Exploiting the Value of the Center-dark Channel Prior for Salient Object Detection

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Saliency detection aims to detect the most attractive objects in images and is widely used as a foundation for various applications. In this paper, we propose a novel salient object detection algorithm for RGB-D images using center-dark channel priors. First, we generate an initial saliency map based on a color saliency map and a depth saliency map of a given RGB-D image. Then, we generate a center-dark channel map based on center saliency and dark channel priors. Finally, we fuse the initial saliency map with the center dark channel map to generate the final saliency map. Extensive evaluations over four benchmark datasets demonstrate that our proposed method performs favorably against most of the state-of-the-art approaches. Besides, we further discuss the application of the proposed algorithm in small target detection and demonstrate the universal value of center-dark channel priors in the field of object detection.

CCS Concepts: • General and reference → Cross-computing tools and techniques; • Computer systems organization → Applications-Computer vision; • Image Processing and Computer → Scene Analysis-Object recognition;

Additional Key Words and Phrases: Salient object detection, Center-dark channel prior

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1 INTRODUCTION

Saliency detection is a process of getting a visual attention region precisely from an image. The attention is a behavioral and cognitive process of selectively concentrating on one aspect within an environment while ignoring other things.

An inherent and powerful ability of human eyes is to quickly capture the most conspicuous regions from a scene, and passes them to high-level visual cortices. The attention selection reduces the complexity of visual analysis and thus makes human visual systems considerably efficient in complex scenes.
Early works on computing saliency aim to locate visual attention regions. Recently, this field has been extended to locate and refine salient regions and objects as shown in Fig. 1. Serving as a foundation of various multimedia applications, salient object detection has been widely used in content-aware editing [8, 22], image retrieval [10, 60], object recognition [2, 29], object segmentation [17, 38], compression [65], image retargeting [48, 51], and etc.

In general, saliency detection algorithms mainly use either top-down or bottom-up approaches. Top-down approaches are task-driven and need supervised learning. Bottom-up approaches usually use low-level cues without supervised learning, such as color, distance and other heuristic saliency features. One of the most used heuristic saliency features [1, 13, 34, 40, 42, 46, 49, 53] is the contrast, such as the pixel-based or patch-based, region-based, multi-scale, and center-surround contrasts, and etc. Although those methods have their own advantages, they are not robust in some specific applications and may lead to inaccurate results on challenging salient object detection datasets illustrated in Fig. 2.
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Recently, advances in 3D data acquisition techniques have motivated the adoption of structural features, improving the discrimination between different objects with similar appearances. Although, depth cues can enhance salient object regions, it is very difficult to produce good results when a salient object has low depth contrast compared to its background shown in Fig. 3.

In order to address the aforementioned difficulties of saliency detection on challenging datasets, we refer to human cognition and use center priors to locate visual saliency and explore the characteristics of salient objects from the perspective of the transmittance. By presenting a new

Fig. 3. The illustration of the effects of different contrast depth maps. The top row represents input images; the middle row represents depth maps; the third row represents ground truth with human annotation. And from the left to right, the contrasts of depth maps are gradually decreasing.

Fig. 4. The illustration of the effect of dark channels, which increases the robustness of detection algorithm when the depth map has the low contrast.
prior knowledge called center-dark channel prior, we can increase the robustness of the detection process and improve the performance of saliency detection algorithm displayed in Fig. 4.

In this paper, we exploit a new prior, which is called center-dark channel prior, to increase the robustness of saliency detection and propose an innovative saliency detection algorithm using center-dark channel priors demonstrated in Fig. 5. First, we generate an initial saliency map based on a color saliency map and a depth saliency map of a given RGB-D image. Second, since salient objects are always located in the center of an image based on cognitive psychology and we also find that the dark channel prior can provide an additional cue for saliency detections, we generate a novel center-dark channel map based on a center saliency prior and a dark channel prior to improve the performance. Finally, we fuse initial saliency maps with center-dark channel priors to generate the final saliency maps.

In summary, major contributions of this work are given as follows:

- A novel algorithm is proposed for saliency detection on RGB-D images, where we exploit center-dark channel priors to gain robust detection processes.
- Unlike existing works, center-dark channel priors are explored for the first time in the field of saliency detection to enhance performance.
- Comparing with previous works, the proposed method achieves dramatical performance improvements on four benchmark datasets.
- The proposed method is further studied in the applications of small target detection and demonstrates great performance improvements.

