SelfReformer: Self-Refined Network with Transformer for Salient Object Detection

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Abstract

The global and local contexts significantly contribute to the integrity of predictions in Salient Object Detection (SOD). Unfortunately, existing methods still struggle to generate complete predictions with fine details. There are two major problems in conventional approaches: first, for global context, CNN-based encoders cannot effectively catch long-range dependencies, resulting in incomplete predictions. Second, downsampling the ground truth to fit the size of predictions will introduce inaccuracy as the ground truth details are lost during interpolation or pooling. To address the abovementioned problems, we employed a Transformer as our encoder backbone for better long-range dependency modeling. Meanwhile, we developed a branch and framed a patch-wise SOD task to learn the global context instead of assuming they are the high-level features in the encoder. Besides, for better details, we adopt Pixel Shuffle from Super-Resolution (SR) to reshape the predictions in each decoder stage back to the size of ground truth instead of the reverse. Furthermore, we developed a Context Refinement Module (CRM) to fuse global context with decoder features and automatically locate and refine the local details. The proposed network can guide and correct itself based on the global and local context generated (Fig.1), thus is named, Self-Refined Transformer (SelfReformer). Extensive experiments and evaluation results on five benchmark datasets demonstrate the outstanding performance of the network, and we achieved the state-of-the-art. Code will be released at https://github.com/BarCodeReader/SelfReformer.

Introduction

SOD aims to locate and segment the object that catches human attention in a visual scene. Due to its wide applications, such as AR/VR (Qin et al. 2020) and image captioning (Xu et al. 2015; Fang et al. 2015), it has gained growing interest in recent years. Most of the state-of-the-art models are CNN-based and often have an architecture of encoder-decoder where images are firstly encoded into multi-level features, followed by a decoder for feature fusion and saliency prediction. To further improve the accuracy, most of the work tries to develop better fusion modules (Wei, Wang, and Huang 2020; Pang et al. 2020), extra refinement networks (Qin et al. 2019; 2020), utilizing different modalities like depth or contour (Zhang et al. 2020; Zhao et al. 2019), and adopting attention modules (Wang et al. 2019; Zhang et al. 2018). These methods achieved remarkable results in the SOD task. However, CNN-based networks are limited in learning long-range relationships, resulting in a lack of global structural consistency in predictions.

In recent years, Transformer (Vaswani et al. 2017) was proposed to model long-range dependencies in language processing and was further extended to vision tasks. The vision transformers (ViT) (Yuan et al. 2021; Chu et al. 2021; Wang et al. 2021b) split the image into patches then apply multi-head self-attention and multi-layer perceptrons to capture long-range dependencies. When applied to SOD, the transformer-based networks (Liu et al. 2021; Ren et al. 2021) are effective in modeling global context, thus generating predictions with better structural integrity.

However, there are still two big challenges for better SOD. First, SOD is a densely supervised task that requires the ground truth in different resolutions for each decoder stage. Using interpolation or pooling, fine features in the ground truth are lost, and the decoder is trained against inaccurate ground truths, resulting in poor details in predictions. Note-worthy, for input size of 224 × 224, transformers like T2T-ViT (Yuan et al. 2021) and PVT (Wang et al. 2021b) usually have much smaller size of feature maps (56 × 56 max), and how to restore the fine features from this small size for accurate SOD still remain unsolved. Second, though existing studies utilizing global and local contexts like feedback network (Wei, Wang, and Huang 2020) and multi-level fusion

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We address the abovementioned problems from three aspects. First, to preserve the structural properties of ground truth, we adopt Pixel Shuffle (PS) (Shi et al. 2016a) from Super-Resolution (SR) as the up/downsampling method. Unlike pooling or interpolation, Pixel Shuffle can reshape a high resolution (HR) image into groups of stacked low resolution (LR) images without changing the pixel values (Fig. 2). Thus each decoder stage will have the same ground truth instead of multiple inconsistent LR images. Second, to obtain the global context more precisely, we reframe the SOD task into a patch-wise saliency detection problem and supervise a branch to learn the information explicitly (Fig. 3). We split input images into $n \times n$ non-overlapping patches whereby the defined branch identifies which patch contains saliency. Compared with existing approaches where global contexts are assumed to be the high-level encoder features, in our work, the obtained global context is learned via a supervised task. Lastly, we developed a Context Refinement Module (CRM) to fuse global context features and refine local unconfident regions. The CRM will firstly fuse global contexts with decoder features and then guided by an attention-based sampler to zoom in the target region, and lastly refining the details by fusing local context features from encoders. It has been proved that context fusion will improve the predictions.

