TransCMD: Cross-Modal Decoder Equipped with Transformer for RGB-D Salient Object Detection

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Abstract—Most of the existing RGB-D salient object detection methods utilize the convolution operation and construct complex interweave fusion structures to achieve cross-modal information integration. The inherent local connectivity of convolution operation constrains the performance of the convolution-based methods to a ceiling. In this work, we rethink this task from the perspective of global information alignment and transformation. Specifically, the proposed method (TransCMD) cascades several cross-modal integration units to construct a top-down transformer-based information propagation path (TIPP). TransCMD treats the multi-scale and multi-modal feature integration as a sequence-to-sequence context propagation and update process built on the transformer. Besides, considering the quadratic complexity w.r.t. the number of input tokens, we design a patch-wise token re-embedding strategy (PTRE) with acceptable computational cost. Experimental results on seven RGB-D SOD benchmark datasets demonstrate that a simple two-stream encoder-decoder framework can surpass the state-of-the-art purely CNN-based methods when it is equipped with the TIPP.

I. INTRODUCTION

Salient object detection (SOD) aims to identify the most significant objects or regions in images or videos from various visual scenes. It plays a fundamental and important role in many computer vision tasks, such as semantic segmentation [1], medical image segmentation [2], [3], video object segmentation [4]–[6], person re-identification [7], object tracking [8], [9] and recognition [10], image editing [11] and compression [12].

Although many purely CNN-based methods [13]–[17] achieve quite promising results on the RGB SOD task, they still struggle with challenges of complex or low-contrast scenes, and obscured or indistinguishable objects. To this end, some recent researches have attempted to introduce additional information, such as the depth signal, to make the model comfortable with complicated and diverse natural scenes. The depth map can explicitly provide complementary spatial structure information and the relative position relationship between objects, which helps to distinguish different objects and alleviate the above issues. Therefore, recent research is gradually shifting towards the integration of modality-specific and modality-complementary cues from RGB and depth images to excavate and capture objects of interest. At the same time, long-range context and contrast information play a key role in identifying and locating salient objects. However, the purely convolution-based architectures [1] possibly encounter the performance bottleneck, which is caused by the localized convolution operation and the fixedness of the learned parameters. Hence, the introduction of a new architecture becomes more and more important.

The transformer [18] has superior performance against existing state-of-the-art CNNs in several computer vision tasks [19], [20], which can be attributed to its powerful ability of extracting feature and modeling long-range dependencies. In this paper, we introduce the transformer to design a simple yet effective RGB-D SOD model, TransCMD. A novel transformer-based top-down multi-level structure is engineered for the cross-modal fusion, which can be easily assembled to a CNN feature extractor, like VGG [21] and ResNet [22]. We leverage the self- and cross-attention to learn feature alignment where each element gathers information from other elements in the global sequence based on semantic similarity. This can naturally achieve the transformation and enhancement of intra-modal features and the matching and fusion of inter-modal features. However, a prominent problem of the transformer is the unbearable quadratic computational complexity caused by the attention operation based on all elements of the feature map. To cope with this, we introduce the patch embedding in the attention block. Instead of using patch-embedding to extract and compress image features in the input stage [19] or at each feature scale [20], we apply it to compute each matrix multiplication of self- and cross-attention with the pixel-wise tokens as the input. We call it “patch-wise token re-embedding” (PTRE) as shown in Fig. 1. When learning multi-scale and high-resolution features, such a design can reduce computation and memory costs by a factor of $p^2$ and $p^4$ ($p$ is the side length of the patch), respectively. And, the proposed components together with the convolutional feed forward network can effectively

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characterize global and local information. Our contributions can be summarized as:

- We introduce the transformer to rethink the SOD modeling from a sequence-to-sequence perspective, which gains better interpretability.
- We construct a top-down transformer-based information propagation path (TIPP), which can align the CNN features of RGB and depth modalities and fully exploit the inter-modal complementary information.
- We boost the matrix operation in the attention by using the patch-wise token re-embedding (PTRE), which improves the efficiency of the transformer for multi-scale and high-resolution features. And aided by the convolutional feed forward network, the locality of features can be further enhanced, and key cues in both global and local contexts can be fully perceived and explored.
- Extensive experiments demonstrate that the proposed model outperforms sixteen purely CNN-based methods on seven RGB-D SOD datasets.

