has an inborn capacity to concentrate on objects of interest for an image while neglecting superfluous foundation data. The ability of an object to get noticed or to emerge out from the rest is known as salience [1]. Saliency detection in an image helps us not only to understand the human perception but also it makes easier to implement some applications object detection, classification, image segmentation, retrieval, image editing, image and video compression, etc. Bottom-up saliency analysis deals with location and object-based feature extraction [2]. Location methods observe continuously human attention shift by tracking eye movement, while the object based approaches tend to find salient objects from images. The early local method [3] used an image pyramid of different scales to calculate pixel contrast based on color and orientation features taking Gabor orientation and intensity values. Ma and Zhang [4] directly computed saliency by considering the local contrast in an image. Harel et al. [5] proposed a graphical method to nonlinearly combine local uniqueness maps from different feature channels where an image is represented as the fully connected graph. But this approach is high time taking to get a real random walker on the graph. In T.N.Vikram et al. [13] a random center-surround method was proposed which operates by computing local saliencies over random regions of an image. In Achanta et al. [7] the saliency of RGB color image can be detected converting it to CILLab color space and generating saliency maps using the local contrast of a region in image concerning its neighborhood at various scales. Hou and Zhang [9] transformed images from the spatial domain to frequency domain to get log amplitude spectrum where unexpected signals are taken as salient objects. But later it was shown that amplitude part contains very less information as the comparison to phase part. Q.Yan et al. [8] focuses on removing background by building a hierarchical model from multiple levels of the image and then integrate them to get the final result. In C.Yang et al. [10] a close graph is constructed in which each node represents a super pixel. Saliency is determined based on the rank of each superpixel. Q.Peng et al. [11] take both local and global features to determine the salient object using the conditional random field(CRF) learning methods where maximum likelihood criterion is considered for getting optimization. In C.Sheth et al. [12] a saliency method is proposed where super pixel segmentations and background priors are combined for producing optimized salient region.

In this paper, a new saliency detection technique has been proposed which combines the salient regions extracted with an elliptical region of interest at each scale. The details about different saliency detection methods, that are compared with the proposed method are provided in Section II. Section III describes the proposed methodology and the algorithm. Simulations and results are discussed in Section IV with a conclusion in section V.

II. Materials and Methods

A. Hierarchical approaches

In hierarchical approaches, Itti's approach is the most popular method [3]. For a given input image, it computes different feature maps generally established on texture, gradient, color and orientaton info. Then all feature maps are combined in to a single map using WTA network. It is very popular method and known as classical benchmark method. As the method is efficient, due to combination of different maps and multiple features, the performance is not an easy task. During fusion, the final saliency map is employed from several feature maps. Hierarchical techniques ignore visually significant patterns. Those patterns locally occoured and directed by the global statistics of images [3].

B. Graph based manifold ranking

In this method, a given node is considered as a query and the remaining nodes are ranked based on their relevancies to that given query. Hence the task is to learn the ranking function, which defines relevance between unlabelled nodes and queries. The manifold ranking is described in [10] with a given image represented with graph i.e. some salient query nodes. The saliency of each node is computed by

$$f^* = Ay \tag{1}$$

where A=learnt optimal affinity matrix$(D - \alpha w)^{-1}$

In conventional ranking approaches, the queries are labelled with GT. A new degree of confidence or saliency value is computed for each query. Then the diagonal elements of A to 0 are set during computation of ranking score by equation

$$f^* = (D - \alpha w)^{-1} y \tag{2}$$

Finally, the saliency is measured using normalized ranking score f^* with given salient queries.

