EDN: Salient Object Detection via Extremely-Downsampled Network

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Abstract

Recent progress on salient object detection (SOD) mainly benefits from multi-scale learning, where the high-level and low-level features work collaboratively in locating salient objects and discovering fine details, respectively. However, most efforts are devoted to low-level feature learning by fusing multi-scale features or enhancing boundary representations. In this paper, we show another direction that improving high-level feature learning is essential for SOD as well. To verify this, we introduce an Extremely-Downsampled Network (EDN), which employs an extreme downsampling technique to effectively learn a global view of the whole image, leading to accurate salient object localization. A novel Scale-Correlated Pyramid Convolution (SCPC) is also designed to build an elegant decoder for recovering object details from the above extreme downsampling. Extensive experiments demonstrate that EDN achieves state-of-the-art performance with real-time speed. Hence, this work is expected to spark some new thinking in SOD. The code will be released.

1. Introduction

Salient object detection (SOD), also called saliency detection, tries to simulate the human visual system to detect the most salient and eye-catching objects or regions in natural images [4, 14]. It has been demonstrated to be useful for far-reaching computer vision applications such as visual tracking [27], scene classification [33], image retrieval [6], and weakly supervised learning [25]. Although much progress has been made recently [2, 9, 12, 19, 24, 30, 62], it is still challenging to detect complete salient objects in complicated scenarios accurately.

In the last several years, convolutional neural networks (CNNs) have achieved vast successes in this field [16, 17, 23, 26, 42, 54]. These networks usually employ multi-scale learning to leverage both high-level semantic features and fine-grained low-level representations, in which the former is effective in accurately locating salient objects and the latter works better in discovering object details and boundaries. In addition, such a multi-scale learning is a natural solution to tackle the large scale variations in practice. Hence, most recent efforts for saliency detection are devoted to designing advanced network architectures to facilitate multi-scale learning [2, 10, 24, 40–42, 52, 54, 55].

Existing multi-scale learning methods in SOD mainly aim at dealing with low-level feature learning for better capturing/utilizing fine-grained object details/boundaries explicitly or implicitly. For exploring fine-grained details explicitly, recent works [5, 19, 22, 32, 37, 43, 45, 46, 48, 59, 63] try to improve the accuracy of salient object boundaries by enhancing boundary representations and imposing boundary supervision to predictions directly. For exploring fine-grained details implicitly, many studies [2, 9, 12, 13, 21, 24, 40, 42, 54, 55] design various multi-level feature fusion strategies to serve high-level semantics with low-level fine details, for example, the hot U-Net [34] or so-called encoder-decoder based saliency detectors [9, 12, 13, 21, 23, 24, 42, 55]. Although workable as reported, recent SOD has reached a bottleneck period as many existing methods can handle object boundaries very well.
To break through this bottleneck of SOD, an intuitive idea is to investigate the other aspect of multi-scale learning, i.e., high-level feature learning, which plays an essential role in scene understanding and further locating salient objects. Unfortunately, this direction is less investigated. For better high-level feature learning, existing SOD methods [22, 40, 53, 54, 61] usually directly apply some well-known modules developed for semantic segmentation, such as ASPP [1] and PSP modules [57]. However, SOD requires different high-level feature learning from semantic segmentation. Specifically, semantic segmentation requires learning the relationship between each pixel and all other pixels so that we can make accurate prediction according to such relationship. As a result, semantic segmentation methods usually aims at enlarging the receptive field to extract large-scale features for each pixel [1, 11, 57, 64]. On the other hand, salient object detection requires locating salient objects, which is an overall understanding of an image. With salient object locations, object details can be easily recovered using a decoder, like previous SOD methods that focus on low-level feature learning. As shown in Fig. 1, the accuracy for locating salient objects has been saturated recently due to the limitation of high-level feature learning. In a word, semantic segmentation needs to learn the global relationship for each pixel, while SOD needs to learn a global view of the whole image. Therefore, directly applying semantic segmentation methods to SOD can only achieve suboptimal performance.