II. RELATED WORK

a) Visual Attention.: Humans can quickly capture significant objects or regions in a scene. The modeling and investigation of such an ability is a fundamental and critical problem in computer vision, i.e. visual attention mechanism. Researches in this area can be divided into two different directions: one is to explore where the observer is looking, i.e. eye fixation prediction (FP) [23], and the other is to locate and segment completely visually attractive regions, i.e. salient object detection (SOD) [24, 25]. In this paper, we focus on the latter. With the FCN-like [26] and UNet-like [27] architectures becoming the dominant paradigm for SOD, the proliferation of CNN-based methods has driven the rapid development of SOD in recent years [28, 29].

b) RGB-D Salient Object Detection.: RGB-D SOD introduces the depth map to supplement spatial information for RGB data, which can provide a more comprehensive understanding of the scene. Roughly speaking, the existing methods can be broadly classified into three categories depending on the cross-modal fusion strategy: early fusion, intermediate fusion, and late fusion. Early fusion methods directly combine the low-level information of two modalities, e.g., concatenating the inputs [30–32] or integrating their low-level features [33]. Although such a scheme may reduce the number of model parameters, it also leads to very difficultly control the interference of the noise within different modalities to the overall model. Unlike early fusion, late fusion methods generally adopt a dual-stream structure and focus more on the cross-modal fusion of high-level features [34–36] or final predictions [37]. Since the semantic information enriched by high-level features has a positive guide for good prediction results, late fusion methods are dominated. In fact, both low-level and high-level features have the same importance in the SOD task, and they complement each other. The low-level features can provide rich texture and structural scene perception, which is missing in the high-level features. Hence, an intermediate fusion strategy that utilizes both simultaneously is gradually becoming the mainstream of RGB-D SOD methods [38–47]. Our proposed method can also be classified in this category. These algorithms construct various cross-modal interaction strategies based on the CNN structures, which typically draw on the plug-and-play modules or their variants to enhance and rectify the representation of features such as ASPP [48] or DenseASPP [49] ( [31], [35], [42], [44–46], [50]), and ConvLSTM [51] ( [42]). Unlike them, we introduce a global sequence perspective for feature enhancement and interaction. This can effectively fill the lack of contextual information caused by the local reception field of the convolution operation.

c) Attention-Based Model.: On the one hand, as mentioned earlier, the attention mechanism is closely related to the SOD task. Some methods [35, 42, 44, 50] apply channel and spatial attention [52, 53] and dynamic convolution [54]. Although these data-adaptive feature enhancement methods in spatial or channel form can improve the flexibility and expressiveness of the model, these convolution-based strategies do not model long-range dependencies well and still have a large room for improvement. Another related work [45] introduces the non-local block [55], but it is only used to enhance feature interaction in the topmost layer, and the model body is still limited by the CNN architecture. In contrast, our approach achieves further exploration by thoroughly building the multi-level cross-modal fusion scheme on a sequence-to-sequence [18] transformation perspective. On the other hand, the transformer [18] is built on the attention mechanism, which has shown powerful performance in natural language processing, is receiving more and more interest from researchers in computer vision. The recent remarkable performance of vision transformers [19, 20, 56] reflects that the transformer is a general and effective architecture to transform features. Most of them use the transformer to extract image features for the classification task. SETR [57] is a pioneering work of applying transformer to the segmentation field and it uses ViT [19] to extract features and builds a lightweight convolutional decoder to obtain predictions. Similar to it, in fact, the existing methods tend to explore the application of transformer in the encoder, and there is little work focusing on the decoder. In the segmentation task, the decoder plays an important role and both transformer-based encoder and decoder are worthy of being explored. So different from the existing methods which propose the transformer-based encoder, our work is more inclined to explore the design of the transformer-based decoder, especially for cross-modal tasks such as RGB-D SOD. We use it to decode the CNN features and build an encoder-decoder architecture for the RGB-D SOD task and this work and the existing methods can complement each other. In addition, we apply the transformer to multi-scale high-resolution features, which faces the computational pressure of higher resolution features. Also, since RGB-D SOD requires considering two modalities, their integration is one of the key points of our model design.

