Data-driven Saliency Region Detection Based on Undirected Graph Ranking

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Abstract: Highlighting saliency region is still a challenging problem in computer vision. In this paper, we present a data-driven salient region detection method based on undirected graph ranking. It consists of two steps: we first compute priori saliency map on super-pixel image by combining region contrast and center prior information, and then extract saliency map by optimized ranking function based on a new affinity matrix. It is simple and efficient. Furthermore, salient objects can be successfully highlighted with precise details and high consistency. We evaluate the proposed method with three image datasets. The experimental results show that the proposed approach has a good performance in terms with the PR curve, the ROC curve.

Key-Words: - Image saliency, salient region, affinity matrix, undirected graph ranking

1 Introduction

Visual saliency is an intractable problem in neuroscience, psychology, neural systems, and computer vision [1]. Gestalt principle states that human vision generally pays more attention to one or more central region rather than background region in the scene. The main task of image saliency detection is to estimate the position of the salient object(s) and make its salient value higher than other background regions in a scene. The extracted saliency map can be applied to: image segmentation [2, 3], image retrieval [4], dominant color detection [5] et al.

Saliency detection can be attributed to two types: one [6, 7] is task-driven, top-down; the other [8-16, 18] is data-driven, bottom-up. The top-down methods pay attention to a specific object and produce salient features by supervised learning on a larger dataset which contains the specific object. While bottom-up methods just rely on underlying data. In this work, we focus on bottom-up saliency region detection.

In this paper, we regard saliency detection as an undirected graph ranking problem, and learn a grading function that directly maps the regional feature to a saliency score. The proposed salient algorithm contains two parts: the first part is priori saliency detection, the second part is optimizing saliency map on undirected graph, and the flow chart is shown in Fig.1. Specifically, the proposed method uses super pixel method SLIC[17] (Simple Linear Iterative Clustering, SLIC) to segment image into different regions, in which each super-pixel represents a node, and then utilizes the image contrast and the center prior relationship to calculate priori saliency nodes. Lastly, regional saliency is calculated by using the optimal sorting based on a constructed affinity matrix, in which priori significant clusters are marked as the given node sequences by the binary segmentation.

The main objective of this work is to propose a data-driven salient region detection method based on undirected graph ranking. By combining region contrast and center prior information, a new method is proposed to compute priori saliency map, and we construct an affinity matrix to weight edges between any pair of nodes on undirected graph. Finally we acquire saliency map by optimizing ranking function.

The remainder of this paper is organized as follows. In Section 2, we review the main work related to saliency detection in recent year. In Section 3, we introduce how to model the salient object. Specifically, in Section 3.1, the priori noteworthy object extraction by combining region contrast and center prior is presented. And then we optimize the salient object by ranking on undirected graph in Section 3.2. The experimental results are shown in Section 4. Finally, conclusions are drawn in Section 5.