To this end, this paper aims to enhance high-level feature learning, which is expected to open a new path for future development of SOD. We propose an Extremely-Downsampled Block (EDB) to learn a global view of the whole image. EDB gradually downsamples the feature map until it becomes a feature vector, i.e., with the size of $1 \times 1$. In such a downsampling process, we continue learning deep features. With the feature map becomes smaller, the learned feature becomes more global. Until downsampling to a feature vector, we obtain a global view of the whole image so that we can locate salient objects accurately. Note that EDB only introduces a little extra computational cost, as it operates on a very low feature resolution. To recover complete salient objects from the global view, we build an elegant decoder to aggregate multi-level features from top to bottom gradually. For this goal, we design a Scale-Correlated Pyramid Convolution (SCPC) for effective feature fusion in the decoder. Unlike traditional methods (e.g., ASPP [1] and PSP [57]) that only adopt multiple parallel branches to extract multi-scale features separately, SCPC adds correlation among various branches/scales. With EDB and SCPC incorporated, the proposed Extremely-Downsampled Network (EDN) achieves state-of-the-art performance on five challenging benchmarks with fast speed and a small number of parameters.

To summarize, our contributions are as below:

- We propose to explore high-level feature learning for locating salient objects instead of previous low-level feature utilization for improving object boundaries, which is expected to open a new path for SOD.
- We propose an intuitive extreme downsampling technique for learning a global view of the whole image, which generates effective high-level features for salient object localization.
- We design an SCPC for effective multi-level feature fusion, which adds correlation among various feature scales and serves as the basic unit of an elegant decoder for accurate SOD.

2. Related Work

SOD is a fundamental problem in computer vision and thus there are a plethora of studies in the literature.

**Initiated SOD methods.** The initiated works utilize hand-crafted features, and many shallow learning methods have been developed [7, 38, 49]. Apart from these approaches, heuristic saliency priors also see heavy usage in this domain. Examples include but are not limited to color contrast [4], center prior [14], background prior [51], and so on. However, those types of methods are lacking, especially compared with more recently-proposed methods, largely due to its limited representational capability.

**CNN-based SOD methods.** Inspired by the vast successes achieved by deep CNNs in other computer vision tasks, CNN-based methods have become the dominant methods for SOD. Early CNN-based methods process and classify image regions for saliency prediction [16, 18, 60], which discards the spatial layout of the input image. Motivated by the superiority of fully convolutional network (FCN) [35], later attention has been shifted toward end-to-end image-to-image SOD [2, 10, 52, 54, 55, 58]. As widely acknowledged that high-level semantic features in the top CNN layers are effective in accurately locating salient objects and low-level fine-grained features in the bottom CNN layers work better in discovering object details, most of the recent efforts are devoted to designing effective networks to facilitate multi-scale learning.

**Multi-level feature fusion.** Most CNN-based SOD methods achieve multi-scale learning by designing advanced network architectures for multi-level feature fusion, so that the final fused features contain both high-level semantics and low-level fine details. The architectures of these methods are usually based on HED [2, 10], Hypercolumns [37, 40, 52, 61], or the typical U-Net [9, 12, 13, 21, 23, 24, 42, 55]. Their target is to add low-level fine-grained
features into the fused features without weakening the representation capability of high-level features, segmenting the located salient objects with clear boundaries.

**Boundary-aware SOD methods.** Besides the above multi-level feature fusion, the recent SOD trend directly uses boundary information to improve the SOD accuracy at object boundaries \([2, 9, 12, 13, 21, 24, 40, 42, 54, 55]\). For example, Zhao et al. \([59]\) applied boundary supervision to low-level features. Liu et al. \([22]\) conducted joint supervision of salient objects and object boundaries at each side-output. Zhou et al. \([63]\) designed a two-stream network that uses two branches to learn the boundary details and locations of salient objects, respectively.

**High-level feature learning.** While tremendous progress has been achieved, existing SOD methods mainly explore the fusion or enhancement of low-level features to better discover object boundaries, leading high-level feature learning less investigated. To strengthen the high-level features, these methods \([22, 40, 53, 54, 61]\) usually adopt some well-known modules developed for semantic segmentation, such as ASPP \([1]\), PSP \([57]\), or their variants. Due to the natural difference between SOD and semantic segmentation, as discussed above, current SOD methods can only achieve suboptimal accuracy in locating salient objects. In this paper, we contribute from this aspect by proposing an extreme downsampling technique for better learning high-level representation in SOD.

### 3. Methodology

In this section, we first provide an overview of our method in §3.1. Then, we introduce an extreme downsampling technique in §3.2. At last, we present the proposed SCPC in §3.3.
effectively fuse multi-level features in an elegant way and obtain decoder outputs $D_1, D_2, D_3, D_4, D_5,$ and $D_6$.

