IJMTARC – VOLUME – V – ISSUE – 20 , DEC , 2017 ISSN: 2320-1363

Salient Region Detection via Integrating Diffusion-Based Compactness and Local Contrast

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ABSTRACT Salient region detection is a challenging problem and an important topic in computer vision. It has a wide range of applications, such as object recognition and segmentation. Many approaches have been proposed to detect salient regions using different visual cues, such as compactness, uniqueness, and objectness. However, each visual cue-based method has its own limitations. After analyzing the advantages and limitations of different visual cues, we found that compactness and local contrast are complementary to each other. In addition, local contrast can very effectively recover incorrectly suppressed salient regions using compactness cues. Motivated by this, we propose a bottom-up salient region detection method that integrates compactness and local contrast cues. Furthermore, to produce a pixel-accurate saliency map that more uniformly covers the salient objects, we propagate the saliency information using a diffusion process. Our experimental results on four benchmark data sets demonstrate the effectiveness of the proposed method. Our method produces more accurate saliency maps with better precision-recall curve and higher F-Measure than other 19 state-of-the-arts approaches on ASD, CSSD, and ECSSD data sets.

Index Terms—Salient region detection, compactness, local contrast, diffusion process, manifold ranking, random walks.

INTRODUCTION

VISUAL attention is an important mechanism of the human visual system. It filters out redundant visual information and effectively selects highly relevant subjects, which are called the salient objects. Visual attention is considered to involve two mechanisms: stimulus driven [1] and task

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driven [2]. The stimulus-driven mechanism is often called bottom-up, and is fast, involuntary, and purely based onlow-level visual stimuli. The task-driven mechanism is called top-down, and is based on high-level information such as prior knowledge of the task, emotions, and expectations. Accordingly, computational visual attention methods can be categorized into bottom-up [3]–[12] and top-down [13], [14] methods. In this paper, we focus on bottom-up salient region detection tasks. Salient region detection methods aim to completely highlight entire objects of interest and sufficiently suppress background regions. Their output can be used for numerous computer vision problems such as image classification [15], [16], object detection and recognition [17], [18], image compression [19], and image segmentation [20], [21]. As a fundamental computer vision task, salient region detection has been extensively studied over the past few years, and a number of algorithms have been proposed [22]–[27]. Most bottom-up salient region detection methods rely on visual cues to consistently separate the salient object and background. These cues include uniqueness [3], [5], [7], compactness [9], [28], [29], and background [10], [12], [30]. Most uniqueness-based methods use low-level features of the image (such as intensity, color, and orientation) to determine the contrast between image pixels or regions and their surroundings. According to the contrastive reference regions, these methods can be roughly divided into local- and global contrast-basedmethods. Local contrast-based methods consider the uniqueness of pixels (or superpixels, image regions) with respect to their surrounding regions or local neighborhoods, whereas global contrast-based methods consider contrast relationships over the entire image. Unlike uniqueness-based methods, which consider the uniqueness of low-level features in the feature space, compactness based methods consider the spatial variance of features. Ideally, salient pixels (or superpixels, image regions) tend to have a small spatial variance in the image space, whereas the background is distributed over the entire image and has a high spatial variance. Background based methods use boundary

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and connectivity priors derived from common backgrounds in natural images [10]. These methods are primarily motivated by the psychophysical observations that salient objects seldom touch the image boundary, and most background regions can be easily connected to each other.

RELATED WORK

Our work focuses on bottom-up salient region detection. A comprehensive survey of visual attention and saliency detection can be foundin [32]–[34],and a quantitative analysis of different methods was provided in [35]. According to the type of visual cue, bottom-up salient region detection methods can be broadly classified into uniqueness, compactness, and background based. Furthermore, uniqueness-based methods can be roughly divided into local and global contrast-based techniques. One of the first local contrast-based methods was the model of Itti et al. [3]. They used a difference of Gaussians approach to extract multi-scale color, intensity, and orientation information from images. This information was then used to define saliency by calculating center-surround differences. Ma and Zhang [36] proposed an alternate local contrast analysis for generating saliency maps. They directly computed center-surround color differences in a fixed neighborhood for each pixel, and then extended the saliency map using a fuzzy growth model. Harel et al. [4] proposed a graph based visual saliency method for non-linearly combining local uniqueness maps from different feature channels to concentrate conspicuity. Hou and Zhang [5] introduced a model in the frequency domain, which defines the saliency of a location based on the difference between the log-spectrum feature and its surrounding local average .Achanta et al. [37] calculated the saliency by computing center-surround contrasts of the average feature vectors, between the inner and outer sub-regions of a sliding square window. Liu et al. [38] computed centersurround histograms over windows of various sizes and aspect ratios in a sliding window. They trained a conditional random field to combine different features for salient object detection. Jiang et al. [8] used the differencebetween the color histogram of a

