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"A Performance Evaluation of Saliency Detection via Graph-based Manifold Ranking"

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Abstract— Most existing base up techniques measure the foreground saliency of a pixel or district based on its contrast inside a local setting or the whole image, whereas a couple of strategies concentrate on fragmenting out background areas and in this manner salient articles. Instead of considering the contrast between the salient articles and their encompassing locales, we consider both foreground and background cues in an unexpected way. We rank the similarity of the image components (pixels or districts) with foreground cues or background cues via graph-based manifold ranking. The saliency of the image components is characterized based on their relevances to the given seeds or inquiries. We speak to the image as a close-loop graph with superpixels as hubs. These hubs are ranked based on the similarity to background and foreground questions, based on affinity matrices. Saliency identification is carried out in a two-stage plan to extract background areas and foreground salient questions productively. Experimental outcomes on databases demonstrate the proposed technique performs well when against the state-of-the-art strategies as far as accuracy and speed.

Keywords— Foreground saliency, graph-based manifold ranking, a close-loop graph, foreground and background cues.

I. INTRODUCTION

The task of saliency revelation is to perceive the most important and informative part of a scene. It has been applied to various vision issues including image segmentation, challenge acknowledgment, image weight, content based image retrieval [8], to name a couple. Saliency methods in general can be categorized as either base up or best down approaches. Base up procedures are data-driven and pre-attentive, while beat down strategies are task driven that entails managed learning with class labels. We take note of that saliency models have been created for eye fixation expectation and salient dissent acknowledgment. The past concentrates on perceiving two or three human fixation locations on natural images, which is important for understanding human attention. The latter is to accurately recognize where the salient dissent should be, which is useful for many abnormal state vision tasks.

The main observation is that the distance between a pair of background regions is shorter than that of an area from the salient dissent and a locale from the background. The center point labeling task (either salient challenge or background) is formulated as a vitality minimization issue based on this criteria. We watch that background regularly demonstrates local or global appearance availability with each of four image boundaries and foreground presents appearance rationality and consistency. In this work, we abuse these cues to figure pixel saliency based on the ranking of superpixels. For each image, we build up a close-loop graph where each center point is a superpixel. We demonstrate saliency location as a manifold ranking issue and propose a two-stage contrive for graph labeling. Figure 1 demonstrates the main steps of the dissertation algorithm. In the principal stage, we abuse the boundary earlier [13, 22] by using the centers on each side of image as labeled background questions. From each labeled result, we figure the saliency of center points based on their relevances (i.e, ranking) to those inquiries as background labels. The four labeled maps are then integrated to generate a saliency map. In the second stage, we apply binary segmentation on the came about saliency map from the primary stage, and take the labeled foreground centers as salient inquiries. The saliency of each center point is handled based on its relevance to foreground inquiries for the final map. To totally capture intrinsic graph structure information and incorporate local gathering cues in graph labeling, we use manifold ranking systems to learn a ranking capacity, which is essential to learn an optimal affinity matrix [20]. Novel in relation to [12], the proposed saliency acknowledgment algorithm with manifold ranking requires just seeds from one class, which are initialized with either the boundary priors or foreground cues. The boundary priors are proposed pushed on the present works of human fixations on images [31], which demonstrates that humans tend to gaze at the focal purpose of images. These priors have also been used as a part of image segmentation and related issues [13, 22, 34]. In contrast, the semi-coordinated method [12] requires both background and salient seeds, and generates a binary segmentation. Moreover, it is hard to choose the number and locations of salient seeds as they are generated by random walks, especially for the scenes with various salient articles. This is a known issue with graph labeling where the results are delicate to the picked seeds. In this work, all the background and foreground seeds can be easily generated via background priors and ranking background inquiries (or seeds). As our model incorporates local gathering cues extracted from the entire image, the proposed algorithm generates especially characterized boundaries of salient articles and reliably highlights the whole salient areas. Experimental results using data sets demonstrate that the proposed algorithm performs viably and favorably against the state-of-the-art saliency identification strategies.