C. Saliency using background prior

To compute the consistent saliency values for an object, the object of interest should lie at one of the four intersections in the centre of the image to approximate the golden ratio is about 1.6/8. The majority of super pixels along the boarder B_l make up the ground model. $BG_l \subset B_l$ Seth et al. used the Bhattacharya distance between the color histograms for distance metric is d_{ij}

$$d_{ij} = \sqrt{1 - \sum_{x=1}^{m} \sqrt{hist_i(x).hist_j(x)}} \tag{3}$$

where $hist_i$= joint CIE L*a*b* histogram of R_i, m=number of bins in histogram The saliency is determined as minimum Bhattacharya distance from any of the background region/super pixel. $R_i \epsilon BG_l$

where

$$BG_l = R_i | \frac{\sum_{j=1}^{N_b} Sort_j(d_{ij})}{N_b} < \tau, \forall_{i,j} \epsilon B_l \tag{4}$$

R_i, R_j are border super pixel with label i, j

N_b minimum number of border super pixel support

III. Proposed method

The proposed method does not down sample the input image to a lower resolution as well as not require the prior training bases. The only parameter that requires for tuning is n, i.e. number of random windows. Let the input image I be of dimension $r * c * 3$. r and c denotes the rows and columns of the image respectively. Gabor filter is used to remove the noise. Then the image is converted to $L^{'}a^{'}b^{'}$ space and disintegrated into $L^{'}a^{'}b^{'}$ channels with the same dimension as input. $L^{'}a^{'}b^{'}$ is a clasic space for computation of saliency maps as it is analogus to psycho-visual zone of human vision. The saliency maps due to $L^{'}a^{'}b^{'}$ channels are attributed as $Sa^L, Sa^a andSa^b$ respectively.

After that, n no of random sub-windows were generated for each $L^{'}a^{'}b^{'}$ channels. Then we choose the random elliptical region of interest of various sizes in the sub images lab to get $s_a s_b ands_c$. Then for a particular coordinate position, within a specified channel, the saliency value is calculated. The calculation for random sub-windows is done by sum of absolute differences (SAD) of pixel intensity and mean intensity value. To achieve the random sub-window co-ordinates, an uniform probability distribution function is used, that helps in establishing the windows without any noise towards spatial region of an image. As salient regions occur differnt scales with arbitrary positions, it is very important to calculate sub-window co-ordinate values. Hence by taking sub window of different uniform sizes we can get good visualization of salient region.

The final saliency S_a of a specific coordinate is evaluated by Euclidean distance of the saliencies of all channels in the $L^{'}a^{'}b^{'}$ space using fusion rule. The resulting saliency map S_a is normalized in the interval [0,255] and subsequently subjected to median filtering. As median filtering preserves the edges despite eliminating the noise, it is used. eta lekhidiantuThe illustrated proposed method is shown in Fig. 1. In this figure we can see the elliptical region of interests are extracted and finally they are fused to get the more informative saliency. The algorithm of the proposed scheme is as follows:

The details about window generation, saliency computation and fusion are described in [13]. In that paper, they have considered the rectangular ROI. but in our case, we have taken the elliptical ROI in to consideration. The elliptical ROI reduces the redundancy which is a lacking point in case of rectangular ROI. Also, elliptical region helps to determine the mutual infrmation among intensity values with in an image as compared to rectangular region of interest.

IV. Simulation and results

To validate our proposed saliency detection method, several sets of images are included for computaion from MSRA dataset. The images are validated with proposed technique and compared with other existing state-of-the arts. The computation is executed in MATLAB R 2017a with a system specification Intel (R) Core(TM) i5$-$2400 CPU @ 3.10GHz. Here, 4 sets of images are shown to prove the efficiency of the proposed scheme. Also the scheme is compared to three other existing schemes [8], [10], [12]. For qualitative evaluation, the deceted saliency for the proposed scleme along with the existing schemes are shown in Fig. 2. From the figure, we can observe that, the detected saliency for the proposed scheme is accurate and more informative as compared to other detected saliency. The quantitative measures such as recall, precision and F-measures metrics are evaluated. They can be computed as