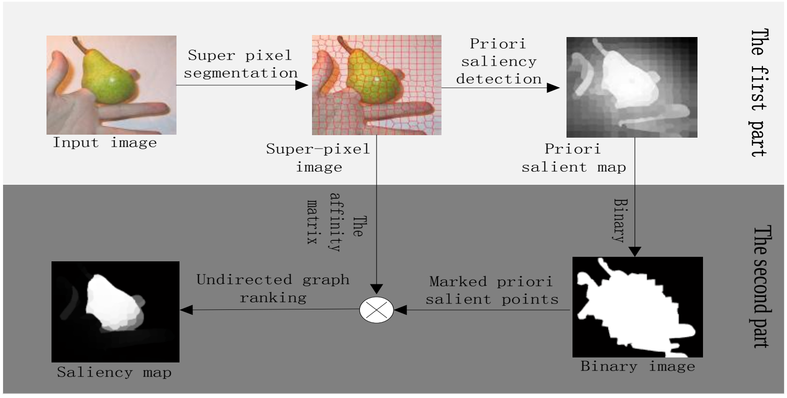


Fig.1 The flow chart of the proposed algorithm

2 Related Works

Bottom-up saliency research has attracted many domestic and foreign scholars attention in the literature. In detail, Itti et al. [8] model the saliency detection algorithm based on center-surround differences across multi-scale image features. Ma and Zhang [10] put forward image saliency by contrast-based fuzzy growing method. Harel et al. [11] propose graph-based salient detection method, in which Itti and colleagues' feature maps are normalized to highlight conspicuous parts and Markov chain is used to extract the saliency map. Zhou and Zhang et al. [12] raise a spectral residual approach to detect saliency. However, these methods concern more with saliency pixels where the salient object could appear in a scene, their common features are that salient object is blurred in saliency map. Later, many scholars tend to pay more attention to salient objects or regions in the scene and the salient object with precise details and high consistency become an important basis for evaluation of the merits of the algorithm. In [13], saliency map is computed by exploiting the center-surround principle which compares color features of each pixel with average values of the whole image. This method is simple and efficient. However, it fails for images with cluttered backgrounds. Goferman et al. [14] present a context-aware salient detection algorithm based on four principles of human visual attention. Xie [15] uses Bayesian framework to detect saliency which obtains clearer salient object. This method can obtain better salient object, however, it does not work well if the salient points do not appear around the saliency region or the points scatter over a rather large region. Luo and Chen [18] base on path price and fuzzy reasoning calculate saliency. Yang et al. [16] propose a graph-based manifold ranking algorithm to detect salient objects, which exploits the nodes of four image boundaries as background to detect saliency regions, it performs better in most cases. Since the algorithm utilizes image boundaries to detect saliency, it can lead to a non-significant area in the image center is highlighted incorrectly.

In recent years, saliency detection has made great achievements, but there are still some issues deserving improvement. Firstly, the methods usually require dealing with more background data than the interesting objects. Secondly, they produce high salient values in the edges of rapidly changed or complex background regions. In addition, some approaches have high complexity.

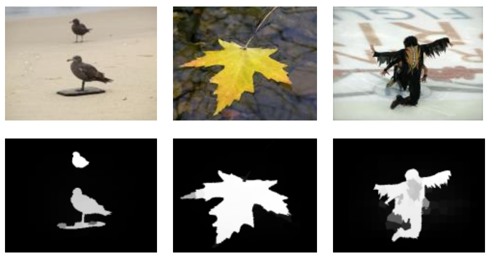


Fig.2 Original images (top) and their saliency maps using our algorithm (bottom).

In this paper, we exploits super-pixel image to detect salient regions or objects based on contrast and center prior information. The results perform well, but we also find that traces between super pixels in saliency map are obvious. Simultaneously the results distinguish small cluttered background regions in some case. To address these issues, we are partially inspired by [16], and reconsider the undirected graph ranking and their relationship with saliency detection. We optimize the saliency map by the ranking of super pixels. Different from [16], we use region contrast and center prior information detect salient object, and reconstruct a close-loop graph based on colour distance and spatial distance metric for each image to rank saliency of nodes, in which each node is a super pixel in the graph. We test our approach on MSRA-B、iCoSeg and SED databases, the experimental results indicate vestiges between super pixels in final saliency map are weakened and the consistency of salient object can be improved. The proposed method performs efficiently and favorably against the state-of-the-art methods. Some examples of final result are shown in Fig.2.

3 Saliency Detection Based on Undirected Graph Ranking

Based undirected graph ranking is a semi-supervised learning algorithm. By marking a set of given nodes, the similarity between the remaining nodes and the labeled nodes can be obtained by ranking function. Image saliency is reflected through the similarity of pixel nodes during the salient detection. In this paper, we detect the priori saliency map to provide the known node sequences, and construct correlation matrix for ranking, finally calculate the saliency map by undirected graph sorting function.

3.1 Priori Saliency Map

In this section, we utilize the prior saliency information to establish a priori significant detection model.

Contrast: Image contrast and spatial relationship are important features for image saliency in previous saliency research [9, 14, and19]. In detail, the pixels which have a higher contrast against others pixels will be marked with high saliency. Conversely, low contrast withstanding other pixels will obtain lower saliency. Furthermore high contrast to its surrounding regions is usually stronger evidence for saliency of a region than high contrast to far-away regions.