To our consideration, this research may help to figure out visually perceptual characteristics of human visual systems for images with complex scenes.
2 RELATED WORK

In this section, we have a brief review of classical eye fixation models, traditional saliency algorithms, deep learning based saliency detection methods, center prior based saliency detection approaches and dark channel prior based saliency detection methods.

2.1 Eye Fixation Model

The first model for saliency prediction is biologically inspired and based on a bottom-up computational model that extracts low-level visual features such as intensities, colors, orientations, textures and motions at multiple scales. Itti et al. [21] propose a model that combines multiscale low-level features to create a saliency map. Harel et al. [7] presents a graph-based alternative that starts from low-level feature maps and creates Markov chains over various image maps, treating the equilibrium distribution over map locations as activation and saliency values.

These models achieve reasonable results. However, the above mentioned models have limited uses because they frequently do not match actual human saccades from eye-tracking data. It seems that not only human attentions are based on low-level features, but also on high-level semantics (e.g., faces, humans, cars, and etc.). Judd et al. [52] introduce an approach that combined low, mid and high-level image features to calculate salient locations. These features are used in combination with a linear support vector machine to train a saliency model. Borji [5] also combines low-level features with top-down cognitive visual features to learn a direct mapping to eye fixations using Regression, SVM and Ada-Boost classifiers.

2.2 Traditional Saliency Algorithm

Saliency detection for conventional images could be implemented based on either top-down or bottom-up models. Top-down models [14, 15, 43, 58] require high level interpretation usually provided by training sets in supervised learning. The contextual saliency is formulated according to the study of visual cognition, where the global scene context of an image is highly associated with a salient object [43]. The most distinct features are selected by information theory based methods [14]. Salient objects are detected by the joint learning of a dictionary for object features and conditional random field classifiers for object categorization [58]. While these supervised approaches can effectively detect salient regions and perform overall better than bottom-up approaches, it is still expensive to perform the training process, especially due to time consuming data collections.

In contrary, bottom-up models [35, 46, 50, 67, 68] do not require any prior knowledge, such as object categories, to obtain saliency maps by using low level features based on center-surround contrasts. They compute the feature distinctness of a target region, e.g., pixels, patches or superpixels and then compare to its surrounding regions locally or globally. For example, the feature difference is computed across multiple scales, where a fine scale feature map represents the feature of each pixel while a coarse scale feature map describes the features of surrounding regions [21]. Also, to compute center-surround feature contrasts, spatially neighboring pixels are assigned different weights [20] or random walks on a graph used in [27].

In addition, most bottom-up models are based on center or boundary priors. The center prior assumes that foreground salient objects are usually positioned near the image center and thus assigned high saliency values [11, 41, 47, 57]. A distance of pixels from the image center is combined with other features to reduce the contribution of pixels far from the image center to compute object saliency [11]. To emphasize the region near the image center, an initial saliency map is multiplied by a Gaussian distribution centered in an image [41]. Multiple Gaussian distribution maps are also employed to weight the features of pixels adaptively according to the locations of salient objects in an image [47]. Convex-hull is used to estimate the center of a salient object when it is not
strictly positioned at the image center [57]. However, this assumption puts a strict constraint on the location of foreground objects in an image, and thus might not be applicable to various images. Bottom-up based approaches do not need data collections and training processes, consequently requiring little prior knowledge. These advantages make bottom-up approaches more efficient and easy to implement in a wide range of real computer vision applications. A complete survey of these methods is beyond the scope of this paper and we refer readers to a recent survey paper [6] for details. In this paper, we focus on bottom-up approaches.

### 2.3 Deep Learning based Saliency Detection Method

As the performance of deep convolutional neural networks achieving near human-level performances in image classification and recognition tasks, many algorithms adopt deep learning based methods [19, 31, 32, 54, 55, 61, 63]. Instead of constructing hand-craft features, these kinds of top-down methods have achieved the state-of-the-art performance on many saliency detection datasets. However, deep learning based algorithms have the following limitations: 1) needing a large number of annotated data for training. (2) requiring very time-consuming training in learning processes even with GPU of high computation ability. (3) Obtaining non-uniformly sampled training instances. (4) Suffering sensitivity to noise in training.

Bottom-up based approaches do not need data collections and training processes and consequently require little prior knowledges. These make bottom-up approaches more suitable for real-time applications. Meanwhile, bottom-up methods are not sensitive to image scales, capacities and types. These advantages make bottom-up approaches even more efficient and easy to saliency detection. In this paper, we focus on the bottom-up approaches.

