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A prior regularized multi-layer graph ranking model for image saliency computation

Yun Xiao [a], Bo Jiang [a], Zhengzheng Tu [a], Jixin Ma [b], Jin Tang [a,*]

[a] School of Computer Science and Technology, Anhui University, Hefei 230601, China
[b] Department of Computing and Information Systems, University of Greenwich, London SE10 9LS, UK

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ABSTRACT

Bottom-up saliency detection has been widely studied in many applications, such as image retrieval, object recognition, image compression and so on. Saliency detection via manifold ranking (MR) can identify the most salient and important area from an image efficiently. One limitation of the MR model is that it fails to consider the prior information in its ranking process. To overcome this limitation, we propose a prior regularized multi-layer graph ranking model (RegMR), which uses the prior calculating by boundary connectivity. We employ the foreground possibility in the first stage and background possibility in the second stage based on a multi-layer graph. We compare our model with fifteen state-of-the-art methods. Experiments show that our model performs well than all other methods on four public databases on PR-curves, F-measure and so on.

1. Introduction

Humans can identify the most salient and important area in a scene. In order to simulate this ability of human vision system in computer vision, more and more researchers pay attention to the study of the visual saliency detection. It has been a pre-processing procedure and widely used in many applications, such as image retrieval [1,2], object recognition [3,4], image compression [5,6] and so on.

Visual saliency detection can be classified into video saliency detection [7,8] and image saliency detection by using different input data. We focus on the second. Image saliency detection tends to find the salient regions, while the mission of segmentation [9,10] is to divide the digital image into multiple image subregions. Image saliency detection can be generally fell into three categories. Top-down methods[11–13] are task-driven by using the high-level knowledge. Bottom-up methods [14–16] are data-driven and rely on the assumptions of the background and foreground. Mixed models [17–19] are combined by top-down and bottom-up models. According to the technical method used, saliency detection can be divided into deep learning models [20–24] and traditional models. To avoid time-consuming training by deep learning models, we focus on traditional and bottom-up methods. Some state-of-the-art bottom-up saliency detection methods are presented in [25]. Boundary prior, contrast prior, boundary connectivity and so on are widespread to use in many models [14,26–28]. Itti et al. [14] propose a fusional model as a pioneer, which get saliency maps by fuse the color, direction and gray features of input images. With decades of development, more and more effective methods are appeared. Harel et al. [15] propose a graph-based visual saliency detection model. Gopalakrishnan et al. [29] firstly construct a completely graph and a k-regular graph by image patch and obtain the global and local properties of image. And then, they regard the saliency detection as Markov random walk on graphs to get the final results. Classically, Wei et al. [26] exploit geodesic saliency by using boundary and connectivity priors, which focus more on the background instead of the object. Yang et al. [27] calculate the saliency values by using a manifold ranking function and the relationships of all super-pixels. Zhu et al. [28] describe the boundary connectivity and present a general energy optimization framework to optimize the final results. Li et al. [30] propose a novel approach that take advantage of both region-based features and image details. Wang et al. [31] put forward a saliency detection approach by exploiting both local graph structure and background priors. Tu et al. [32] explain an minimum spanning tree representation instead of the super-pixel representation and propose an exact and iteration free solution on the tree. Xia et al. [33] try to find what is and what is not a salient object, and present a new model by ensembling linear exemplar regressors.

* Corresponding author.
E-mail address: tj@ahu.edu.cn (J. Tang).

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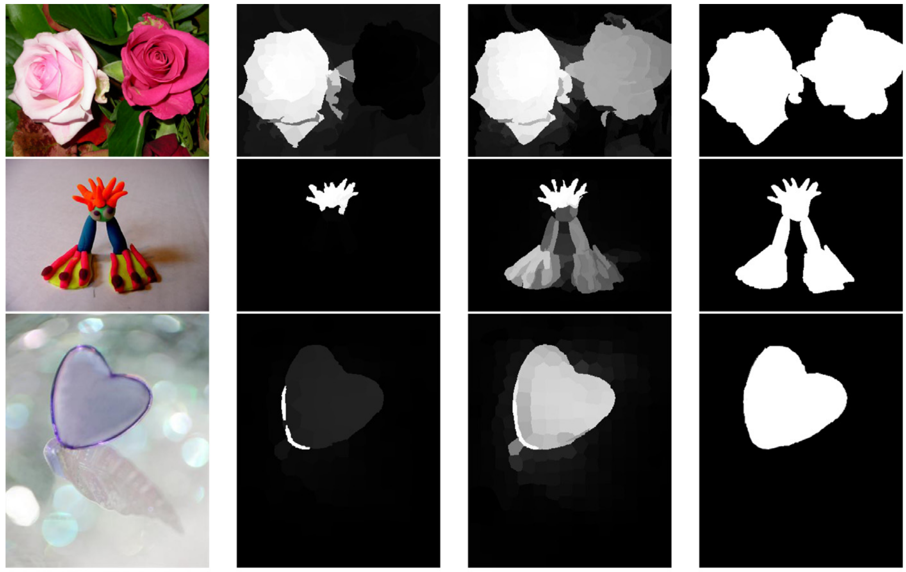

(a) Input (b) MR (c) Ours (d) GT

Fig. 1. (a) Input image; (b) The results by using MR method; (c) The results by using our method; (d) The ground truth.