Center Prior: when humans take pictures, they naturally frame an object of interest near the image center, and saliency map based on the distance of each pixel to the center of the image provides a better prediction of the salient object than many previous saliency models [14, 31].

Inspired by this, we further incorporate a center prior to our saliency estimation. That is, an object near the center of the image is more likely to be a salient object. The closer the pixels with high contrast get to the image center, the higher saliency should be obtained. Fig.3 shows the contribution of the contrast and the spatial relationship (relative and absolute spatial relationship) to image saliency. In this paper we define the relative spatial relationship is the spatial distance between super pixels (or regions), and the absolute spatial relationship is the distance from super pixels to the center of the image.

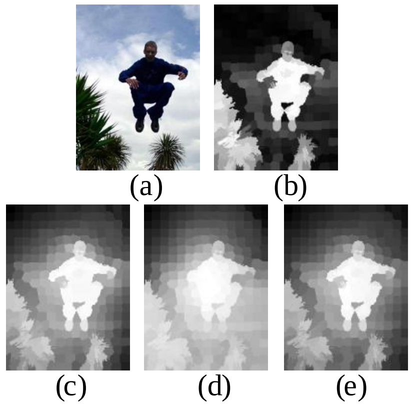


Fig.3 The results of saliency detection by using priori saliency knowledge. (a)-(e): the source image, priori saliency map based on the contrast, priori saliency map which results of the contrast and relative spatial relationship, the priori saliency map which results of the contrast and absolute spatial relationship, our priori saliency map.

Based on the analysis above, we use the following formula to calculate significant contribution degree $d\ (p_i,\ p_j)$ for the super pixel p_i against super pixel p_j:

$$d(p_i,\ p_j) = \frac{d_{color}(p_i,\ p_j)}{d_{c-position}(p_i,\ p_j) + c * d_{s-position}(p_i)} \tag{1}$$

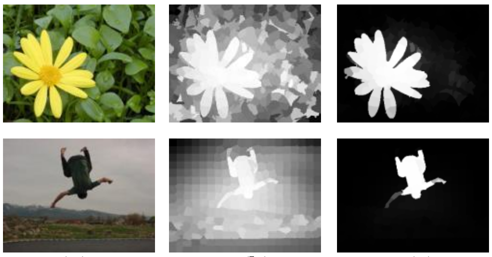
Where, c is the location parameter, $d_{c\text{-}position}\ (p_i,\ p_j)$ is Euclidean distance of the position between super pixel p_i and p_j. The $d_{s\text{-}position}\ (p_i)$ is the Euclidean distance from the super-pixels p_i to the image center. This paper regards the centroid of the super pixel region as super-pixel spatial position, and normalized to the range [0 1]. The $d_{color}\ (p_i,\ p_j)$ is Euclidean distance between super pixel p_i and p_j in the CIE L * a * b color space, normalized to the range [0 1] through the maximum. Super-pixel p_i is denoted by the mean of the pixels in corresponding super-pixel image region.

As mentioned above, the super-pixel p_i is salient when $d\ (p_i, p_j)$ is high $\forall j \in \{1, 2, 3, ..., K\}$. Hence, the priori salient nodes $S_{priori}\ (pi)$ of the super-pixel p_i can be calculated as:

$$S_{priori}(p_i) = 1 - e^{-\frac{1}{K}\sum_{j=1}^{K} d(p_i,\ p_j)} \tag{2}$$

Where, K is the total number of super-pixels.

'Center prior' used in the proposed approach is valid in many cases. However, it is not valid in general cases. For example in first saliency map of Fig.4 (b), we can find that the salient object is outstanding well when salient object deviate from the image centre regions, but the some small background regions are highlighted incorrectly. In addition, traces between super pixels in saliency map are not suppressed well. So it may be not sufficient detect salient object based on contrast and centre prior. We need more information to improve the performance. In this paper, we use an undirected graph sorting method to solve these problems.