We continue by introducing our loss function for optimizing the proposed EDN. Let $\mathcal{L}$ stands for the combination of commonly-used binary cross-entropy loss $\mathcal{L}_{bce}$ and Dice loss $\mathcal{L}_{dice}$ [29], which can be defined as

$$\mathcal{L}_{bce}(P, G) = G \log P + (1 - G) \log(1 - P),$$

$$\mathcal{L}_{dice}(P, G) = 1 - \frac{2 \cdot G \cdot P}{||G|| + ||P||},$$

$$\mathcal{L}(P, G) = \mathcal{L}_{bce} + \mathcal{L}_{dice},$$

where $P$ and $G$ denote the predicted and ground-truth saliency map, respectively. “$\cdot$” operation indicates the dot product. $|| \cdot ||$ denotes the $\ell_1$ norm. The Dice loss is known as an effective way to solve the class imbalance of foreground and background. The total loss for training EDN can be calculated as

$$P_1 = \sigma(\text{Upsample}(\text{Conv}_{1 \times 1}(D_1))),$$

$$L = \sum_{i=1}^{5} \mathcal{L}(P_i, G),$$

in which $\text{Conv}_{1 \times 1}(\cdot)$ does not have batch normalization and ReLU activation. $\text{Upsample}(\cdot)$ upsamples the prediction into the size of the input image. $\sigma(\cdot)$ is the standard sigmoid function. We do not use $D_6$ in Eqn. (4) due to its small size. During testing, $P_1$ is viewed as the final output prediction of EDN.

### 3.2. Extremely-Downsampled Block

In the above, we have discussed that existing SOD methods only focus on learning or utilizing low-level features, but ignore high-level feature learning. Hence, we propose EDB to strengthen high-level features by learning a global view of the whole image, which leads to more accurate salient object localization (as shown in Fig. 1). In this part, we clarify the design details of EDB.

Suppose that the input of an EDB is $X$. We first design a simple downsampling block to downsample the input feature map by a factor of 2 (“Down1” in Fig. 2). This can be formulated as

$$X_1 = \text{Conv}_{3 \times 3}(\text{Conv}_{3 \times 3}(\text{Downsample}(X))),$$

where $\text{Downsample}(\cdot)$ downsamples the input by a factor of 2. $\text{Conv}_{3 \times 3}(\cdot)$ is a $3 \times 3$ convolution with 256 output channels, followed by batch normalization and ReLU activation. We repeat this block to get $X_2$ (“Down2” in Fig. 2), like

$$X_2 = \text{Conv}_{3 \times 3}(\text{Conv}_{3 \times 3}(\text{Downsample}(X_1))).$$

$X_2$ is in a small scale and thus has a very large receptive field. To get a global view of the whole image, we further downsample $X_2$ into a feature vector using global average pooling (GAP), which can be written as

$$X_3 = \sigma(\text{GAP}(X_2)).$$

The value range of $X_3$ is squeezed into $[0, 1]$ using a sigmoid function. Although $X_3$ is a global representation of the input image, its size of a single pixel makes it unsuitable to start decoding from it. Instead, we adopt it as a self-attention to recalibrate $X_2$ as

$$X'_2 = X_2 \otimes X_3,$$

in which $\otimes$ represents element-wise multiplication and $X_3$ is replicated into the same size as $X_2$ before multiplication. We also adopt $X_3$ as a nonself-attention to recalibrate $X_1$ as

$$X'_1 = X_1 \otimes X_3.$$ 

In this way, $X'_1$ and $X'_2$ are enhanced by the global representation. Then, we fuse $X'_1$ and $X'_2$, which can be formulated as

$$X''_2 = \text{Upsample}(\text{Conv}_{1 \times 1}(\mathcal{H}(X'_2))),$$

$$Y = \mathcal{H}(\text{Concat}(\text{Conv}_{1 \times 1}(X'_1), X''_2)),$$

where $Y$ is the output, i.e., $Y = \mathcal{F}(X)$. $Y$ is expected to be equipped with a global view of the whole image for better locating salient objects.