II. LITERATURE SURVEY

In this paper, we concentrate on the base up salient question acknowledgment tasks. Salient dissent identification algorithms usually generate bobbing boxes, binary foreground and background segmentation, or saliency maps which indicate the saliency probability of each pixel. Liu et al. [23] propose a binary saliency estimation demonstrate via training a conditional random field to join an arrangement of novel features. Wang et al. [32] analyze various cues in a united vitality minimization framework and use a graph-based saliency demonstrate [14] to perceive salient articles. In [24] Lu et al. develop a hierarchical graph demonstrate and utilize concavity setting to enlist weights between center points, from which the graph is bi-partitioned for salient question revelation. On the other hand, Achanta et al. [1] enlist the saliency probability of each pixel based on its shading contrast to the entire image. Cheng et al. [9] consider the global area contrast as for the entire image and spatial relationships across the locales to extract saliency map. In [11] Goferman et al. propose a setting aware saliency algorithm to recognize the image areas that speak to the scene based on four standards of human visual attention. The contrast of within and encompass circulation of features is prepared based on the Kullback-Leibler disparity for salient question identification [21]. Xie et al. [35] propose a novel model for base up saliency inside the Bayesian framework by abusing low and mid level cues. Sun et al. [30] enhance the Xie's model by displaying boundary and delicate segmentation. As of late, Perazzi et al. [27] demonstrate that the total contrast and saliency estimation can be formulated unifiedly using high-dimensional Gaussian channels. In this work, we generate a full-determination saliency map for each information image. Most above-said systems measure saliency by measuring local concentration encompass contrast and rarity of features over the entire image. In contrast, Gopalakrishnan et al. [12] formulate the dissent location issue as a binary segmentation or labeling task on a graph. The most salient seed and several background seeds are recognized by the behavior of random walks on a total graph and a k-regular graph. At that point, a semi-coordinated learning technique is used to initiate the binary labels of the unlabelled centers. As of late a procedure that adventures background priors is proposed for saliency acknowledgment [34].

III. SYSTEM SOLUTION

The subject of how to measure the performance of learning algorithms and classifiers has been investigated. This is an intricate question with many aspects to consider one complete of the analysis is that classifier performance is often

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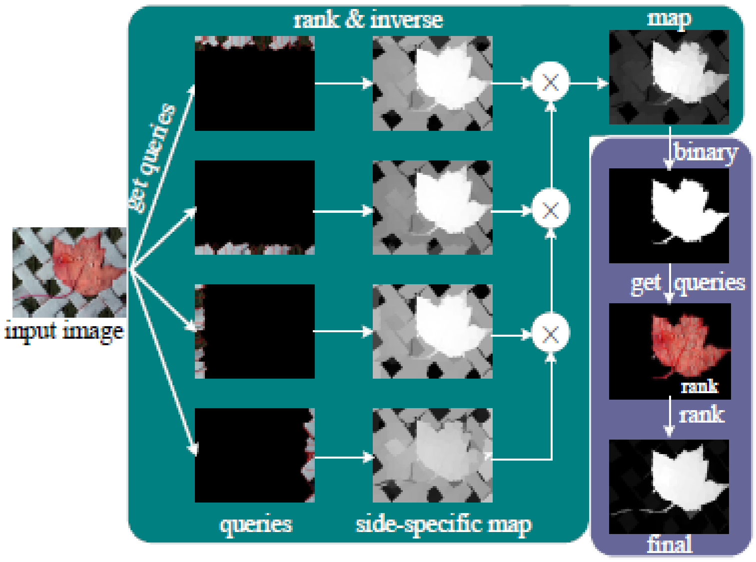
measured as far as classification accuracy, e.g., with cross validation tests. A couple of strategies were seen to be general in the way that they can be used to evaluate any classifier (regardless of which algorithm was used to generate it) or any algorithm (regardless of the structure or representation of the classifiers it generates), while distinctive methods simply are applicable to a certain algorithm or representation of the classifier.



First Stage Second Stage

Fig.1 System Model

1. Manifold Ranking

In [39], a ranking method that exploits the intrinsic manifold structure of data (such as image) for graph labeling is proposed. Given a dataset X = (x1, . . . , xl, xl+1, . . . , xn) ∈ Rm×n, some data points are labelled queries and the rest need to be ranked according to their relevances to the queries. Let f: X → Rn denote a ranking function which assigns a ranking value fi to each point xi, and f can be viewed as a vector f = [f1, . . . , fn]T .