(a) (b) (c)

Fig.4 Saliency map of two parts. (a): the original image, (b) the saliency map, (c) the results based on undirected graph ranking.

3.2 Saliency Detection Based on Undirected Graph Ranking

We introduce undirected sorting algorithms briefly, and construct an affinity matrix based on an undirected K-regular graph to optimize ranking function. Finally, we compute the saliency map by ranking the super pixel nodes.

3.2.1 Undirected Graph Ranking

Firstly, let $G = (V, E, \omega)$ be a weighted data graph, where $V= \{v_1, \ldots, v_n\}$ is a finite set of vertices corresponding to data points, $E \in V \times V$ a set of edges, and ω: $E \rightarrow R^+$ a weight function, together with a small number of examples of order relationships among vertices in V (data points). The set of order relationships among elements of V can be expressed as a weighted graph of its own, which we shall call the order graph and represent by $\Gamma = (V, \Sigma, \tau)$, where $\Sigma \in V \times V$ and τ: $\Sigma \rightarrow R^+$; the interpretation is that if $(v_i, v_j) \in \Sigma$, then v_i is to be ranked higher than v_j, and the penalty for mis-ordering such a pair is given by (v_i, v_j). The order graph can thus be thought of as providing labelled nodes for ranking [20].

In this paper we treat the case when the data graph $G = (V, E, \omega)$ is undirected, i.e., when E consists of unordered pairs of vertices in V. The goal is to find a function F: $V \rightarrow R$ that minimizes a suitable combination of the empirical error and a regularization term that penalizes complex functions. The initial value of F is $y= \{y_1, \ldots, y_n\}^T$, if v_i is labelled then $y_i = 1$, else $y_i=0$. Edges E are weighted by an undirected graph matrix $W_{n\times n}$; F must satisfy the smoothness constraint and fitting constraint [21]. Therefore, we can get the optimal scheduling problem according to the PageRank algorithm and spectral clustering algorithms [16, 20, 22, and 23]:

$$F^* = \arg\min_{F\in R^n}[F^T LF + \mu(DF-y)^T(DF-y)] \tag{3}$$

Where, $\mu>0$ for the optimization parameters, $w_{ij} \in W$, $L=D-W$, W is n order affinity matrix $W_{n\times n}$, D is n order diagonal matrix, and $D_{ii} = \sum_{j=1}^{n} w_{ij}$. Optimized sorting function F^* can be expressed as:

$$F^* = \beta(D-\alpha W)^{-1} y \tag{4}$$

Where

$$\alpha = \frac{1}{1+\mu}, \text{ and } \beta = \frac{\mu}{1+\mu}.$$

As stated in [16, 30], defining a suitable affinity matrix W is of key importance. Since Neighbouring nodes may have a similar salient values, we use a K-regular undirected graph to represent the relationship of nodes, and structure the affinity matrix W based on image contrast and spatial information, and the formula can be expressed as (5).

$$w_{ij} = \begin{cases} e^{-\frac{1}{\sigma^2} * \frac{\| p_i - p_j \|}{d_{c-position}(p_i,\, p_j)}} & , p_j \in K(p_i) \\ 0 & , p_j \notin K(p_i) \end{cases} \tag{5}$$

Where, let $K(p_i)$ be the neighbouring node sets of super pixel p_i. $\sigma>0$ is the affinity coefficient to measure the strength of the association between the two nodes.

3.2.2 Undirected Graph Ranking for Saliency Detection

The priori salient clusters $S_{priori}(p_i)$ are marked as labelled nodes by the binary segmentation, which facilitates selecting the nodes of the salient objects as the known node sequences. The value F_i of the pixel salient clusters is calculated by the sorting mapping (4). In order to make salient object nodes labelled as accurately as possible during binary, the threshold T is set by Otsu method [26] among priori salient nodes $S_{priori}(p_i)$. Otsu takes the maximum variance between regions as threshold selection criteria, and can achieve better results. And the threshold is calculated as (6).

$$\delta_b^2(T_A) = \max_{0\le T\le L} \delta_b^2(T) \tag{6}$$

Where, $\delta_b^2(\cdot)$ is variance between regions, T represents the threshold, and L=max{ S_{priori} (p_i) }. T_A expresses a threshold when variance takes the maximum. So we can compute the initial value of F as follow:

$$y_i = \begin{cases} 1, S_{priori}(p_i) \geq T_A \\ 0, S_{priori}(p_i) < T_A \end{cases} \quad (7)$$

Where, K is the total number of super-pixels.