Vision Transformers

Transformers were firstly introduced in natural language processing (Vaswani et al. 2017; Devlin et al. 2019; Lan et al. 2020) and were extended to computer vision tasks such as image classification (Dosovitskiy et al. 2021) and semantic segmentation (Zheng et al. 2021) due to their capability of modeling long-range dependencies. Networks like DETR (Carion et al. 2020) and its variants (Dai et al. 2021; Kim et al. 2021) used a combination of CNN and Transformer for various computer vision tasks (Wang et al. 2021a; Li et al. 2021). Following the Visual Transformer’s (ViT) success in image classification, some studies extend the Transformer for dense prediction tasks, e.g., semantic segmentation or depth estimation. SETR (Zheng et al. 2021) and PVT (Wang et al. 2021b) employ ViT as the encoder and use several convolutional layers to upsample encoder features for dense prediction. In SOD, VST (Liu et al. 2021) adopted T2T-ViT (Yuan et al. 2021) as the backbone and achieved remarkable results. The input images were unfolded into partially overlapped patches for self-attention, and a reverse T2T (rT2T) mechanism was developed to reconstruct the predictions gradually. The effectiveness of self-attention in modeling long-range dependencies makes Transformer promising in SOD tasks.

Pixel Shuffle

Pixel Shuffle (Shi et al. 2016b) was originally applied in the task of Single Image Super-Resolution (SISR) to upscale a
the input image from \((\text{Fig.2})\). Different from interpolation methods, by reshaping the \(HR\) image, and its reverse operation is Pixel-unshuffle. 

Average pooling (kernel = 4, stride = 4), (e) stacks of pixel shuffled images, (f)-(h) examples of different channels of pixel shuffled image. Best view in zoom-in.

As shown in \((\text{Fig.2})\), input image in the shape of \(224 \times 224\) will be cut into patches for self-attention, and PVT will obtain four groups of features in the shape of \(56 \times 56\), \(28 \times 28\), \(14 \times 14\), and \(7 \times 7\). For more efficient computation of the multi-head self-attention, PVT introduced a sequence reduction method to reduce the scale of \(K\) and \(V\) by firstly reshaping the input sequence \(X_i \in \mathbb{R}^{(HW \times C)}\) into \(\hat{X}_i \in \mathbb{R}^{(\frac{HW}{r} \times C \times r)}\) then apply an MLP network to reduce the channel of \(C \times r\) back to \(C\), the process is formulated as:

\[
\hat{X}_i = LN(MLP(\text{Reshape}(X, r)))
\]

where \(LN(\cdot)\) stands for layer normalization (Ba, Kiros, and Hinton 2016). The self-attention is performed based on the reduced \(K\) and \(V\):

\[
\text{Attention}(Q, \hat{K}, \hat{V}) = \text{Softmax}(\frac{Q \hat{K}^T}{\sqrt{d_{\text{head}}}})\hat{V}
\]

As a result, the total computation is reduced \(r\) times and hence more efficient.

**Pixel Shuffle as the Up/down Sampling Method**

SOD is a densely supervised task where the ground truth image needs to be downsamplied into multiple LR images to fit the size of each decoder stage. We noticed that given the input size of \(224 \times 224\), PVT’s largest feature map size is \(56 \times 56\), and conventional downsampling methods like interpolation or pooling are no longer viable to generate accurate ground truth images for the decoder. As shown in \((\text{Fig.2})\) in (b), fine structures are damaged and inconsistent in the bilinear sampled ground truth. In (c) and (d), the generated GTs via max and average pooling become inaccurate. As we increase the downsampling factor, the methods mentioned above will discard or change more and more pixel values, resulting in different inconsistent GTs for each decoder stage. In contrast, Pixel Shuffle rearranges the GT from \(I_{H \times W \times 1}\) into multi-channel LR images \(I_{\frac{H}{r} \times \frac{W}{r} \times r^2}\), since no pixel is discarded nor changed thus the structural properties are preserved. Though each pixel shuffled channel contains incomplete GT in (e) - (h) due to the reshaping process, the overall image is still the same once we shuffle them back to a single channel. Thus Pixel Shuffle is a more suitable method for downsampling the ground truth owing to its ability to unshuffle an HR image into LR images without changing the value, as illustrated in \((\text{Fig.2})\) previously. Different from all downsampling methods, by using Pixel Shuffle, we will train each decoder stage against the full-scale ground truth instead of its downgraded LR images. Predictions from each decoder stage will now become \(P_{\frac{H}{r} \times \frac{W}{r} \times 1}\) instead of \(P_{\frac{H}{r} \times \frac{W}{r} \times r^2}\), and this training scheme will enable each decoder stage to capture as much information as possible to restore the fine structures of the salient object. To formulate the unshuffle process, given an HR image or feature map \(I \in \mathbb{R}^{H \times W \times C}\) and a scaling factor \(r\), it can be described as:

\[
\mathcal{P}(I_{x,y,c}, r) = I_{\lfloor x/r \rfloor \cdot \lfloor y/r \rfloor \cdot C : \text{r.mod}(y,r)+C \cdot \text{mod}(x,r)+c}
\]

where \(x, y\) and \(c\) represent pixel coordinates and channel index in high-resolution (HR) space.
Figure 4: Network architecture for SelfReformer. Pre-trained PVT-v2 is employed as the encoder backbone. Encoder features are fed into the global context branch for patch-wise classification to obtain a low-resolution global context map. The map is further fused in CRM to locate the salient object. A CRM is developed for detail refinement where it utilizes its first prediction as a clue and generates features to improve its second prediction. In between each stage, Pixel Shuffle is applied to avoid the loss of details caused by interpolation methods.

Global-Context Branch

The global context is the clue indicating where are the salient objects. Though evidence indicates high-level encoder features contain global context and contribute to the completeness of predictions, we still lack a method to evaluate how much and how good are the global context we obtained from the encoder. Hence, we aim to design a supervised task to explicitly learn the information from the input image and the ground truth pair. Since in Transformer, input images are split into patches, therefore, we frame this supervised task as which patch contains salient object. The ground truth of this task can thus be easily obtained from the original ground truth images. For each patch, the branch is only required to predict a single value indicating the likelihood of the presence of the salient object, and the obtained global-context map will be passed to the decoder as guidance to locate the salient object. Since it is a patch-wise prediction instead of full-scale pixel-wise, the designed task is easier than the salient object detection scoped for the decoder. The developed branch will learn a representation of the global context in a controllable manner, and its features will be used as a map to guide the decoder network.

To build the branch, as shown in Fig 5, we firstly apply Pixel Shuffle to reshape all encoder features to $14 \times 14$ then concatenate and use a few Conv-BN-ReLU layers for feature fusion. Then a transformer block $\mathcal{T}_F$ from the original Transformer and an MLP layer are employed for patch-wise saliency prediction $P_g$. For simplicity, let $f_{\text{fuse}}$ represent the fused features being passed to the Transformer, and the global context branch can be described as:

$$P_g = \text{Sigmoid}(\text{MLP}(\mathcal{T}_F(\text{Reshape}(f_{\text{fuse}})))) \quad (4)$$

where $\text{Reshape}$ is the tensor operation from $[B, C, H, W]$ to $[B, H \times W, C]$. The self-attention in $\mathcal{T}_F$ is the same as the original transformer:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_{\text{head}}}}\right)V \quad (5)$$

To obtain the ground truth $G_g$ for this branch, we firstly apply Pixel Shuffle to reshape the original ground truth $G$ from $224 \times 224 \times 1$ to $14 \times 14 \times 256$, then apply $\max(\cdot)$ function along the channel dimension $c$:

$$G_g = \max_{c \in C}(\mathcal{PS}(G)_{i,j,c}) \quad (6)$$

where $i, j$ and $c$ represent pixel coordinates and channel indices. The branch is supervised using Binary Cross-
The obtained map is then passed to Context Refinement Module (CRM) for fusion, and Pixel Shuffle is applied accordingly to match different scales in each decoder stage.

**Context Refinement Module (CRM)**

We propose CRM to guide the network for better semantic integrity and refine its predictions for richer details. Key steps and results are shown in Fig 6 where the global context map is fused with decoder features; then a local refinement map is generated for fine structure segmentation. Thus CRM is a two-stage module where we handle global and local information separately, as shown in Fig 4.