### 2.4 Center Prior based Methods

RGB-D saliency computation is a rapidly growing field and offers object detection and attention prediction in a manner that is robust to appearance. Therefore, some algorithms [12, 16, 44, 66, 69] adopt depth cues to deal with the challenging scenarios. In [69], Zhu et al. propose a framework based on the cognitive neuroscience and use depth cues to represent the depths of real scenarios. In [12], Cheng et al. compute salient stimuli in both color and depth spaces. In [44], Peng et al. provide a simple fusion framework that combines existing RGB-based saliency with new depth-based saliency. In [16], Geng et al. define saliency using depth cues computed from stereo images. Their results show that stereo saliency is a useful consideration compared to previous visual saliency analysis. All of them demonstrate the effectivity of depth cues to improve salient object detection.

However, depth cues cannot warrant the robustness of saliency detection when a salient object has a low depth contrast compared to the background. Inspired by cognitive neuroscience, we find that an image always possesses salient objects in its center position. As a result, many algorithms adopt center priors to enhance salient regions. In [69], Zhu et al. give a framework based on cognitive neuroscience and use center priors to imitate human central fovea. Furthermore, in [25], the contrast against image boundaries is used as a new regional feature to enhance the center position. In [46], Qin et al. compare boundary clusters with center clusters and then generate different color distinction maps with complementary advantages and integrate them by taking the spatial distance into consideration. All of them demonstrate that the center prior can strengthen saliency regions.

### 2.5 Dark Channel Prior based Methods

The dark channel prior, which was first put forward in [18], is used for single image haze removal. The dark channel prior is based on the statistics of outdoor haze-free images and it is found that the dark pixels often have very low intensities in at least one color channel. After that, many dehazing
methods [4, 26, 56] based on dark channel priors are proposed and good results are obtained. Using the dark channel prior is a classic method on calculating the transmission map. We use the dark channel prior, which can distinguish the foreground from background by the transmission map, to make a more accurately saliency detection.

Partially inspired by the well-known dark-object subtraction technique [23] widely used in multispectral remote sensing systems, we figure out that salient objects tend to have different transmissivities in most regions of the background. As a result, we propose an algorithm to combine dark channel priors with saliency detection results to enhance the performance of saliency detection.

3 THE PROPOSED ALGORITHM

3.1 Saliency map initialization

We initialize the saliency map by extracting color and depth features from original image $I_o$ and depth map $I_d$, respectively. First, image $I_o$ is segmented into $K$ regions based on colors via $K$-means algorithm, which is defined as follows:

$$S_c(r_k) = \sum_{i=1, i \neq k}^K P_i W_d(r_k) D_c(r_k, r_i),$$

where $S_c(r_k)$ is the color saliency of region $k$, $k \in [1, K]$. $r_k$ and $r_i$ represent regions $k$ and $i$, respectively. $D_c(r_k, r_i)$ is Euclidean distance between region $k$ and $i$ in $L'$a"b' color space. $P_i$ represents the area ratio of region $r_i$ compared with whole image. $W_d(r_k)$ is the spatial weighted term of region $k$ as follows:

$$W_d(r_k) = e^{-\frac{D_o(r_k, r_i)}{\sigma^2}},$$

where $D_o(r_k, r_i)$ is Euclidean distance between the centers of region $k$ and $i$. $\sigma$ is the parameter controlling the strength of $W_d(r_k)$.

Similar to the color saliency, we define:

$$S_d(r_k) = \sum_{i=1, i \neq k}^K P_i W_d(r_k) D_d(r_k, r_i),$$

where $S_d(r_k)$ is depth saliency of $I_d$. $D_d(r_k, r_i)$ is Euclidean distance between region $k$ and $i$ in depth space.

In most cases, a salient object is always located in the center of an image or close to a camera center. Therefore, we assign the weights to both center-bias and depth for both colors and depth.