Therefore, the F_i can be ranked by (4). The final saliency map of the image can be expressed:

$$S(p_i) = F_i \quad (8)$$

Where, $S(p_i)$ is saliency map, $F_i \in F^*$.

4 Experimental Results

To demonstrate the efficiency of the proposed approach, we evaluate our algorithm on three common image databases, and evaluate the priori saliency maps and saliency maps based on undirected graph ranking by PR (Precision-Recall, PC) curves and ROC (Receiver operating characteristic, ROC) curves to explain the validity of the method based on undirected graph ranking. In addition, we also report both quantitative and qualitative comparisons of our approach against state-of-the-art methods (DRFI [1], IT [8], RC [9], GBVS [11], SR [12], FT [13], CA [14], GBMR [16], SVO [30], RA [32], and LC [33]).

4.1Test Database Set of Experiment

MSRA-B [6]. The database contains 5000 images, and the salient objects in the image were annotated with a bounding box. Later, salient objects were manually labeled by Jiang et al [1].

iCoSeg [27,28]. The data set is a co-segmentation set, provides 38 groups of 634 images, along with pixel ground-truth hand annotations. We use this set to test image saliency algorithm.

SED [29]. The data set has two subsets: one is SED1, which has 100 images, and each image contains a significant object; the other is SED2 with 100 images, each image has two significant objects. And the SED provides annotation with the labeled salient object for each image.

4.2 Evaluation Metrics

The PR curve and ROC curve are used to evaluate the algorithm performance. The precision value is the ratio of salient pixels correctly assigned to all the pixels of extracted regions, which reflects the accuracy of the detection algorithm. The recall value corresponds to the percentage of detected salient pixels in relation to the ground-truth number, which represents the detection sensitivity. The PR curve represents their relationship in this paper, similar with prior works [1, 25], the PR curves are obtained by binary segmented the saliency map using thresholds in the range of 0 and 255. The ROC curve can also be generated based on true positive rates and false positive rates obtained during the calculation of PR curve.

4.3 Performance Comparison

Setup and Experimental Environment. In all the algorithms tested, the number of super-pixels K = 300. In equation (1), the location parameter c=0.8, weighting the relative and the absolute spatial relationship. The optimizing parameter μ = 0.01 in equation (3), weighing smoothness constraint and fitting constraint (keep the same with Zhou et al [20, 21]). In calculating the affinity matrix W, taking σ^2= 0.1 measures strength of the association between two nodes. All algorithms were tested on a Dual Core 2.8GHz machine with 2GB RAM.

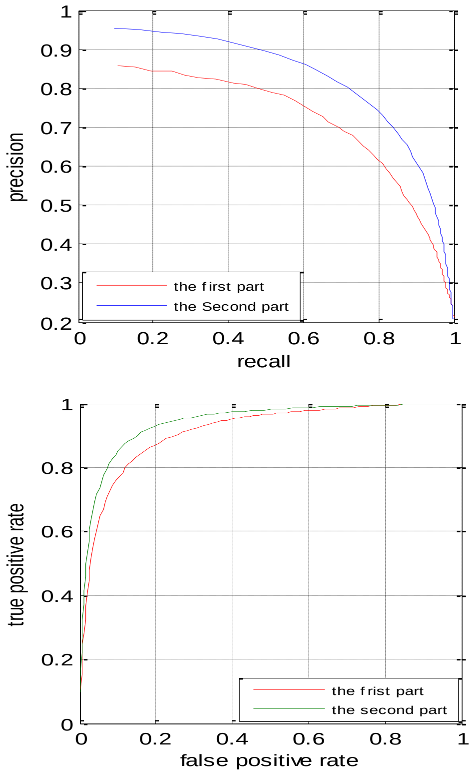


Fig. 5 Two part quantitative comparison of the proposed method on the MSRA-B database. Bottom: PR curves, the ROC curves.