Let y = [y1, y2, . . . , yn]T denote an indication vector, in which yi = 1 if xi is a query, and yi = 0 otherwise. Next, we define a graph G = (V, E) on the dataset, where the nodes V are the dataset X and the edges E are weighted by an affinity matrix W = [wij]n×n. Given G, the degree matrix is D = diag{d11, . . . , dnn}, where dii = Pj wij. Similar to the PageRank and spectral clustering algorithms [5, 26], the optimal ranking of queries are computed by solving the following optimization problem:

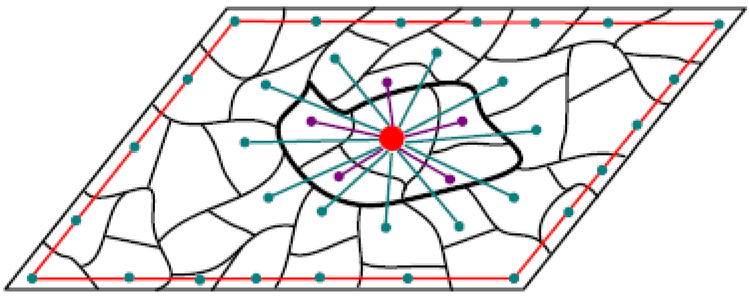


Fig.2 Our graph model.

The red line along the four sides indicates that all the boundary nodes are connected with each other.

$$\mathbf{f}^{*}=\arg\min_{f}\frac{1}{2}\left(\sum_{i,j=1}^{n}w_{ij}\left\|\frac{f_i}{\sqrt{d_{ii}}}-\frac{f_j}{\sqrt{d_{jj}}}\right\|^2+\mu\sum_{i=1}^{n}\|f_i-y_i\|^2\right), \tag{1}$$

where the parameter μ controls the balance of the smoothness constraint (the first term) and the fitting constraint (the second term). That is, a good ranking function should not change too much between nearby points (smoothness constraint) and should not differ too much from the initial query assignment (fitting constraint). The minimum solution is computed by setting the derivative of the above function to be zero. The resulted ranking function can be written as

$$\mathbf{f}^* = (\mathbf{I} - \alpha\mathbf{S})^{-1}\mathbf{y}, \tag{2}$$

where I is an identity matrix, $\alpha = 1/(1 + \mu)$ and S is the normalized Laplacian matrix, $S = D-1/2WD-1/2$. The ranking algorithm [39] is derived from the work on semi-supervised learning for classification [38]. Essentially, manifold ranking can be viewed as an one-class classification problem [29], where only positive examples or negative examples are required. We can get another ranking function by using the unormalized Laplacian matrix in Eq. 2:

$$\mathbf{f}^* = (\mathbf{D} - \alpha\mathbf{W})^{-1}\mathbf{y} \tag{3}$$

We compare the saliency results using Eq. 2 and Eq. 3 in the experiments, and the latter achieves better performance. Hence, we adopt Eq. 3 in this work.

2. Saliency Measure

Given an input image represented as a graph and some salient query nodes, the saliency of each node is defined as its ranking score computed by Eq. 3 which is rewritten as $f* = Ay$ to facilitate analysis. The matrix A can be regarded as a learnt optimal affinity matrix which is equal to $(D - \alpha W)-1$. The ranking score $f*(i)$ of the i-th node is the inner product of the i-th row of A and y. Because y is a binary indicator vector, $f*(i)$ can also be viewed as the sum of the relevances of the i-th node to all the queries. In the conventional ranking problems, the queries are manually labelled with the ground-truth. However, as

Fig.3 Graph labeling results using the top boundary prior. Top: input images. Center: Results without enforcing the geodesic distance constraints. Bottom: Results with geodesic distance constraints.

Queries for saliency detection are selected by the proposed algorithm; some of them may be incorrect. Thus, we need to compute a degree of confidence (i.e., the saliency value) for each query, which is defined as its ranking score ranked by the other queries (except itself). To this end, we set the diagonal elements of A to 0 when computing the ranking score by Eq. 3. We note that this seemingly insignificant process has great effects on the final results. If we compute the saliency of each query without setting the diagonal elements of A to 0, its ranking value in $f*$ will contain the relevance of this query to itself, which is meaningless and often abnormally large so as to severely weaken the contributions of the other queries to the ranking score. Lastly, we measure the saliency of nodes using the normalized ranking score $f*$ when salient queries are given, and using $1 - f*$ when background queries are given.

3. Ranking with Background Queries

It is commonly observed that objects of interest in a photograph often occur such that they are rarely connected to image boundaries. We use image boundary regions as query samples to rank the relevance of all other regions.Based on the attention theories of early works for visual saliency, we use the nodes on the image boundary as background seeds, i.e., the labelled data (query samples) to rank the relevances of all the other regions. Specifically, we construct four saliency maps using boundary priors and then integrate them for the final map, which is referred as the separation/combination (SC) approach.