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regionand its immediately neighboringregionsto evaluate the saliency score. Global contrast-based methods compute the saliency of individual pixels or image regions using contrast relationships over the complete image. Zhai and Shah [39] computed pixel-level saliency using the contrast with all other pixels. Bruce and Tsotsos [40] exploited Shannon's selfinformation measure in a local context to compute saliency. Achanta et al. [6] achieved globally consistent results based on a frequency-tuned method, which directly defines pixel saliency using the difference from the average image color. Goferman et al. [41] highlighted salient objects with their contexts by simultaneously modeling local low-level clues, global considerations, visual organization rules, and high-level features. Cheng et al. [7] proposed a regional contrast-based saliency extraction algorithm, which simultaneously considers the global region contrast over the entire image in the Lab color space and the spatial coherence, and used them to compute a saliency map. Lang et al. [42] detected salient positions by determining the consistently sparse elements from the entire image. Cheng et al. [43] proposed a soft image abstraction approach that captures large-scale perceptually homogeneous elements, thus effectively estimating global saliency cues. Zhu et al. [44] proposed a tag-saliency model for estimating the probability that each over-segmented region is salient, according to the global contrast of low- and high-level information in the scene. Compactness-based methods have recently produced promising results. Gopalakrishnan et al. [28] considered that low-level features in the background have a larger spread than the salient regions. They presented a robust salient region detection framework based on the color and orientation distribution of images, and used the compact assumption to select a saliency map using the smaller spatial variances. Perazzi et al. [9] derived a pixel-accurate saliency map by simultaneously exploiting color and position to rate a region's uniqueness and spatial distribution. These are formulated in a unified way using high-dimensional Gaussian filters. Shi et al. [29] proposed a generic and fast computational framework

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called PISA, which imposes spatial prior terms on the color and structure contrast measures, so that the salient pixels are constrained to be compact and centered in the image. They concluded that fusing complementary contrast measures with a spatial prior significantly improved the effectiveness of the detection process. Cheng et al. [43] considered that a spatially compact distribution is another important saliency indicator, and is an important complementary cue to the contrast. They used the appearance similarity and spatial distribution of image pixels to produce perceptually accurate salient region detection results.

PROPOSED METHOD

In this section, we present an efficient and effective saliency region detection method that integrates diffusion-based compactness and local contrast, as shown in Fig. 3. We first abstract the image into superpixels and construct a graph. Next, we compute two complementary saliency maps using the compactness visual cue and local contrast. The resulting saliency maps are propagated using a diffusion process and the constructed graph. Finally, we integrate the two computed saliency maps to generate a pixel-wise saliency map. A. Graph Construction Following the observation of Perazzi et al. [9] that abstracting an input image into homogeneoussuperpixels can improve the performance of salient object detection, we used the SLIC model [52] to abstract the input image into uniform and compact regions.

CONCLUSION

In this paper, we proposed a bottom-up method for detecting salient regions in images by integrating two complementary visual cues (compactness and local contrast) with diffusion processes. After considering the advantages and limitations of different visual cues, we found that compactness and local contrast are complementary to each other. Additionally, local contrast can effectively recover the incorrectly suppressed salient regions using compactness cues. To produce a pixelaccurate saliency map that more uniformly covers the salient objects, we

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propagate the saliency information using a manifold ranking diffusion process on a graph. Our experimental results using four benchmark datasets demonstrated the effectiveness of the proposed method; it produced more accurate saliency maps with better precision-recall curves and higher F-measures than 19 state-of-the-art approaches, when applied to the ASD, CSSD, and ECSSD datasets.

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