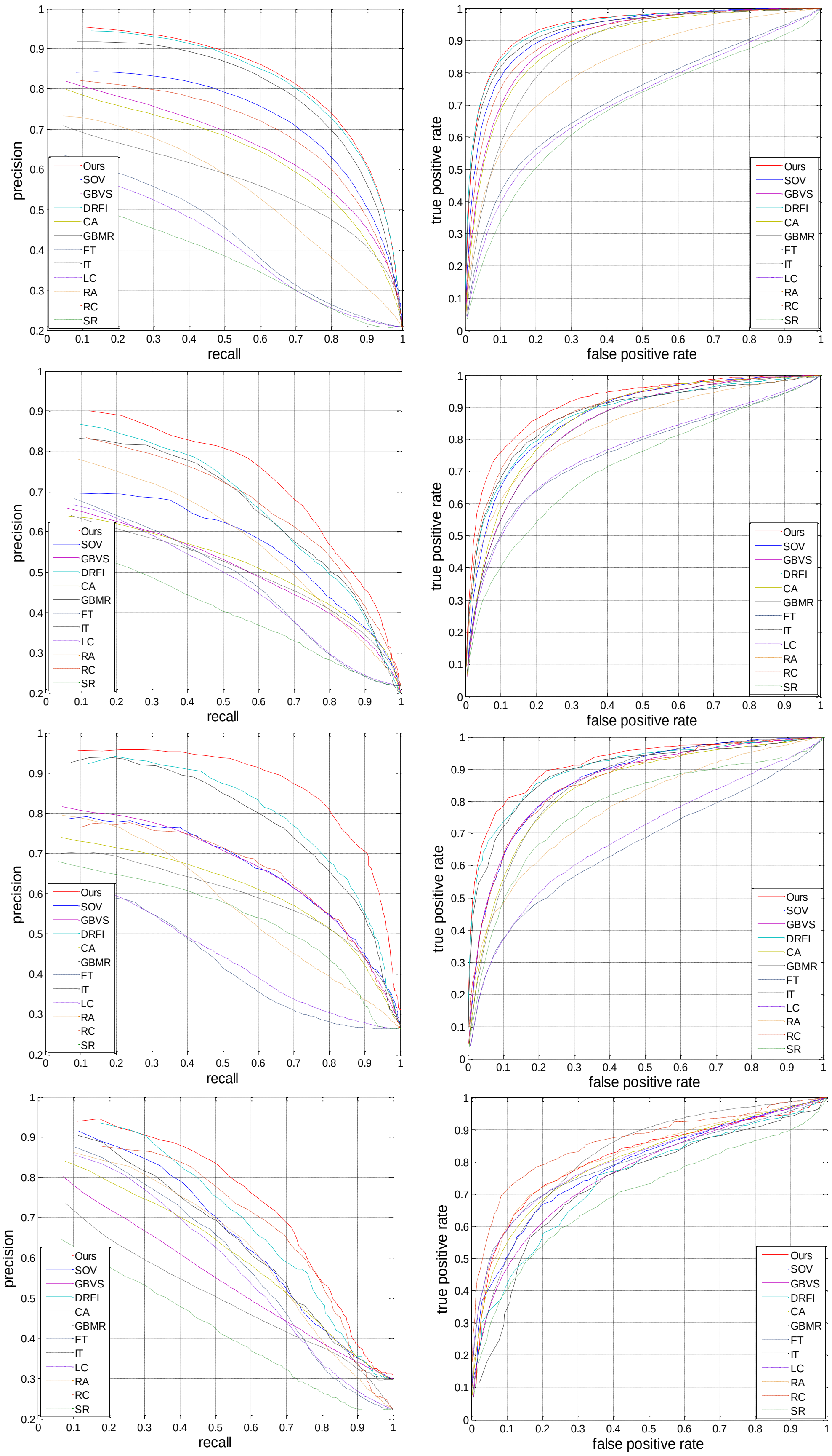
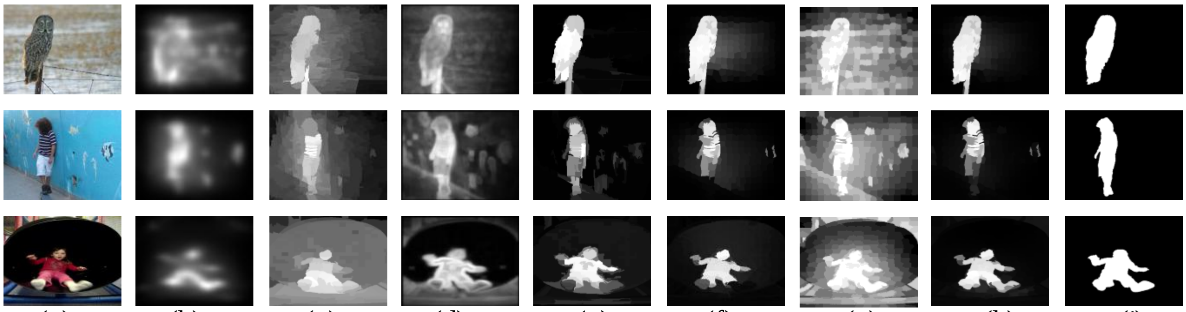