The saliency map using the top boundary prior, St can be written as:

$$S_t(i)=1- {}^{*}(i) \qquad i=1,2.....,N \qquad (5)$$

The four saliency maps are integrated by the following process:

$$S_{bq}(i) = S_t(i) \times S_b(i) \times S_l(i) \times S_r(i) \qquad (6)$$

There are two reasons for using the SC approach to generate saliency maps. First, the superpixels on different sides are often disimilar which should have large distance. If we simultaneously use all the boundary superpixels as queries (i.e., indicating these suprerpixels are similar), the labeled results are usually less optimal as these nodes are not compactable

4. Ranking with Foreground Queries

The saliency map of the first stage is binary segmented (i.e., salient foreground and background) using an adaptive threshold, which facilitates selecting the nodes of the foreground salient objects as queries.

We expect that the selected queries cover the salient object regions as much as possible. Thus, the threshold is set as the mean saliency over the entire saliency map. Once the salient queries are given, an indicator vector **y** is formed to compute the ranking vector $\mathbf{f}^*$ using Eq. 3. As is carried out in the first stage, the ranking vector $\mathbf{f}^*$ is normalized between the range of 0 and 1 to form the final saliency map by

$$S_{fq}(i) = \mathbf{f}^*(i) \quad i = 1, 2, \ldots, N \qquad (7)$$

IV. ALGORITHM

Bottom-up Saliency based on Manifold Ranking

Input: An image and required parameters

1: Segment the input image into superpixels, construct a graph G with superpixels as nodes, and compute its degree matrix D and weight matrix W by Eq. 4.

2: Compute $(D - \alpha W)^{-1}$ and set its diagonal elements to 0.

3: Form indicator vectors y with nodes on each side of image as queries, and compute their corresponding side-specific maps by Eq. 3 and Eq. 5. Then, compute the saliency map Sbq by Eq. 6.

4: Bi-segment Sbq to form salient foreground queries and an indicator vector y. Compute the saliency map Sfq by Eq. 3 and Eq. 7.

Output: a saliency map Sfq representing the saliency value of each superpixel

V. PERFORMANCE ANALYSIS

The experimental result shows all the steps and relevant details of the saliency detection. The algorithm proposed here has been implemented in Matlab R2010b and has been executed in system with configuration Intel Dual Core i3- 2120 3.3 GHz CPU and 2GB RAM. For generating saliency map. So taking input image.

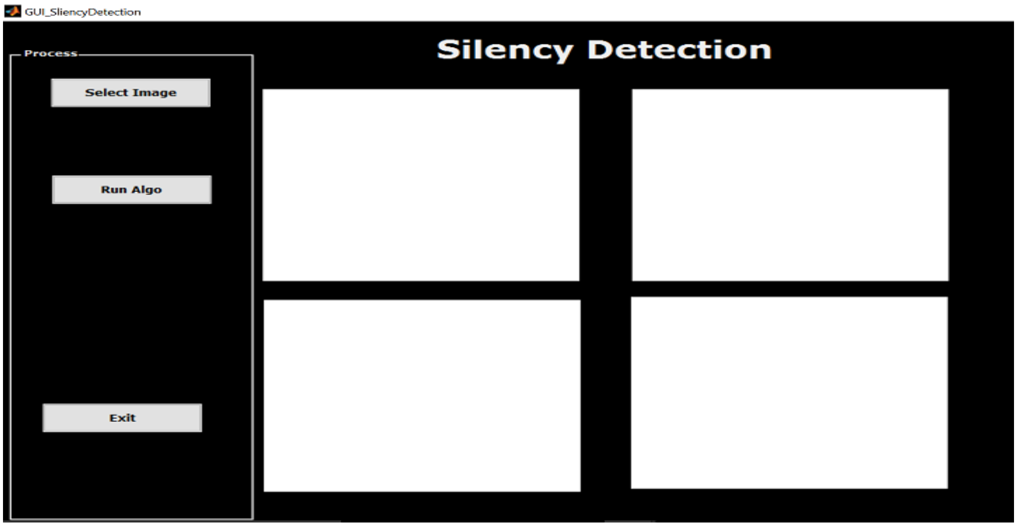


Fig.4 Saliency Detection

This Saliency Detection Software is having overview like above image. It works in a following Phases

1. **Select Image**: By selecting original image it will initiate the process.

2. **Run Algo**: This function start the Algorithm for processing. And Algorithm processes in following manner.