For global information, to match the feature map dimension, Pixel Shuffle $\mathcal{P}S$ is applied on the global context features $f_g$ with different scaling factors $r$ depending on the decoder stage. Decoder features $f_d$ are fused with $f_g$ via a few Conv-BN-ReLU layers denoted as $\mathcal{F}_1$, and the first stage prediction $P_1$ is obtained and supervised against the ground truth. Mathematically, this process can be described as:

$$P_1 = \text{Sigmoid}(\mathcal{F}_1(f_d, \mathcal{P}S(f_g, r)))$$  

(8)

Above obtained $P_1$ contains unconfident regions in the presence of grey areas in the image. These areas are considered as hard pixels to the network. Noteworthily, due to the property of the Sigmoid function, values of hard pixels are close to 0.5 while values are close to 0 or 1 for confident predictions. By multiplying $P_1$ with $1 - P_1$, the unconfident area are highlighted, and features can be extracted as the local-context map $\mathcal{M}_l$ to guide the second stage to focus and refine the unsure regions in $P_1$. Denote the designed multiplication as $\mathcal{H}$, we adopt a single Conv-BN-ReLU layer $\mathcal{F}_2$ to obtain the map:

$$\mathcal{H}(P_1) = P_1 \ast (1 - P_1)$$  

(9)

$$\mathcal{M}_l = f_d \ast \mathcal{F}_2(\mathcal{H}(P_1)) + f_d$$  

(10)

where $\ast$ represents element-wise multiplication. We further adopt a transformer block $\mathcal{T} \mathcal{F}$ and another Conv-BN-ReLU layer $\mathcal{F}_3$ to generate the final prediction $P_2$:

$$P_2 = \text{Sigmoid}(\mathcal{F}_3(\mathcal{T} \mathcal{F}(\mathcal{M}_l)))$$  

(11)

The obtained $P_2$ has better quality in fine structures than $P_1$, which will be discussed in ablation studies. The proposed CRM achieves self-refine as it adopts global context to guide the decoder for better completeness, and automatically refines the details in the prediction.

We apply the weighted BCE loss ($\mathcal{L}_w$) for each decoder stage as used in F3Net (Wei, Wang, and Huang 2020):

$$\mathcal{L}_w = \sum_{i=1}^{4 \lambda_i(L_w^{P_1}(P_1, G)) + L_w^{P_2}(P_2, G))}$$  

(12)

where subscript $i$ represents each decoder stage as listed in Fig 4 and the values of $\lambda_{1-4}$ are [0.5, 0.7, 0.9, 1.1] respectively. The total loss of the network $\mathcal{L}$ is simply the sum of $\mathcal{L}_g$ and $\mathcal{L}_l$ as described above.
Table 1: Quantitative comparisons between our SelfReformer and other 11 methods on five benchmark datasets. Text in bold indicates the best performance, and superscript * stands for Transformer based network. Postfix BI of our work stands for network using bilinear interpolation instead of Pixel Shuffle, and full represents our proposed network.

| Methods | DUTS-TE | HKU-IS | PASCAL-S | ECSSD | DUT-OMRON |
|---------|---------|--------|----------|-------|-----------|
| FNet20  | 0.891   | 0.901  | 0.888    | 0.936 | 0.952     |
| GateNet20 | 0.887   | 0.889  | 0.885    | 0.933 | 0.949     |
| GCPA20  | 0.888   | 0.890  | 0.900    | 0.938 | 0.949     |
| MiNet20 | 0.883   | 0.897  | 0.884    | 0.934 | 0.953     |
| U2Net20 | 0.872   | 0.868  | 0.873    | 0.935 | 0.948     |
| LDF20   | 0.897   | 0.909  | 0.892    | 0.939 | 0.953     |
| MSFNet21| 0.877   | 0.911  | 0.875    | 0.927 | 0.953     |
| PFSNet21| 0.896   | 0.902  | 0.892    | 0.943 | 0.956     |
| DCN21   | 0.894   | 0.903  | 0.892    | 0.937 | 0.957     |
| PAKRN21 | 0.906   | 0.916  | 0.900    | 0.942 | 0.954     |
| VST21   | 0.890   | 0.891  | 0.896    | 0.942 | 0.952     |
| Ours-BI | 0.905   | 0.919  | 0.904    | 0.943 | 0.956     |
| Ours-full* | 0.916  | 0.920  | 0.911    | 0.947 | 0.959     |

Figure 7: Precision-Recall Curves (first row) and F-measure Curves (second row) comparison on five saliency benchmark datasets. As shown above, our network achieved the best results among all networks across five datasets.