Fig. 6 Quantitative comparison of saliency methods on three image databases. From top to bottom: the MSRA-B database, the iCoSeg database, the SED1 database, the SED2 database. From left to right: the PR curve, the ROC curve.

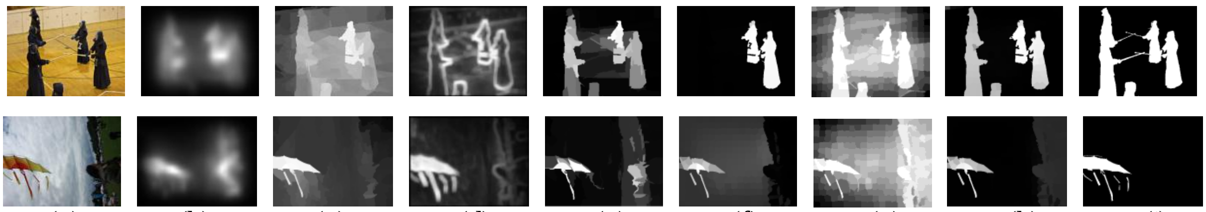
Comparison between The First Part and The Second Part. We examine the design options of the proposed algorithm. The PR and the ROC curves between two parts of the proposed methods on MSRA-B are provided, which are shown in Fig.5. Results of first part illustrate that the priori saliency detection performs well in terms of PR and ROC curves, while the ranking based on undirected graph can enhance the performance of the proposed algorithm.

Quantitative Comparison. We evaluate the proposed method against eleven state-of-the-art methods. Fig. 6 shows the PR and the ROC curves of the mentioned algorithms on three image databases. From Fig. 6 we find that the proposed method has better performance than the other methods on the ICoSeg and SED datasets. On the MSRA-B database, DRFI [1] algorithm and the proposed algorithm perform better, which is shown in first figure of Fig. 6(a), but different from DRFI, the proposed algorithm needn't training data set. On the SED2, the ROC of RC [9] performs better, while RC propose a regional contrast based saliency extraction algorithm, it fails to cluttered and textured sense. However, the IT [8], GBVS [11], and SR [12] force on salient points, and the objects of prominence are imprecision in their saliency maps, so there is no obvious advantage to detection salient objects compared with the proposed approach.