### 3.3. Scale-Correlated Pyramid Convolution

We propose SCPC for better fusing multi-level features, which is also an important aspect of multi-scale learning. Our motivation comes from that existing modules usually conduct separate multi-scale feature extraction. For example, ASPP [1], PSP [57], and their numerous variants use separate branches to extract multi-scale features, with different branches responsible for different feature scales. An intuitive idea is that the feature extraction at different scales should be correlated and benefit from each other. Suppose that $M$ represents the input of SCPC. We first apply a $1 \times 1$ convolution for transition as

$$M_1 = \text{Conv}_{1 \times 1}(M).$$

![Figure 3. Illustration of SCPC for multi-scale learning.](image-url)
Then, $M_1$ is split into four feature maps evenly along the channel dimension, i.e.,

$$M_1^1, M_1^2, M_1^3, M_1^4 = \text{Split}(M_1).$$  \hspace{1cm} (12)

Next, we conduct multi-scale learning in a scale-correlated way, which can be formulated as

$$M_3^i = \text{Conv}^{a_3}_{3 \times 3}(M_2^i),$$

$$M_5^i = \text{Conv}^{a_5}_{3 \times 3}(M_2^i + M_4^{i-1}), \quad i \in \{2, 3, 4\},$$  \hspace{1cm} (13)

in which $\text{Conv}^{a}_{3 \times 3}()$ is a $3 \times 3$ atrous convolution with an atrous rate of $a_i$. At last, we concatenate multi-scale features and add a residual connection, like

$$O = \text{Conv}_{1 \times 1}(\text{Concat}(M_3^1, M_3^2, M_3^3, M_3^4)) + M,$$  \hspace{1cm} (14)

where $O$ is the output, i.e., $O = \mathcal{H}(M)$. All convolutions in SCPC are followed by batch normalization and ReLU activation, except that Eqn. (14) puts the ReLU of $1 \times 1$ convolution after the residual sum with $M$, as commonly used [8]. In this way, SCPC learns scale-correlated features effectively using small-scale features (with small atrous rates) to fill the holes of large-scale features (with large atrous rates) gradually through Eqn. (13).

4. Effect of Extreme Downsampling

Before experiments, we first discuss the effect of the proposed extreme downsampling technique. In the above, we have clarified that existing SOD methods mainly focus on learning or better utilizing low-level fined-grained features to facilitate multi-scale learning. However, this paper explores another direction of multi-scale learning by enhancing high-level feature learning, i.e., learning a global view of the whole image. Here, we statistically show the benefits from extreme downsampling. To this end, we divide the foreground of the ground-truth saliency map into boundaries, center regions, and other regions. Boundaries are foreground pixels whose Euclidean distance to the nearest background pixel is smaller than 5 pixels, while center regions cover foreground pixels whose Euclidean distance to the nearest background pixel is in the top 20%. Other regions refer to foreground regions other than boundaries and center regions. Some visualization examples of such division are displayed in the 3rd column of Fig. 4.

With the above definition, we compute mean absolute error (MAE) for center, boundary, and other regions, respectively. Please see §5.1 for more details about the metric and datasets. Note that when we compute MAE for one type of regions, the other two types of regions are ignored. The statistical results are shown in Tab. 1. We remove EDB from the proposed EDN to serve as the baseline. The relative improvement in Tab. 1 is the fraction of $\Delta_{\text{MAE}}$ and MAE of the baseline, where $\Delta_{\text{MAE}}$ is the decrease of MAE by adding EDB to the baseline. With applying EDB, we observe that the relative improvement in terms of center regions is much larger than that in terms of boundaries and other regions, which suggests that the improvement brought by EDB mainly comes from the accurate localization of salient objects. Fig. 1 shows that the accuracy of salient object localization has been saturated since 2019, while EDB boosts such accuracy significantly. Therefore, EDB has achieved its goal for improving SOD through better salient object localization. Moreover, it is interesting to find that EDB also has some improvement in terms of boundaries, although it is designed for high-level feature learning. Maybe this is because powerful high-level features make the decoding process easier, leading to better

| Setting      | Type   | ECSSD  | DUTS-TE | DUT-O | HKU-IS | PASCAL-S |
|--------------|--------|--------|---------|-------|--------|----------|
| Baseline     | Center | 0.060  | 0.084   | 0.178 | 0.053  | 0.110    |
| +EDB         | Center | 0.046  | 0.062   | 0.124 | 0.043  | 0.082    |
| Rel. Impv.   |        | 23.6%  | 26.6%   | 30.1% | 19.3%  | 25.7%    |
| Baseline     | Boundary| 0.223 | 0.243   | 0.335 | 0.202  | 0.262    |
| +EDB         | Boundary| 0.210 | 0.226   | 0.291 | 0.196  | 0.236    |
| Rel. Impv.   |        | 6.1%   | 7.0%    | 13.0% | 3.1%   | 10.2%    |
| Baseline     | Other  | 0.078  | 0.093   | 0.181 | 0.073  | 0.141    |
| +EDB         | Other  | 0.062  | 0.076   | 0.133 | 0.065  | 0.112    |
| Rel. Impv.   |        | 20.8%  | 18.1%   | 26.2% | 11.5%  | 20.7%    |