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images. The weights of region $k$ are as assigned by:

$$W_{cd}(r_k) = \frac{G(\| P_k - P_o \|)}{N_k} DW(d_k),$$  \hspace{1cm} (4)$$

where $G(\cdot)$ represents Gaussian normalization. $\| \cdot \|$ is Euclidean distance. $P_k$ is the position of region $k$. $P_o$ is the center position of this map. $N_k$ is the number of pixels in region $k$. $DW(d_k)$ is the depth weight, which is given as follows:

$$DW(d_k) = (\max\{d\} - d_k)^\mu,$$  \hspace{1cm} (5)$$

where $\max\{d\}$ represents the maximum depth of the image. $d_k$ is the depth value of region $k$. $\mu$ is a fixed value for a depth map formulated by:

$$\mu = \frac{1}{\max\{d\} - \min\{d\}},$$  \hspace{1cm} (6)$$

where $\min\{d\}$ represents the minimum depth of the image.

Then, the initial saliency value of region $k$ is calculated by the following equation:

$$S_1(r_k) = G(S_c(r_k)W_{cd}(r_k) + S_d(r_k)W_{dc}(r_k)).$$  \hspace{1cm} (7)$$

### 3.2 Center-dark channel prior

By mixing the center saliency and the dark channel priors to generate a new prior, we define this prior as the center dark channel prior. By using this prior, we can get a more accurate saliency map.

**Center saliency prior.** According to cognitive neuroscience, human eyes use central fovea to locate objects and make them clearly visible. Therefore, most of the images taken by cameras always locate salient objects around the center. It was shown in [25] that a saliency map based on
the distance of each pixel to the center of the image provides a better prediction of salient objects than many previous saliency models, as shown in Fig. 7. Inspired by this observation, we further incorporate a center prior into our saliency estimation.

Fig. 8 provides a visual comparison between saliency maps obtained with and without center priors and more accurate results are obtained when the center prior is included.

To get the center saliency map, we use the BSCA algorithm [46]. It constructs the global color distinction and the spatial distance matrix based on clustered boundary seeds and integrates them into a background-based map. Thus, it can improve the accuracy of center objects by erasing the image edges’ effects. As shown in the Fig. 6(f), the center saliency map can remove the surroundings area and reserve most of salient regions of an image. We denote this center-bias saliency map as $S_{esp}$.

**Dark channel prior.** The dark channel prior is a popular prior which is widely used in the image haze removal field [18]. It is based on the statistics of outdoor haze-free images. The dark channel can detect the most haze-opaque region and improve the atmospheric light estimation. Inspired by dark channel priors, we find that the foreground and background have different transmissivities, so we can distinguish salient objects from backgrounds as shown in Fig. 6(g). We apply this theory in the field of saliency detection and denote the transmissivity map of the dark channel prior as $S_{dcp}$.

Based on the statistics of outdoor haze-free images, He et al. [18] find that, for the patches of general images, at least one color channel has very low intensity. In other words, the minimum intensity of a general image should has a very low value. Formally, for an image $J$, we define

$$J_{dark}(x) = \min_{c \in r,\; g,\; b} \left( \min_{y \in \Omega(x)} (J^c(y)) \right) \approx 0$$

where $J_c$ is a color channel of $J$ and $\Omega(x)$ is a local patch centered at $x$. We call $J_{dark}$ the dark channel of $J$. According to the experiments of the dark channel processing on general images, we find that the dark channel image tends to be zero, as provided in Fig. 9.

$$\hat{t}(x) = 1 - \min_{c \in r,\; g,\; b} \left\{ \min_{y \in \Omega(x)} \left\{ \frac{I^c(y)}{A_c} \right\} \right\}.$$  

According to [18], the estimated transmission value can be calculated using Eq. (9), where $I_c$ is a color channel of $I$ and $I$ is an image with haze. $A_c$ is the global light which is constant for most images. The transmissivity of an image is the reverse value of dark channel results. Since the

![Fig. 8. Comparing saliency results without (b) and with (c) the center prior, and (d) is the ground truth.](image_url)
objects that are closer to the camera have less photographic fog, the foreground part will be the haze_free part and the dark channel result tends to be zero. So the transmissivity of the foreground is larger than that of the background as illustrated in Fig. 10.

3.3 Saliency refinement with an updated fusion

Based on the initialized saliency map, we utilize an updated fusion to refine saliency maps. The updated fusion consists of the depth cue, the center-dark channel prior and the updated fusion based enhancements.

**Depth cue based enhancement.** The depth cue makes salient objects prominent. We denote it by:

\[
D_{dce}(d_k) = \text{Norm}(-DW(d_k)),
\]

where \(\neg\) is the negation operation which can enhance the saliency degree of front regions as shown in Fig. 2(c), because the foreground object has a low depth value while the background one possesses a high depth value in depth map. \(\text{Norm}()\) is a normalized operation.