Fig.5 Transition Phase: Original to Super Pixel

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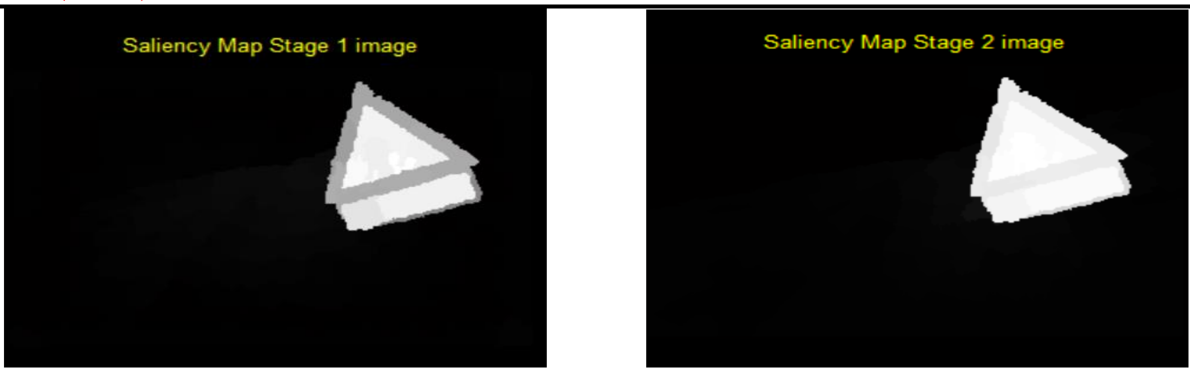


Fig.6 Saliency Map Stages

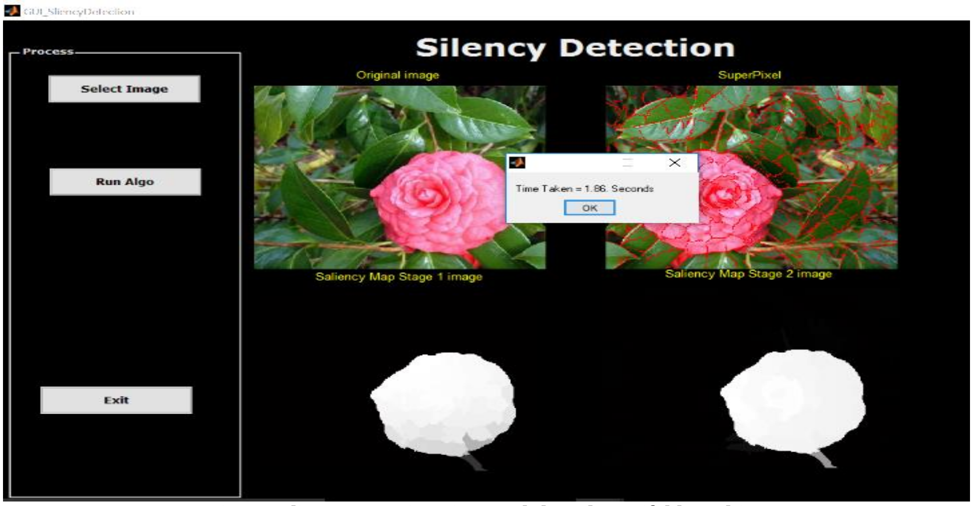
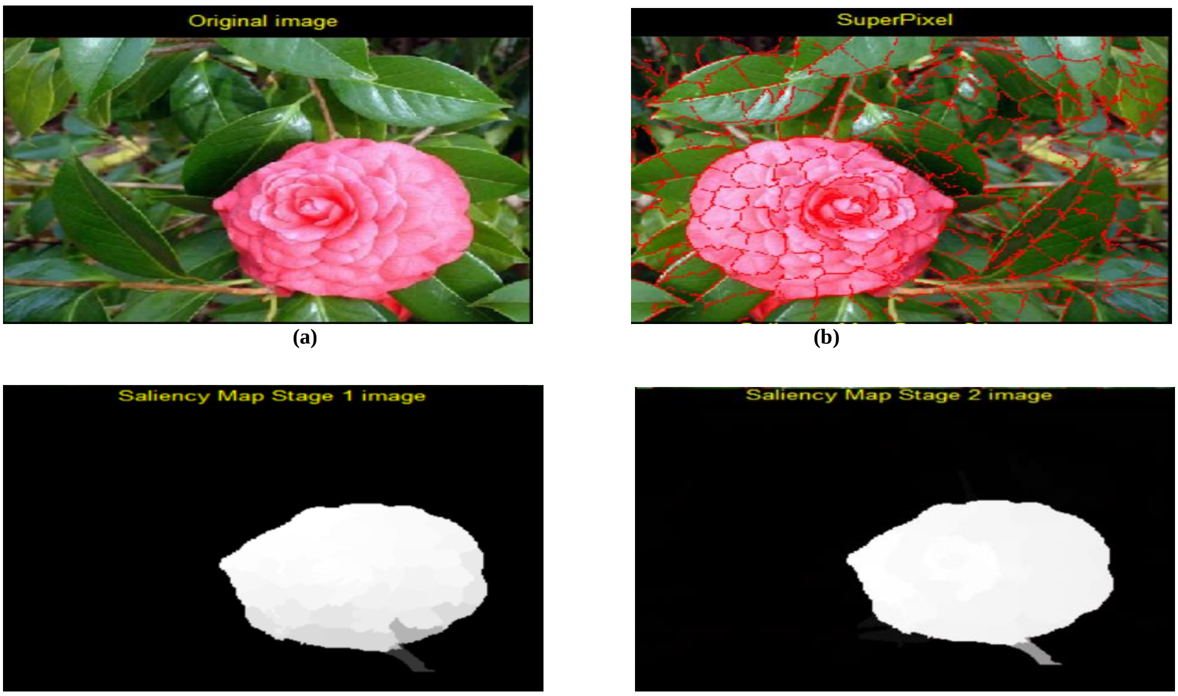