Comparisons with state-of-the-art

We compare our method against 11 state-of-the-art networks in the field, namely, FNet (Wei, Wang, and Huang 2020), GateNet (Zhao et al. 2020), GCPA (Chen et al. 2020), MiNet (Pang et al. 2020), U²Net (Qin et al. 2020), LDF (Wei et al. 2020), MSFNet (Zhang et al. 2021), PFSNet (Ma, Xia, and Li 2021), DCN (Wu, Su, and Huang 2021), PAKRN (Xu et al. 2021), and VST (Liu et al. 2021). Results were calculated using the code provided by FNet.

Quantitative Evaluation. As shown in Table 1, our network achieved the best results in all metrics calculated across the five benchmark datasets. It demonstrates outstanding performances of the proposed SelfReformer. Besides, Fig 7 shows the precision-recall curve of the above-listed networks, and our network consistently outperformed all other methods.

Qualitative Evaluation. Visual comparisons are listed in Fig 8. Compared with other methods, our predictions are more accurate in structural completeness and contain richer details (rows 1, 2, and 6). Prediction completeness demonstrates the effectiveness of the global context branch, while rich details indicate the success of Pixel Shuffle and CRM. Moreover, our network excels in dealing with challenging scenarios like a small object among complex backgrounds (row 3), the unique object among its peers (row 4), and multiple salient objects (row 5).

Ablation Studies

We investigate the effectiveness of proposed modules and methods, i.e., global-context branch, CRM and Pixel Shuffle. For more ablation studies, please refer to supplementary materials.

Effectiveness of Global-Context Branch

We study the impact of the global-context branch by removing it and training the rest of the network, i.e., the first stage of CRM in Fig 9 will no longer fuse $f_g$ with decoder features. The evaluation results on DUTS-TE and PASCAL-S are listed in Table 2 and we can observe significant improvement with the presence of a global context branch.
In this work, we have proposed a novel Transformer-based network named SelfReformer which can guide itself with global and local contexts. In order to obtain a better global context, we framed a supervised patch-wise saliency detection task to obtain the global feature explicitly. Meanwhile, since interpolation or pooling methods damage fine features in the ground truth, we adopted Pixel Shuffle as the up-/downsampling method for details preservation. Besides, we developed CRM to guide the decoder with global context information and generate a local context map for better details in predictions. The proposed network demonstrated excellent performance in locating salient objects accurately with rich fine features. Evaluation results indicate the SelfReformer achieved the state-of-the-art across five benchmark datasets in all four related evaluation metrics.

**Conclusion**

Table 2: Quantitative comparisons for the effectiveness of global-context branch.

| DUTS-TE | PASCAL-S |
|---------|----------|
| w/o global context | 912 .028 .914 .904 | 892 .053 .869 .867 |
| w/ global context | 916 .026 .920 .911 | 894 .050 .872 .874 |

**Effectiveness of CRM**

We compare the two predictions obtained in the CRM visually and quantitatively. Table 3 reflects the improvement in accuracy between the predictions. In Fig.9, we can observe that the second prediction is refined by the local context features generated from the first prediction.

Table 3: Quantitative comparisons for the effectiveness of local-context branch on predictions at decoder stage 2.

| Decoder Stage 2 | HKU-IS | DUT-OMRON |
|-----------------|--------|-----------|
| w/o global context | 926 .035 .945 .914 | 817 .051 .866 .847 |
| w/ global context | 927 .033 .947 .915 | 818 .049 .872 .848 |

**Effectiveness of Pixel Shuffle**

We replace Pixel Shuffle (PS) with bilinear interpolation (BI) in our network to compare the difference. Better details are restored in the predictions when using PS during training, as shown in Fig.10.

**Figure 8:** Visual comparisons between the proposed method and 10 state-of-the-art networks. * stands for Transformer based networks. More comparisons are listed in the supplementary material. Best view in zoom-in.

**Figure 9:** Qualitative comparisons for CRM. (a) top to bottom: Input, Global-context map, GT. (b)-(e) maps generated from decoder stage 4 to stage 1: first row: first stage predictions, second row: local context maps, last row: second stage predictions. MAE is marked at the top left corner.

**Figure 10:** Qualitative comparisons of predictions when using BI and PS during training. Pixel Shuffle is effective in restoring more details in the salient object prediction.
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