III. OUR METHOD: TRANSCMD

In this paper, we propose a simple yet effective cross-modal feature integration network based on the transformer. In the
The TIPP is proposed mainly to process and integrate top-down features from both RGB and depth modalities with different scales, which consists of four cascaded cross-modal integration units (CMIU), as shown in Fig. 2. Among them, the 4th CMIU is only responsible for the integration of cross-modal information. It takes feature maps $f_{rgb}^i$ and $f_d^i$ with the same scale as input. While each of the remaining CMIUs needs to additionally integrate the output feature map from the adjacent higher level. In addition, each input map of the CMIU needs to be converted into a D-dimensional pixel-wise embedding map in a separate embedding layer. Before the integration of modalities through the inter-modal cross attention block, $f_{rgb}$ and $f_d$ are first reconstructed and self-reinforced by $N_{im}$ stacked intra-modal self-attention blocks, respectively. For the following $N_{cs}$ cross-scale self-attention blocks, if there exists the feature $f_{rgb}^{i+1}$ from the previous CMIU, the input is the sum of the upsampled $f_{rgb}^{i+1}$ and the output $f_{rgb}^{i+1}$ of the cross-attention block, otherwise, the input is only $f_{rgb}^{i+1}$. The resolution of $f_{rgb}^{i+1}$ is half of that of the input $I_{rgb}$ and $I_d$.

The intra-modal and cross-scale self-attention blocks play different roles, but their structures are the same. The specific details of the self-attention block can be found in Fig. 4a, which is characterized by a patch-wise multi-head self-attention (PMHSA), a convolutional feed forward network (CFFN), normalization layers, dropout layers and residual connectors. The PMHSA follows a pre-normalization [58, 59] layer and

**Fig. 2.** The overview of the proposed model. “$N_{im}$” and “$N_{cs}$” represent the number of the stacked intra-modal and cross-scale SA blocks in the TIPP and default values are 2 and 1, respectively. Note that the dashed arrow denotes an optional input for the decoder, and in our model, the 4th decoder block contains only two inputs, i.e. $f_{rgb}^4$ and $f_d^4$. The feature $f_{rgb}^{i+1}$ is upsampled using bilinear interpolation in the 2D form.

**Fig. 3.** Conversion between the 2D feature map and the 1D feature sequence.
they are wrapped by a residual connector. The output is then passed to a pre-normalized CFFN whose input and output are similarly connected in a residual way. Moreover, a dropout operation is also applied to the output of the PMHSA or the CFFN. The overall process can be expressed as:

\[
X = \text{Dropout}(\text{PMHSA}(\text{Norm}(X))) + X,
\]
\[
X = \text{Dropout}(\text{CFFN}(\text{Norm}(X))) + X,
\]
(1)

where \(X \in \mathbb{R}^{N \times D}\) refers to the flattened image features. \(N = H \times W\) and \(D\) denote the number of tokens (or pixels) and the embedding dimension.

\(a\) Multi-Head Self-Attention (MHSA).: At first, we introduce its original form of in the transformer [18]. This operation is actually a feature alignment process, which computes the feature correlation to reconstruct the query itself. And a single head of it can be defined as:

\[
Y_h = \text{Softmax}(\frac{Q_h K_h^T}{\alpha}) V_h,
\]
\[
[Q_h, K_h, V_h] = X [W_q, W_k, W_v],
\]
(2)

where \(Q_h, K_h, V_h\) are a single head of query, key and value, respectively. \(W_q, W_k, W_v \in \mathbb{R}^{D \times D_N}\) are the corresponding projection matrices. \(N_h\) is the number of heads and \(\alpha = \sqrt{D/N_h}\) is a scaling factor. The outputs from different heads are concatenated together and fused by a dense layer. The final output \(Z \in \mathbb{R}^{N \times D}\) can be expressed as \(Z = \text{Dropout}([Y_1, \ldots, Y_{N_h}] W_o)\) and \(W_o \in \mathbb{R}^{D \times D}\) is an output projection layer. It is noted that the dot product operation in the attention matrix \(Q_h K_h^T\) has a quadratic complexity w.r.t. the input sequence length, i.e. \(N^2\), which limits it to handling multi-scale high-resolution features. We introduce the patch-wise re-embedding to alleviate the issue and propose the patch-wise multi-head self-attention.