Fig. 7 Saliency Detection via Graph-based Manifold Ranking



(a) **(b)**

(c) **(d)**

Fig. 8 (a)(b)(c)(d) Change of State for Image of Rose

- **Survey Sample Saliency detection results of different method :**

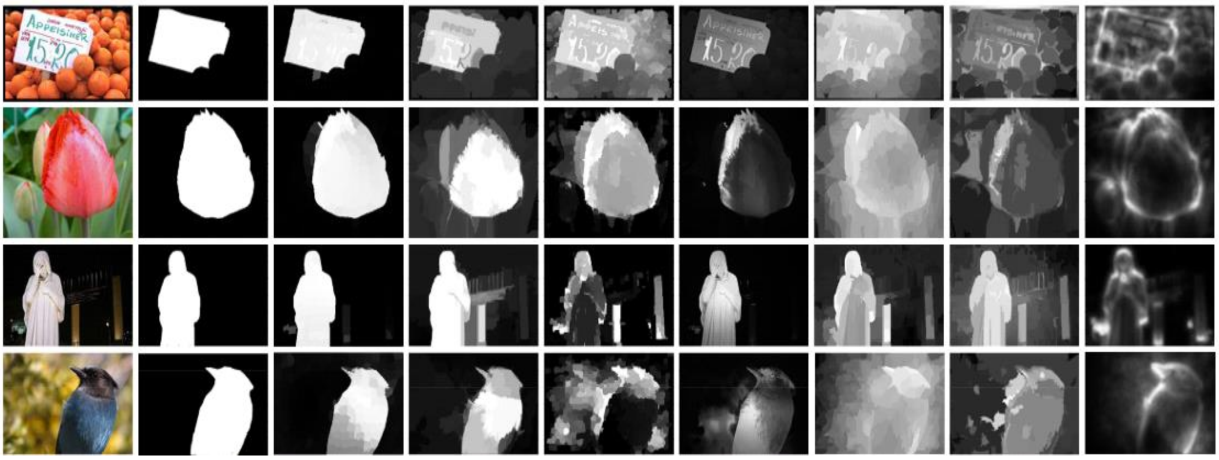


Image **Ground Truth** **GBMR** **CB** **GS-SP** **SF** **SVO** **RC** **Gof**

Fig.9 Saliency detection results of different methods, The proposed algorithm consistently generates saliency maps close to the ground truth.

- **Run Time**

The average runs time of currently top-performance methods using matlab implementation. Our run time is much faster than that of the other saliency models.

Table 1. Comparison Of Average Run Time (Seconds Per Image).

Method	Ours	Gof [12]	SVO [8]
Time(s)	3.29	38.896	79.861

V. CONCLUSION

We propose a base up strategy to distinguish salient areas in images through manifold ranking on a graph, which incorporates local gathering cues and boundary priors. We adopt a two-stage approach with the background and foreground in quiries for ranking to generate the saliency maps. We evaluate the dissertation algorithm and outcomes with comparisons to state-of-the-art strategies. Moreover, this dissertation algorithm is computationally proficient. Our future work will concentrate on integration of numerous features with applications to other vision issues.

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