$$Recall = \frac{t_p}{t_p + f_n} \tag{5}$$

$$Precision = \frac{t_p}{t_p + f_p} \tag{6}$$

$$F - measure = \frac{2 * precision * recall}{precision + recall} \tag{7}$$

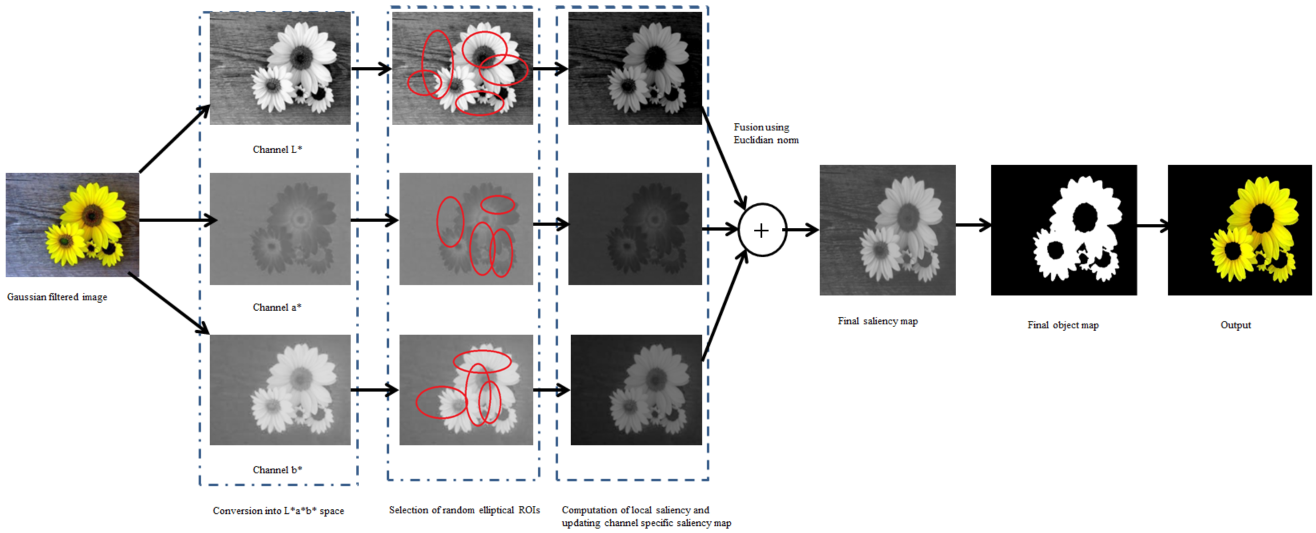


Fig. 1: Illustration of proposed method

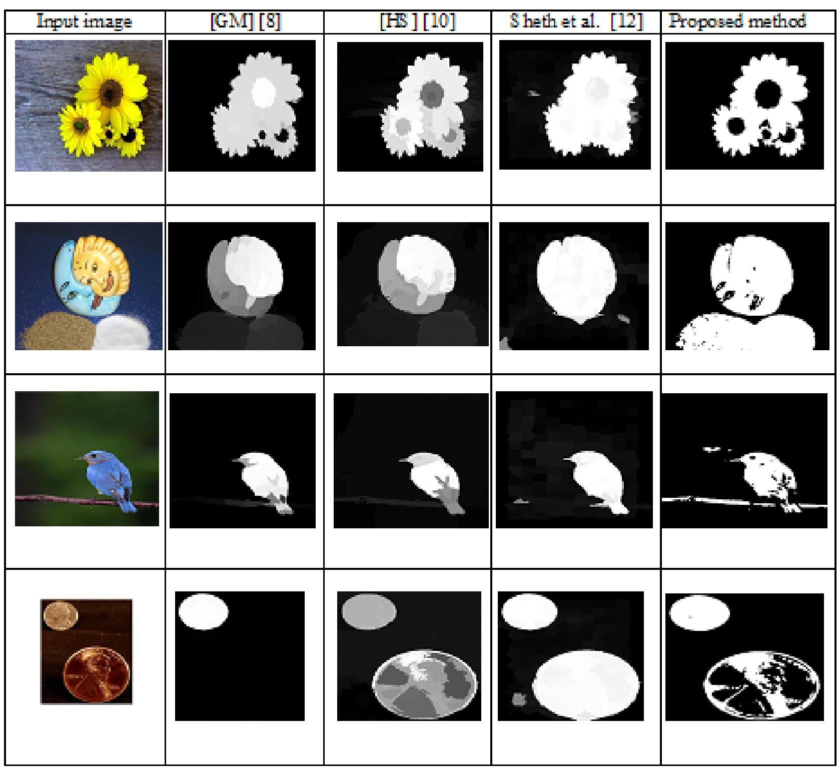
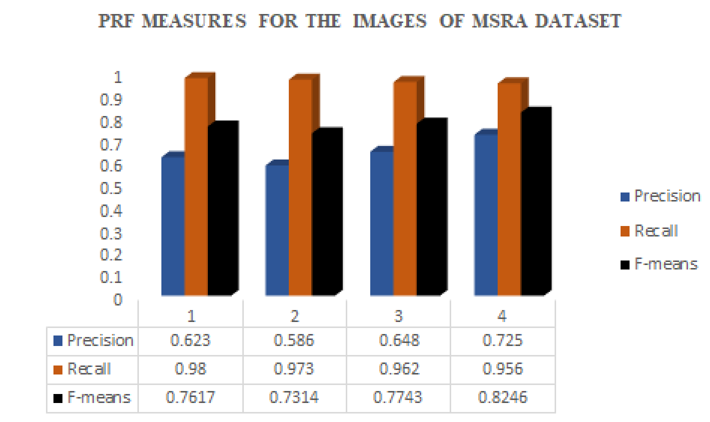