\(b\) Patch-wise Multi-Head Self-Attention (PMHSA).: The PMHSA improves the matrix operation from the pixel-wise form to the patch-wise form compared with the MHSA, which reduces the complexity by a factor of \(p^2\). Here, \(p^2\) is the number of elements in a patch. Specifically, \(Q_h, K_h\) and \(V_h\) in Equ. 2 are unflattened to the 2D form (Fig. 3) and performed the patch-wise token re-embedding (PTRE) operation. In the PTRE, the map with \(D/N_h\)-dimensional embedding is unfolded to \(N/p^2 \times D p^2/N_h\) (Fig. 1). After the operation in Equ. 2 the patch-wise result is reshaped back to \(N \times D/N_h\) and subsequent operations are consistent with those of the MHSAS.

\(c\) Convolutional Feed Forward Network (CFFN).: Although the transformer can better model the long-range interaction, the local correlation still has a strong practical value as a kind of inductive bias for image data in the vision task. The original position-wise feed forward network (FFN) in the transformer only performs separate channel transformations for each element of the sequence, which lacks attention to the local context. Hence, we adapt the FFN by using the convolution operation. The original two fully-connected layers are replaced with the common combination of “3 × 3 convolution → batch normalization → activation” and finally a 1 × 1 convolution layer is utilized to obtain the feature with the same dimension as the output of the original FFN.

\(D\) Inter-Modal Cross-Attention

The inter-modal cross-attention block (Fig. 4b) is used to associate and interact information between modalities. Its input is from the outputs of two separated intra-modal self-attention blocks. Similar to the self-attention block, the input features are also normalized. Then, they are passed into the patch-wise multi-head cross-attention (PMHCA) for cross-modal alignment and enhancement, and are regularized by the dropout layer. Next, the features from two modality streams are concatenated and then locally enhanced by the CFFN followed by a dropout. In the skip connection, a simple linear layer is applied to match the channel dimension. Finally, the output is the sum of the two results.
The PMHCA is the core component for cross-modal information fusion and aggregation, which is based on the multi-head cross-attention. It conducts two streams (i.e., RGB and depth) and is also equipped with the PTRE to reduce the complexity. The single head of it can be formulated as:

\[
Y_{rgb}^{h} = \text{Softmax}(Q_{h}^{rgb}K_{h}^{TT}V_{h}^{rgb}),
\]

\[
Y_{d} = \text{Softmax}(Q_{h}^{d}K_{h}^{TT}V_{h}^{d}),
\]

where \(Q_{h}^{rgb}, K_{h}^{rgb}, V_{h}^{rgb}\) in the RGB stream and \(Q_{h}^{d}, K_{h}^{d}, V_{h}^{d}\) in the depth stream correspond to a weight matrix, respectively. For each stream, the output of all heads is concatenated together and passed through a dense layer and a dropout layer, similar to the PMHSA (Sec. III-C2).