**Center-dark channel prior based enhancement.** We combine the center saliency and the dark channel priors to enhance the final saliency results denoted as follows:

\[
S_{cdcp}(r_k) = \text{Norm}(S_{csp}(r_k))\text{Norm}(S_{dcp}(r_k)),
\]

**Updated fusion based enhancement.** We fuse the depth cue and the center-dark channel prior based enhancements with the initial saliency values as shown below:

\[
S(r_k) = (1 - e^{-(S_1(r_k)+D_{dce}(d_k)+S_{cdcp}(r_k))})S_1(r_k)S_{csp}(r_k),
\]
where $S(r_k)$ is the fusion enhanced saliency value and $S_1(r_k)$ is the initial saliency value denoted in Section 2.1.

To refine saliency results, we updated the fusion enhanced saliency value in the following equation:

$$S_f(r_k) = 1 - e^{-(S_1(r_k)S_{csp}(r_k)S(r_k))}.$$  

where $S_f(r_k)$ is the final saliency value.

From the Fig. 6, we can see the visual results of the proposed algorithm. The main steps of the proposed salient object detection algorithm are summarized in Algorithm 1.

### Algorithm 1

**The proposed saliency algorithm using centre-dark channel prior**

**Input:** original maps $I_o$, depth maps $I_d$;

**Output:** final saliency values $S_f$;

1. for each region $k = 1, K$ do:
   2. compute color saliency values $S_c(r_k)$ and depth saliency values $S_d(r_k)$;
   3. calculate center-bias and depth weights $W_{cd}(r_k)$;
   4. get initial saliency value $S_1(r_k)$;
   5. end for
   6. obtain center saliency priors $S_{csp}$ and dark channel priors $S_{dcp}$;
   7. figure out final saliency values $S_f$ by updated fusion;
   8. return final saliency values $S_f$;

### 4 EXPERIMENTAL EVALUATION

#### 4.1 Datasets

In this section, we evaluate the proposed method on four RGB-D datasets.

- **NJU2000** [24]. The NJUDS2000 dataset contains 2000 stereo images as well as the corresponding depth maps and manually labeled ground truths. The depth maps are generated using an optical flow method.

- **NLPR** [44]. The NLPR RGB-D salient object detection dataset contains 1000 images captured by Microsoft Kinect in various indoor and outdoor scenarios.

- **RGBD135** [12]. This dataset has 135 indoor images taken by Kinect with the resolution $640 \times 480$.

- **SSD100** [33]. This dataset is built on three stereo movies. It contains 80 images with both indoors and outdoors scenes.

#### 4.2 Evaluation Metrics

Four most widely used evaluation metrics are used to serve as the performance measurements of saliency algorithms, including the precision-recall (PR) curves, F-measure, receiver operating characteristics (ROC) curve and mean absolute error (MAE).

The precision is defined as follows:

$$\text{Precision} = \frac{\|p_i \mid d(p_i) \geq d_t \cap p_g\|}{\|p_i \mid d(p_i) \geq d_t\|},$$  

where $p_i \mid d(p_i) \geq d_t$ indicates the set that binarized from a saliency map using threshold $d_t$. $p_g$ is the set of pixels belonging to ground truth salient objects.

The recall is defined below:

$$\text{Recall} = \frac{\|p_i \mid d(p_i) \geq d_t \cap p_g\|}{\|p_g\|}.$$  

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The precision-recall curve is plotted by connecting P-R scores for all thresholds.

The F-measure is a weighted average of precision and average recall and can be calculated by the following formula:

\[
F_\beta = \frac{(1 + \beta^2) \cdot \text{Precision} \cdot \text{Recall}}{\beta^2 \cdot \text{Precision} + \text{Recall}}.
\]  

(16)

Here, as suggested by previous works, we set \(\beta^2\) to 0.3 to emphasize the precision rather than recall.

The ROC curve is the plot of true positive rates (TPR) versus false positive rates (FPR) by testing all possible thresholds.

The MAE captures the average difference between the produced saliency map and the ground truth map and it is expressed as:

\[
\text{MAE} = \frac{1}{W \times H} \sum_{x=1}^{W} \sum_{y=1}^{H} |G(x, y) - S(x, y)|
\]

(17)

where \(G\) is the binary ground truth mask. \(W\) and \(H\) are width and height of the saliency map \(S\), respectively.