Fig. 2: 1^{st} column: original images from MSRA data sets, 2^{nd}, 3^{rd} and 4^{th} column: detected saliency using [8], [10] and [12] respectively, 5^{th} column: proposed saliency detected

where t_p, f_p are the no. of true positives and false positives. Similarly, t_n and f_n are true and false negatives.

The recall, precision and F-measure metrics for the three existing method along with the proposed scheme are shown in Fig. 3. The X-axis defines different methods such as 1: [8], 2: [10], 3: [12] and 4: Proposed scheme. Also the values of the quantitative mwasures are shown in that same figure. From the Fig. 3 it can be observed that the precision and F-measure values for the proposed scheme is higher as compared to other schemes. Here number of sub-window is taken as 0.02*r*c as a standard for determining the saliency. In Fig. 4 the performance of the proposed algorithm is evaluated by varying the number of subwindow.



	1	2	3	4
Precision	0.623	0.586	0.648	0.725
Recall	0.98	0.973	0.962	0.956
F-means	0.7617	0.7314	0.7743	0.8246

Fig. 3: Quantitative measure plot for four different methods

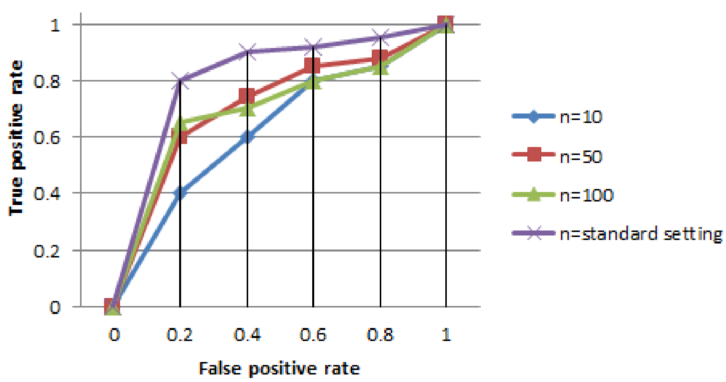


Fig. 4: Variations in ROC plots of the proposed method due to change in n on the MSRA dataset

V. Conclusion

The paper proposed a new saliency detection method, combining different salient regions from differnent scales with elliptical region of interest. At each scale, the extracted salient information helps to find the whole saliency accurately without any background noise. The ability of opting the elliptical region of interest makes the saliency detection technique more effiecient interms of precision and recall. The elliptical region of interest is invariant to contrast and scale. The precision, recall value for the proposed scheme is higher than that of existing saliency detection schemes. Though the proposed scheme takes more time to detect the saliency, it gives more accurate salient regions as compared to other schemes. The saliency detection method can be applied to medical image registration and also to segmentation.

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