IV. Experiments

A. Datasets

To validate the proposed model and components, we conducted experiments on seven data benchmarks that have been widely used to evaluate RDB-SOD methods. NLPR [30], captured by Microsoft Kinect, contains 1000 pairs of RGB and depth images covering rich indoor and outdoor scenes. NJUD [61] (also known as NJU2K) involves more complex data, which consists of 1985 images collected from the Internet, 3D movies, and photos acquired by Fuji W3 stereo camera, with their corresponding depth images. RGBD135 [62] (also known as DES), also collected by Kinect, contains 135 sets of RGB-D images, mainly for indoor scenes. SIPP [32] containing 929 pairs of images is a recent high-resolution dataset. It is collected by the Huawei Mate10 in an outdoor scene, and contains complex lighting conditions and diverse human poses. SSD [63] is another RGB-D SOD dataset and only includes 80 samples covering indoor and outdoor scenes. The 1000 stereoscopic images in STERE [64] were collected from Flickr, NVIDIA 3D Vision Live, and Stereoscopic Image Gallery. DUTRGBD [42] is a recently proposed large-scale RGB-D SOD dataset, which contains 1200 pairs of RGB-D images, 800 from indoors and 400 from outdoors. It captures a large number of challenging objects and scenes. Following the dataset setting in recent works [31], [32], [35], [42], [44], we choose 700 images from...
NLPR and 1485 images from NJUD as the training set, and the remaining data of these datasets except DUTRGDB as the testing set. For DUTRGDB, the proposed model is trained on 800 images and tested on the remaining 400 images.

B. Evaluation Metrics.

To fully demonstrate the performance differences of different methods, we introduced 9 metrics to quantitatively evaluate the models. Specifically, S-measure [65] \((S_m)\) focuses on region-aware and object-aware structural similarities between the saliency map and the ground truth. MAE [66], \((\text{MAE})\) indicates the average absolute pixel error. F-measure [67] \((F_B)\) is a region-based similarity metric and based on precision and recall. E-measure [68] \((E_m)\) is characterized as both image-level statistics and local pixel matching. \(F_B\) and \(E_m\) rely on specific thresholds to binarize prediction maps and the adaptive version \(F_B^{\text{adp}}\) and \(E_m^{\text{adp}}\) can be obtained when twice the average of the saliency probability map is used as the threshold. If \(F_B\) and \(E_m\) are calculated using a series of binary maps corresponding to thresholds varying from 0 to 255, we can plot their curves w.r.t. the threshold. The maximums of the \(F_B\) curve and the \(E_m\) curve are \(F_B^{\text{max}}\) and \(E_m^{\text{max}}\), respectively. And the series of paired precision and recall values used to calculate \(F_B\) can form PR curve. Weighted F-measure [69] \((F_B^w)\) improves the metric \(F_B\) by using a weighted precision for measuring exactness and a weighted recall for measuring completeness.

C. Implementation Detail

As shown in Fig. 2, we stack \(N_{im}\) intra-modal self-attention blocks and \(N_{cs}\) cross-scale self-attention blocks in the CMIU. The ablation analysis of \(N_{im}\) and \(N_{cs}\) can be found in ablation studies. If not specified, \(N_{im}\) and \(N_{cs}\) are set to 2 and 1 by default.

The backbone network is initialized by the weight of VGG-16 [21] or ResNet-101 [22] pre-trained on ImageNet, and the remaining structures are initialized randomly using the default method of the PyTorch toolbox. All our models are trained for 22K steps with a batch size of 4 using a momentum SGD optimizer with a momentum of 0.9 and a weight decay of 0.0005 on an NVIDIA GTX 2080Ti GPU. The learning rate is initialized as 0.005 and scheduled by the “poly” strategy with a factor of 0.9. And the dropout regularization technology with the probability of 0.1 is applied for all attention blocks to avoid over-fitting. The single-channel depth input is repeated three times along the channel dimension to facilitate the use of pre-trained parameters, and RGB and depth images are resized to \(256 \times 256\). All RGB-D image pairs are augmented by random horizontal flipping and random rotating, and random color jittering and normalization are only used for RGB images. In the testing stage, the normalized RGB and repeated depth images are resized to \(256 \times 256\) and the final prediction is resized back to the original size for evaluation. For all experiments, the model is supervised by the binary cross entropy loss. And we also supplement the results of the model based on the hybrid loss [13, 50] in ablation studies.