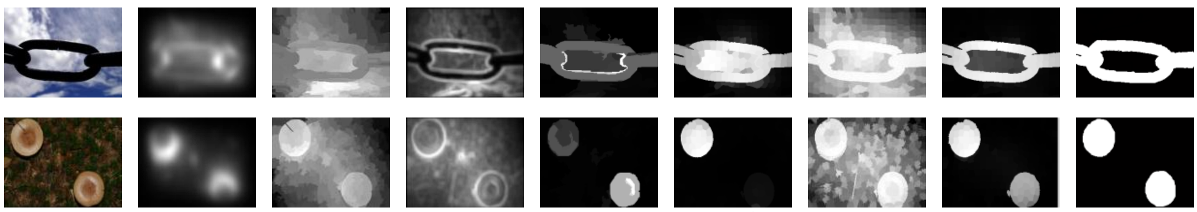
(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 7 The saliency maps of different methods on the MSRA-B database. (a) the original images , (b)GBVS, (c) SVO, (d) CA, (e) DRFI, (f) GBMR, (g)Priori map in the first part, (h) Ours, (i)true-ground.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 8 The saliency maps of different methods on the iCoSeg database. (a) the original images , (b)GBVS, (c) SVO, (d) CA, (e) DRFI, (f) GBMR, (g)Priori map in the first part, (h) Ours, (i)true-ground.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 9 The saliency maps of different methods on the SED database. (a) the original images , (b)GBVS, (c) SVO, (d) CA, (e) DRFI, (f) GBMR, (g)Priori map in the first part, (h) Ours, (i)true-ground. From top to bottom: the SED1 database, the SED2 database.

Table 1 Average running time taken to compute a saliency map for images in the MSRA-B database.

Method	CA	SVO	GBVS	GBMR	Ours
Time(s)	72.29	53.42	2.085	0.255	0.822

Qualitative Comparison. The visual comparison of different methods are provided in Fig. 7、Fig. 8、Fig. 9, and the true-grounds are provided at the same time. Compared with the prior saliency map in the first part, our final results can suppress interference of the non-significant area, and further improve the performance by undirected graph sorting. GBMR yield good salient object in most case, but algorithm over-enhance non-significant region near the center area of some images, as can be seen in the first salient map in Fig. 9 (f). Compared with the presented algorithm, DRFI has stronger inhibitory ability for the non-notable back-ground region. However, the consistency of the salient object is weaker, which can be shown the second salient map in Fig. 8 (e) and Fig. 9 (e). CA algorithm highlights the feature of the salient object edges (shown the second salient map in Fig. 7 (d). However, it is weaker for SVO algorithm to inhibit the non-notable back-ground region, and salient map of GBVS is more blurred.

4.4 Running Time

We compare the running time of saliency maps between the proposed method and others. Table 1 shows the average time taken by each method for all the 5000 images in the MSRA-B database. All the compared algorithms are implemented in matlab so as to enhance the comparability of the different algorithms. Note: The super pixel generation by SLIC [17] spends 0.163s, we have no considered in GBMR and the proposed method.

The running time of experimental results on the MSRA-B database demonstrated that using super pixel method SLIC [17] to detect the image saliency (the proposed method and GBMR) can run more efficiently than the pixel-by-pixel salient detection algorithms (CA, SVO, and GBVS). Compared with the per-pixel salient detection algorithms, running time of the proposed algorithm is faster 71.13s、52.60s、1.236s respectively than CA algorithm、SVO algorithm、GBVS algorithm on the MSRA-B database. Although GBMR algorithm runs faster, our algorithm has better performance in terms of PR curve, ROC curve, and visual quality.

5 Conclusion

We presented a bottom-up saliency detection algorithm based on undirected graph ranking, which incorporates region contrast and center prior. Firstly, the proposed method detected salient regions on super-pixel image, which made our algorithm running faster than per-pixel methods. Then the priori conspicuous object was proposed. Further-more we exploited ranking based on a constructed affinity matrix to weaken the traces between super pixels in saliency map as well as inhabit the saliency of small background regions. Experimental results on three databases show that the proposed method consistently outperformed existing saliency detection methods, yielding higher PR curve and ROC curve, as well as had a satisfactory visual quality and the running time. In future work, we will pay more attention on improving the proposed method running time or building a new model by incorporating high-level knowledge, which makes the algorithm has even better performance.

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