| Image | GT | Colored GT | w/ EDB | w/o EDB |
|-------|----|------------|--------|---------|

Figure 4. Visualization examples of our method with or without EDB. Red, green, and blue pixels in the colored ground-truth saliency map indicate the center, boundary and other pixels of salient objects, respectively. GT: Ground-truth.
utilization of low-level features. Some visualization examples are provided in Fig. 4. EDB can help the system detect all salient objects. Without EDB, some salient objects will be lost completely (the 1st, 3rd, and 4th rows) or partially (the 2nd and 5th rows).

5. Experiments

5.1. Experimental Setup

Implementation details. The proposed method is implemented using the PyTorch library [31]. The training of all experiments is conducted using the Adam [15] optimizer with parameters $\beta_1 = 0.9$, $\beta_2 = 0.99$, weight decay $10^{-4}$, and batch size 24. The backbone network of EDN is pretrained on ImageNet. The training lasts for 30 epochs in total. We adopt the poly learning rate scheduler so that the learning rate for the $n$th epoch is $\text{init}_{lr} \times \left(1 - \frac{n}{\text{max epochs}}\right)^{\beta}$, where we have $\text{init}_{lr} = 5 \times 10^{-5}$ and $\beta = 0.9$. In the training, we freeze the batch normalization layers of the backbone network as commonly used.

Datasets. We extensively evaluate the proposed EDN on five datasets, including DUTS [39], ECSSD [50], HKU-IS [18], PASCAL-S [20], and DUT-OMRON [51] datasets. These five datasets consist of 15572, 1000, 4447, 850 and 5108 natural images with corresponding pixel-level labels. Following recent studies [24, 40, 41, 52], we train EDN on the DUTS training set and evaluate on the DUTS test set (DUTS-TE) and other four datasets.

Evaluation criteria. We evaluate EDN against previous state-of-the-art methods with regard to three widely-used metrics, i.e., F-measure score ($F_\beta$), mean absolute error (MAE), and weighted F-measure score ($F_{\beta}^w$). For the first metric, F-measure is the weighted harmonic mean of precision and recall, like

$$F_\beta = \frac{(1 + \beta^2) \times \text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}},$$

where we set $\beta = 0.3$ to emphasize the importance of precision, following previous works [10, 22, 24, 55]. Higher F-measure indicates better performance. The second metric, MAE, measures the similarity between the predicted saliency map $P$ and the ground-truth saliency map $G$, which can be computed as

$$\text{MAE}(P, G) = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} |P_{i,j} - G_{i,j}|,$$

where $H$ and $W$ denote the height and width of the saliency map, respectively. The lower the MAE is, the better the
SOD method is. The third metric, weighted F-measure $F^w_β$, solves the problems of F-measure that may cause interpolation flaw, dependency flaw, and equal-importance flaw [28]. We use the official code with the default setting of the authors to conduct evaluation. The higher the weighted F-measure is, the better the performance is.

5.2. Comparison with State-of-the-art Methods

In this part, we compare the proposed EDN with existing 20 recent methods, including DHSNet [23], ELD [16], NLDF [26], DSS [10], Amulet [55], UCF [56], PiCANet [24], C2S [19], RAS [2], PoolNet [22], AFNet [5], CPD [47], EGNet [59], GateNet [62], ITSD [63], MINet [63], BRN [41], SRM [40], BASNet [32], and GCPANet [3]. We evaluate them using both VGG16 [36] and ResNet-50 [8] backbones. For a fair comparison, we use the saliency maps provided by them and if not provided, we directly use their official code and models to compute the missing saliency maps. We also report the speed and parameters of each method for reference. The speed is tested using a single NVIDIA TITAN Xp GPU.

Quantitative comparison. We show the results in Tab. 2. EDN consistently achieves the best performance in most cases, and in the remaining several cases, EDN is also very close to the best performance. EDN also has real-time speed and a relative small number of parameters. This demonstrates the efficacy and efficiency of EDN.