D. Comparison

To demonstrate the effectiveness of our method, we compared it with the recent 16 state-of-the-art RGB-D SOD methods, including CoNet [44], JLDCF [46], HDFNet [35], DANet [31], UCNet [50], ICNet [60], D3Net [32], S2MA [45], CMWNet [43], DisenFuse [56], DMRA [42], TANet [59], MMCI [40], CPFP [41], PCANet [38] and CTMF [34]. They are all based on deep learning and CNN architecture. All data used in experiments are from the resources released by the authors.

a) Quantitative Comparison. In Tab. I the detailed results from all competitors on seven datasets and nine metrics.
are listed and our method performs best on most datasets. In particular, our ResNet-based method achieves the best performance on DUTRGBD, NJUD, SIP, and SSD. Specifically, the average performance gain of our method on three datasets,
Fig. 7. Visualization of the attention maps from different attention operations in the 1st CMIU. “⋆_SA_i” denotes the attention map from the i-th SA block corresponding to the ⋆ modality. “⋆_CA” and “RGBD_SA” are from the specific stream in the CA block and the cross-scale SA block, respectively. Also, normalization and upsampling based on the bilinear interpolation are applied to show them more clearly. We choose the red square in the RGB and depth images to mark the positions in the query corresponding to the attention map and visually compare the attention maps of two different positions in the same image.

DUTRGBD, NJUD, and SIP, is significant, especially on the metric MAE, which is over 15% relative to the second-best method, HDFNet [35], and nearly 20% relative to the third-best method, JLDCF [46]. And it is also significantly competitive on other datasets. It is worth emphasizing that this work focuses on exploring and designing a new architecture suitable for RGB-D SOD. Therefore, the whole network is very simple and is not equipped with some other modules to further improve performance, such as ASPP, DenseASPP, and channel and spatial attention. When an additional loss that has been used in the works [13], [50] is introduced, the proposed model can yield more impressive performance, which is shown in Sec. IV-E0g. To compare the overall performance of different methods, we also show PR curves and $F_β$ curves in Tab. 5. It can be seen that our method corresponds to a curve positioned more upward, which indicates that the proposed model performs better.

b) Qualitative Comparison.: Some visual comparisons of different models are listed in Fig. 6, which covers ten methods published in 2020. As we can see that these samples have various types of scenes and objects, including the multiple large or small objects (Row 1st and 5th), the large and out-of-bounds object in the high-contrast scene (Row 2nd), the medium-sized objects with unclear and complex boundaries (Row 3rd) or strong background interference (Row 4th, 6th and 8th) and the objects with large internal variability (Row 1st, 2nd and 7th). The results fully demonstrate the robustness of the proposed algorithm against different data, which can be attributed to the powerful information modeling capability of the attention mechanism.

E. Ablation Analysis

In order to evaluate the effectiveness of the proposed components and investigate their importance and contributions, we construct the ablation study on the NJUD, NLPR, SIP, and STERE datasets. At first, we build a CNN-based FPN-like two-stream model as the baseline network in which the features of the same resolution from both modalities are added directly. From the results in Tab. II we can see that it is a sufficiently strong baseline model, which also makes the gains from our approach more convincing. Besides, a linear version equipped with the proposed TIPP is constructed, which uses linear projection layers and FFNs. We also attach some other ablation analysis about the visualization of attention maps, the hybrid loss [13], [50], the comparison between LN [70] and BN [71], the setting of $N_{im}$ and $N_{cs}$ and some typical failure cases.

a) Positional Embedding (PE).: When the CNN is taken as the encoder, the zero padding operation means that the position information is already implicitly encoded in features [72], which makes the explicit PE unnecessary. In Tab. II
by comparing the linear model 2.1 with 2.2, we find that removing the PE does not affect the performance. And for the PTRE-based version, the models 3.2 and 3.4 without the PE achieve a slight performance improvement over the models 3.1 and 3.3. These experiments indicate that the explicit PE can be safely removed when the features are extracted by the CNN. Moreover, since the PE fixes the sequence length, the model without it can handle variable-length sequences more flexibly.

b) Region-wise or Position-wise?: The utilization of the local context is one of the key factors for the success of convolution in 2D vision tasks. Although the transformer can facilitate the propagation of global information, it does not pay enough attention to the local region, which may lead to important local details being overlooked. To alleviate this problem, we introduce locality to assist the attention operations. Specifically, the $3 \times 3$ convolution is used to replace the original linear projection layer, and the CFFN (Sec. III-C6) is used to replace the original position-wise FFN. The experimental results in Tab. [I] reflect that the region-wise operations at different locations affect the overall performance and the FFN is more suitable to be enhanced than the projection layer by using these operations. We finally choose an optimal combination of “No. 3.4” for other experiments. Interestingly, in Tab. [I] “No. 3.4” outperforms “No. 3.2” on NLPR, SIP, and STERE, but the performance on NJUD of the two is the same. This may be because most of salient objects in NJUD dataset have not complex local details, which makes the effects of local operation in the CFFN be not obvious.