### 4.3 Ablation Study

We first validate the effectiveness of each step in our method: initial saliency detection, depth cue enhanced saliency detection, center-dark channel prior saliency detection, updated fusion saliency detection and final saliency detection. Table 1 shows the validation results on NLPR and RGBD135 datasets. The accumulated processing gains can clearly be seen after each step and the final saliency results shows the good performance. After all, it proves that each step in our algorithm is effective for generating the final saliency maps.

|       | NLPR   | RGBD135 |
|-------|--------|---------|
|       | \(F_\beta\) | MAE     | \(F_\beta\) | MAE     |
| \(S_1\) | 0.6497 | 0.1978  | 0.6528  | 0.2004  |
| \(D_{dce}\) | 0.6725 | 0.1528  | 0.6785  | 0.1685  |
| \(S_{cdcp}\) | 0.6764 | 0.1442  | 0.6889  | 0.1489  |
| \(S\)   | 0.6875 | 0.1206  | 0.6958  | 0.1343  |
| \(S_f\) | 0.7056 | 0.0860  | 0.7105  | 0.0794  |

### 4.4 Comparison

To further illustrate the effectiveness of our algorithm, we compare our proposed methods with FT [1], SIM [42], HS [49], BSCA [46], LPS [34], DES [12], NLPR [44]. We use the codes provided by the authors to reproduce their experiments. For all the compared methods, we use the default settings suggested by authors. And for the Eq. 2, we take \(\sigma^2 = 0.4\) which has the best contribution to the results.

The precision and recall evaluation results and ROC evaluation results are shown in Fig. 11 and Fig. 12, respectively.

From the precision-recall and ROC curves, we can see that our saliency detection method can achieve better results on all four datasets.
MAE results on four datasets are listed in Table 2, where the lower value generates the better performance. And F-measure results on four datasets are provided in Table 3, where the higher value produces the better performance. The best results are emphasized in boldface. Comparing

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Table 2. MAE evaluation results. The best results are shown in boldface.

|                  | RGBD135 Dataset | NLPR Dataset | SSD100 Dataset | NJU2000 Dataset |
|------------------|-----------------|--------------|----------------|-----------------|
| FT               | 0.2049          | 0.2168       | 0.2738         | 0.2637          |
| SIM              | 0.3740          | 0.3957       | 0.4184         | 0.4012          |
| HS               | 0.1849          | 0.1909       | 0.2582         | 0.2516          |
| BSCA             | 0.1851          | 0.1754       | 0.2386         | 0.2148          |
| LPS              | 0.1406          | 0.1252       | 0.1960         | 0.2059          |
| DES              | 0.3079          | 0.3207       | 0.3132         | 0.4465          |
| NLPR             | 0.1165          | 0.1087       | 0.1784         | 0.1669          |
| OURS             | **0.0794**      | **0.0860**   | **0.1779**     | **0.1589**      |

Table 3. F-measure evaluation results. The best results are shown in boldface.

|                  | RGBD135 Dataset | NLPR Dataset | SSD100 Dataset | NJU2000 Dataset |
|------------------|-----------------|--------------|----------------|-----------------|
| FT               | 0.4361          | 0.4488       | 0.4687         | 0.4723          |
| SIM              | 0.4411          | 0.4525       | 0.4889         | 0.4912          |
| HS               | 0.5361          | 0.6003       | 0.5716         | 0.6090          |
| BSCA             | 0.5826          | 0.5925       | 0.5755         | 0.6290          |
| LPS              | 0.5452          | 0.5890       | 0.5935         | 0.5692          |
| DES              | 0.5410          | 0.5915       | 0.5797         | 0.6202          |
| NLPR             | 0.4912          | 0.5957       | 0.6415         | 0.6165          |
| OURS             | **0.7105**      | **0.7056**   | **0.7212**     | **0.7198**      |

with the MAE values and F-measure values, it can be observed that our saliency detection method is superior and can obtain the most precise salient regions among tested approaches.

The visual comparisons are given in Fig. 4 and the advantages of our method are clearly demonstrated. Our method can detect both a single salient object as well as multiple salient objects more precisely. In contrast, the compared methods may fail in some situations.

5 SMALL TARGET DETECTION

It is very interesting to find that the proposed saliency detection algorithm using center-dark channel priors is also valid in small target detection.