2. Related work

Manifold ranking is firstly proposed to exploit the intrinsic manifold structure of data [34], which is used in many computer vision problems including image retrieval [35], person re-identification [36], video concept detection [37], co-saliency detection [38,39], object tracking [40,41] and object co-segmentation [42]. He et al. [35] propose a a general transductive learning framework, in which they initialize a pseudo seed vector firstly and then spread its scores via manifold ranking to all the unlabeled images. Loy et al. [36] obtain results by propagating the query information along the unlabeled data manifold in their model. Tang et al. [37] raise structure sensitive manifold ranking model by taking local distribution differences into account to more accurately measure pairwise similarity by instead of using distance only. Yao et al. [38] present a novel co-saliency detection framework to solve the two sub-problems by using two-stage multi-view spectral rotation co-clustering. Han et al. [42] employ a novel two-stage co-segmentation framework to address the robustness issue by using the background prior instead of strong prior knowledge.

As a popular graph-based method, manifold ranking model plays an important role in saliency detection. But the traditional manifold ranking saliency model [27] is not considering the existing prior information. In actual conditions, the prior is useful to the saliency detection, which can lead to raise a better performance. We can get many prior information from multiple ways. For better to employ them, we propose a prior regularized graph ranking model (RegMR) to obtain the saliency maps. Our preliminary work on RegMR has been present in work [43]. Moreover, we extend our prior regularized graph ranking model (RegMR) to multi-layer case and propose a multi-layer RegMR model by using a multi-layer graph. The results are showed in Fig. 1. The main contributions of this work are enunciated as follows: Firstly, we propose a prior regularized multi-layer graph manifold ranking model to make better use of the existing prior information. Secondly, we can get the close-form solution and obtain the final results of the function. At last but not the least, we get more efficient results by many experiments.

3. Brief review of manifold ranking

For an image, Yang et al. [27] use simple linear iterative clustering (SLIC) algorithm [44] to gain n super-pixels as graph nodes in manifold ranking(MR) method. A graph $G=(V,E)$ is first constructed, where nodes V represent the super-pixels X and edges E denote the affinities $\mathbf{W}$ between pairs of super-pixels. Formally, let $X=\{x_1,x_2,\cdots,x_n\}$ be the set of super-pixels as graph nodes. Let $\mathbf{q}=(\mathbf{q}_1,\mathbf{q}_2,\ldots\mathbf{q}_n)$ be the indication vector of queries. If x_i is a query super-pixel, $\mathbf{q}_i=1$, else $\mathbf{q}_i=0$. The aim of MR is to gain a ranking value $\mathbf{r}_i$ for each node $x_i \in X$ according to its relevance to the queries $\mathbf{q}$. Then, MR computes the optimal ranking $\mathbf{r}$ by solving

$$\min_{\mathbf{r}} \quad J_{\mathrm{MR}} = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\mathbf{W}_{ij}\Big(\frac{\mathbf{r}_i}{\sqrt{\mathbf{d}_i}}-\frac{\mathbf{r}_j}{\sqrt{\mathbf{d}_j}}\Big)^2+\mu_0\sum_{i=1}^{n}(\mathbf{r}_i-\mathbf{q}_i)^2, \quad (1)$$

where $\mathbf{d}_i=\sum_{j=1}^{n}\mathbf{W}_{ij}$. It is known that the above MR model has a closed-from solution and the optimal solution [27] $\mathbf{r}^*$ is given by

$$\mathbf{r}^*=\Big(\mathbf{I}-\frac{1}{1+\mu_0}\mathbf{S}\Big)^{-1}\mathbf{q},$$

where $\mathbf{S}=\mathbf{D}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}^{-\frac{1}{2}}$, $\mathbf{D}=\mathrm{diag}(\mathbf{d}_1,\mathbf{d}_2,\ldots\mathbf{d}_n)$ and $\mathbf{I}$ is an identity matrix.

To get more effective result, MR model obtains another ranking function [27] by using the un-normalized Laplacian matrix as,

$$\mathbf{r}^*=\Big(\mathbf{D}-\frac{1}{1+\mu_0}\mathbf{W}\Big)^{-1}\mathbf{q} \quad (2)$$

4. Prior regularized multi-layer graph ranking model

Model formulation. Let $X^k=\{x_1^k,x_2^k,\ldots,x_{N_k}^k\}$ be the set of graph nodes in L_k layer $(k=1,2,\ldots,K)$, $\mathbf{W}^k$ is an affinity matrix of relationship between pairs of nodes in the L_k layer, $\mathbf{C}^{kk'}$ is an affinity matrix of relationship between pairs of nodes separately from the L_k and L'_k layers. Let $\mathbf{q}^k=(\mathbf{q}_1^k,\mathbf{q}_2^k,\ldots\mathbf{q}_{N_k}^k)$ be the indication vector of queries. if x_i^k is a query node, $\mathbf{q}_i^k=1$, otherwise, $\mathbf{q}_i^k=0$. Then, we can get the ranking value r_i^k of the node x_i in the L_k layer by