c) Effectiveness of the CMIU.: In order to explore the effects of CMIU, we gradually replace the CMIU in the original TransCMD with the commonly used “Convolution-BN-ReLU” structure in the order from shallow to deep. The experimental results are listed in Tab. [V] It can be seen from the table that with the gradual application of CMIU from shallow to deep, the performance of the model has been consistently improved on multiple datasets.

d) Number of SA Blocks.: The number of the intra-modal self-attention blocks (i.e. $N_{im}$) and the number of the cross-scale self-attention blocks (i.e. $N_{cs}$) are also important hyper-parameters that directly affect the capacity of the model, and we also show a careful ablation analysis in Tab. [VI] for different combinations of them. The results in the table reflect that, as the number of blocks grows, the performance is no longer improved and reaches its best at $N_{im} = 2$ and $N_{cs} = 1$. This also implies that for our model, stacking more self-attention blocks does not necessarily improve performance, that is, performance is not simply positively correlated with model capacity.

e) Position of Patch-wise Embedding.: In this work, the PTRE is designed to reduce the complexity of the attention operation for high-resolution and multi-scale features, which makes our attention block have a different structure from those existing vision transformer methods [19], [20]. In addition, from Tab. [I] we can see that, for our pure linear model, the introduction of PTRE also improves the accuracy of the method compared to the version with PVT-style patch-wise embedding.

f) Patch Size of the PTRE.: The size of the patch embedding in the PTRE is an important parameter. We compare three choices in Tab. [V] From the specific metrics in the table, we can see that with the increase of patchsize, the performance has changed. Compared with $4 \times 4$ and $8 \times 8$, $16 \times 16$ has a slight decrease, especially in some metrics ($S_m$, $F^2_m$ and $F^{adp}_m$) of NLPR, SIP and STERE. In our opinion, the performance degradation here is due to the sequence being too short. It should be also noted that since the input image of our method is $256 \times 256$, the resolution of the highest feature is $16 \times 16$ after being downsampled 16 times by the VGG backbone. When the patch size is $16 \times 16$, the size of the attention map corresponding to the feature map is $1 \times 1$, and the process of gathering information from the value is then simplified to scale the value using a specific scalar factor. Too large a window would result in too short a sequence length, which would weaken the transformer’s ability to model global interactions. The sequence lengths corresponding to these patchsizes have a small difference, which reduces the range of performance changes, for example, the length difference of the topest sequences of $8 \times 8$ and $16 \times 16$ is 3. The performance of the current model itself is already high, this can be seen from the comparison of existing methods based on VGG-16 and without additional loss.
functions, such as ICNet, D3Net and S2MA. These may cause the overall performance of the model to appear less sensitive to different patchsizes. Finally, in order to better adapt to the ResNet-50 model with a downsampling rate of 32 at the same time (the downsampling rate of the VGG-16 mode without the final pooling layer used in the ablation experiment is 16), we uniformly set the patchsize of the PTRE to $4 \times 4$ in other experiments.

g) Hybrid Loss.: During the training phase, we use only binary cross entropy loss (BCE) and the specific mathematical form is as follows:

$$L = \frac{1}{H \times W} \sum_{h} \sum_{w} - \log \mathcal{P}_{h,w}$$

where $\mathcal{P}_{h,w}$ denotes the value at position $(h, w)$ on the ground truth $\mathcal{G}$ and prediction $\mathcal{P}$, respectively. Since BCE only focuses on the pixel-level error and ignores the overall region constraint, some recent SOD works [13], [14], [17], [35], [50], [73], [74] additionally introduce the auxiliary region-level constraint to construct the hybrid loss, which has achieved significant results. The main focus of this paper is to improve the structural design for RGB-D SOD, therefore, the overall experiment is still based on BCE only. Therefore, we keep the structure as simple as possible and do not apply some of the existing complex modules and loss functions. The most experiments are still based on BCE only. However, to facilitate a full and detailed comparison with existing methods, we retrain our VGG-based and ResNet-based models with the hybrid loss used in [13], [50] and list results in Tab. VII. And we additionally add the results on the dataset RGDDBD35. Although it may cause a slight decrease in $S_{m}$, on the other metrics and most datasets, the hybrid loss can significantly improve performance and have an overall positive gain.