Qualitative comparison. The qualitative comparison is displayed in Fig. 5. While other competitors may not detect the whole salient objects or even not find some salient object in various scenarios, EDN can segment salient objects with clear boundaries.

5.3. Ablation Study

In this section, we conduct the ablation study for EDN equipped with the proposed EDB and SCPC. All experiments in this part are based on the VGG-16 backbone [36]. Other settings are the same as §5.1.

Effect of various design choices for EDB. Other than showing the effect of the whole EDB in §4, here we conduct analyses on the interior design choices of EDB. More specifically, we control the number of downsampling operations and the allowance of global attention to the output features in EDB. The results are summarized in Tab. 3. “Backbone” means to predict saliency maps directly from the last stage of the VGG16 backbone. “EDB (A)” indicates EDB only with one downsampling block, i.e., “Down1” in Fig. 2. “EDB (B)” refers to EDB only with two downsampling blocks, i.e., “Down1” and “Down2” in Fig. 2. “EDB (C)” only removes downsampling operations but remains all convolutions and global attention (Equ. (7) - Equ. (9)). We can see that “EDB (B)” outperforms “EDB (A)”, and both of them substantially outperforms “EDB (C)” and the baseline without EDB. This demonstrates the significance of downsampling and global attention in EDB, and removing each element will substantially affect the performance.

Comparison of EDB with other alternatives. Here, we replace EDB with other modules for high-level feature learning, like ASPP [1], PSP [57], and Non-local (NL) [44] modules. ASPP and PSP modules perform multi-scale feature learning using multiple separate branches. The results are shown in Tab. 5. We can find that adding ASPP, PSP, or NL module to the baseline only achieves slightly better or even worse performance. In contrast, EDB outperforms ASPP, PSP, NL, and the baseline by a large margin, demon-
stratifying the superiority of our extreme downsampling technique. Please refer to supplementary for complete results on five datasets.

**Atrous rate configurations of SCPC.** EDN has six downsampling operations, downsampling the feature map by half each time. Correspondingly, there are seven SCPC modules whose atrous rates are set according to the size of the feature map, as shown in Fig. 2. We show the results of different atrous rate settings for SCPC in Tab. 4. We divide our seven times of multi-level feature fusion into 3 groups. “L” (low) includes the first two stages that output feature maps with the highest resolutions. “H” (high) includes the last two extra scales of feature maps in EDB. For different groups, we apply different atrous rate settings. By default, the atrous rates of four branches in SCPC for the group “L”, “H”, and “EH” are set as \{1,2,4,8\} (a), \{1,2,3,4\} (b), and \{1,1,1,1\} (c), respectively. In Tab. 4, we tried other two types of atrous rate settings for each group. We can observe that the results only fluctuates slightly with various atrous rates, demonstrating that the proposed SCPC is robust for different atrous rate settings. Since the 7th setting in Tab. 4 achieves the overall best performance, we employ it as the default setting for SCPC.

**Comparison of SCPC with other alternatives.** In this part, we compare the proposed SCPC with the vanilla convolution (“Conv”) and ASPP. Specifically, we first replace SCPC with 3 x 3 convolutions that have the same number of output channels as SCPC, resulting in a decoder similar to U-Net [34]. Then, we replace SCPC with ASPP by removing the scale correlation in SCPC, i.e., removing the sum term of $M_i^{-1}$ in Eq. (13). The results are displayed in Tab. 6. We can see that ASPP outperforms “Conv” significantly, and SCPC further improves ASPP substantially, suggesting the effectiveness of SCPC in feature fusion.

**6. Conclusion**

Multi-scale learning is the core for SOD by leveraging high-level semantic features for salient object localization and low-level fine details for boundary discovering [2, 10, 24, 40, 42, 52, 54, 55]. However, existing SOD methods mainly focus on learning/utilizing low-level features by designing various multi-level feature fusion strategies [2, 9, 12, 13, 21, 23, 24, 40, 42, 54, 55] or imposing boundary supervision directly [5, 19, 22, 32, 37, 43, 45, 46, 48, 59, 63], while leaving high-level feature learning less investigated. This paper suggests that we should put more efforts on high-level semantic features for salient object localization and effective decoder to recover object details from the above extreme downsampling. This research is expected to spark some new thinking in SOD.
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