Small target detection plays an important role in many computer vision tasks, including early warning systems, remote sensing and visual tracking. Different from traditional objects detection, small target detection is usually more difficult since the resolution is low and the feature is fuzzy. Meanwhile, several factors such as sensor noises, size variations and artificial interferences make the task even more challenging. Over the past decades, numerous small targets detection models have been proposed. Their strategies can be divided into three main categories: target enhancement [62], background suppression [3], and figure-ground segregation [9]. With the advantage of simultaneously enhancing target signals and suppressing background clutters, the third category of methods usually exploits different contrast techniques to model this task. In computer vision, the contrast mechanisms, including local center-surround difference and global rarity, are closely related to human visual perception and widely used in bottom-up saliency detection models. Since the visual saliency which stemmed from psychological science has attracted more attention, some saliency map based methods are also proposed in recent years [28, 37, 45].
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In many cases, small targets are immersed in cloud clutters. For outdoor scenes, dark channel priors can be used to distinguish sky background easily and capture objects flying in sky. Combining with saliency detection, we can gain a better result. We present parts of our experimental results on these challenging dataset [39]. The experimental results by applying the proposed algorithm to small target detections are shown in Fig. 14 to support our claims. The reason behind why the proposed algorithm can be transplanted in small target detections is that (1) the proposed center-dark channel prior can be used to locate small objects and (2) the proposed saliency detection algorithm can be applied to refine small targets features. Therefore, we claim that the proposed center-dark channel prior can be used for small target detections in addition to saliency detections.

6 DISCUSSION AND FUTURE DIRECTIONS

6.1 Fail Case
For dark channel priors, it is more suitable for outdoor scenes to emphasize the brightness of the background. So when the background is too dark, the transmission map of images will be difficult to distinguish foregrounds from backgrounds as shown in Fig 15(b). The resulting saliency map is shown in Fig 15(c) and we can see that the borders are not clear.

6.2 Future Directions
In the past two decades, hundreds of algorithms have been proposed for saliency detection. On all these commonly-used datasets, top-down algorithms can achieve wonderful precision (over 80%). However, the performance improvement has encountered a bottleneck. In order to solve this challenging issue, we suggest the following ideas based upon our research experience:

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(1) More innovative researches should be conducted based upon cognitive science, such as cognitive mechanism based algorithms.

(2) More multi-level annotated datasets should be built. Since almost all datasets only provide rough binary masks as ground truth, we suggest that ground truth maps should be annotated in multiple levels. Different labeled levels correspond to different levels of the saliency.

(3) More diversified medias should be introduced into this field, such as speech and text based saliency detection. In addition, we should take a look at the field of saliency detection from diversified perspectives as shown in Fig.16. Some suggestions are given as follows:

**Personalized Saliency Detection** [59]. From the psychological point of view, different people have different focuses of attention (FOV) on the same scene. This is produced by different personal characteristics, such as hobbies, habits, and etc. Therefore, it is highly necessary for us to develop personalized saliency detection datasets for studying personalized saliency detection.

**Saliency Detection in Videos** [36]. Video sequences provide temporal cues in addition to spatial information. It is difficult to explore saliency detection in videos with temporal cues, which has led to many uncertain issues such as being out of nothing, increasing or decreasing, and etc. Moreover, for saliency detection in videos, we will face all the challenges of saliency detection in images. How to incorporate temporal cues in an unified and effective way needs further study.

**Instance-Level Saliency Detection** [30]. Existing saliency models are object-agnostic (i.e., they do not split salient regions into objects). However, similar to human capability of recognizing multiple instances of salient locations, instance-level saliency can be useful in several applications, such as image editing and video compression.

**Saliency Detection for Panoramic Images** [64]. Almost all the previous works on saliency detection have been dedicated to conventional images. However, with the outbreak of panoramic images due to the rapid development of VR or AR technologies, it is becoming more challenging to extract salient contents in panoramic images.
CONCLUSION

In this paper, we proposed an innovative saliency detection algorithm using center-dark channel priors. The proposed algorithm first detects an initial saliency maps based on color and depth cues. Then we figure out the center-dark channel saliency map based on center saliency and dark channel priors. At last, we fuse them together to get the final saliency map by the updated fusion. The experiments results show that the proposed algorithm outperforms existing algorithms in both accuracy and robustness for different scenarios. Besides, by experiments, we claim that the proposed algorithm can also be applied to small object detection as well. To encourage future work, our source codes, experiment data and other related materials are all made public, which can be found on our project website.

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