h) Visualization of Attention Maps.: To visualize the impact of attention operations at different positions, we show in Fig. 7 the learned alignment score map, i.e., the attention map, which is calculated by the dot product between the patchwise query token corresponding to the red marker in RGB and depth images and the global key token sequence. Some interesting points are shown in these results. From “*_SA_0” to “*_SA_1”, the semantic discriminability of the features themselves is enhanced, and the scores on the related token positions are boosted, that is, the model focuses more on specific locations. From “*_CA_1” to “*_CA_2”, it is obvious that an information interaction between RGB and depth is carried out. From “*_CA” to “RGBD_SA”, due to the integration of features with stronger semantic information from the previous layer, the foreground token of the query pays more attention to those tokens from the saliency region. From the results in the 2nd, 3rd and 4th rows of Fig. 7, the highlighting of salient objects in the attention map of the background token also demonstrates that the attention operation does not focus only on those semantically relevant regions, but also cues that help determine their own attributes, including irrelevant regions with the reference value (i.e., saliency regions in this case).

i) Layer Normalization or Batch Normalization?: In the original transformer [18] and recent vision transformer methods [19], [20], [50], the authors usually choose the layer normalization [70] to normalize the tokens sequence. However, when used with convolution, batch normalization [71] may be a more efficient choice because it can be fused into the preceding convolution operation to accelerate the inference time. Besides, the results in Tab. III show the performance difference between LN and BN is not significant. So, for our models in other experiments, BN is the default choice.

j) Some Typical Failure Cases.: We show some typical failure cases in Fig. 8. In the first and second cases, the objects with similar structure types yet require different coverage types for prediction. Specifically, in $\mathcal{G}$, the gap inside the salient object is completely covered in the first sample, but not in the second. Such data may interfere with the learning process of the model. Besides, in the second case, there are some artifacts with a similar color to the foreground in the gaps of the foreground object in $I_{rgb}$, which interferes with the prediction of the model. And, the model has more difficulty in predicting the narrow foreground region at the edge of the image, which can also be seen in its feature map, where the lowermost part of the object region is significantly different from the rest. The
foreground and interfering objects in the latter three samples are extremely similar in appearance. It is very difficult for the model to accurately capture the object and exclude the background interference in this case. Moreover, the depth maps of these samples either have a relatively clear outline of the foreground object and the interference objects (e.g., Row 3 and 5), or the foreground object is directly blended with the background objects (e.g., Row 4). These depth maps do not provide enough valid information, and even the depth contour of the background objects brings interference to the prediction. This makes the separation of foreground and background in the prediction more complicated and directly leads to significant misclassification. In fact, all the above problems can be attributed to the ambiguity caused by low-quality depth data. To solve these problems, we need to further improve the model’s ability to tolerate inaccurate depth information and adapt to low-quality data and make the model able to discover more essential differences between samples. These will be the focus of future research.

V. CONCLUSION

In this paper, we rethink the architecture design for the RGB-D SOD task. A novel transformer-based top-down information propagation path is proposed to enhance the capability of perceiving and excavating the important global cues in intra-modal features and simplify the cross-modal long-range interaction and alignment. And by using the PTRE, the computational and storage intensity of the matrix operation in the attention block is effectively reduced, which makes it possible to process multi-scale high-resolution features. In addition, the convolutional FFN further enhances the critical local details in the feature map. We also verify that the position encoding can be safely removed from the hybrid structure, which makes our model more flexible. Extensive experimental comparisons demonstrate the effectiveness of the proposed method.

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