CMF: CASCADED MULTI-MODEL FUSION FOR REFERRING IMAGE SEGMENTATION

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ABSTRACT

In this work, we address the task of referring image segmentation (RIS), which aims at predicting a segmentation mask for the object described by a natural language expression. Most existing methods focus on establishing unidirectional or directional relationships between visual and linguistic features to associate two modalities together, while the multi-scale context is ignored or insufficiently modeled. Multi-scale context is crucial to localize and segment those objects that have large scale variations during the multi-modal fusion process. To solve this problem, we propose a simple yet effective Cascaded Multi-modal Fusion (CMF) module, which stacks multiple atrous convolutional layers in parallel and further introduces a cascaded branch to fuse visual and linguistic features. The cascaded branch can progressively integrate multi-scale contextual information and facilitate the alignment of two modalities during the multi-modal fusion process. Experimental results on four benchmark datasets demonstrate that our method outperforms most state-of-the-art methods. Code is available at https://github.com/jianhua2022/CMF-Refseg.

Index Terms— Referring Image Segmentation, Natural Language Expression, Context Modeling

1. INTRODUCTION

Referring image segmentation (RIS) [1] is a challenging task which associates semantics of natural language expressions with contents of images. As illustrated in Fig. 1, given an image and a natural language expression, the goal of RIS is to predict a binary mask for the object specified by the expression. The categories of semantic segmentation are predefined and fixed, while RIS can take arbitrary expressions as input to describe the object of interest. The expressions may contain diverse semantic concepts, such as entities, attributes and actions. Thus, how to align these semantic concepts with visual contents is a main challenge of this task.

Previous works [1, 2, 3] usually concatenated visual and linguistic features extracted from the convolutional neural network (CNN) and long short-term memory (LSTM) [4] network respectively, and then predicted the mask from integrated multi-modal features via a fully convolutional network (FCN) [5]. These works ignored the linguistic variations of input expressions, and treated each word equally to each visual region. Thus it is hard to accurately distinguish the referred object from the background. Some works applied dynamic filters [6] or word attention [7] to learn adaptive expression representations but lacked interactions between vision and language. Interactions between two modalities can associate each word with each image region, and further highlight the features of the target object for accurate segmentation. Recent works proposed to model the interactions by introducing unidirectional [8, 9] or bi-directional [10] attention mechanisms.

Although promising results have been achieved in these works, the multi-scale visual context in the multi-modal fusion process has not been explored. Multi-scale context modeling has verified its effectiveness on boosting the segmentation accuracy of objects in semantic segmentation [11, 12, 13, 14]. Recent works also have shown that the performance of RIS can be further improved through aggregating long-range context from concatenated visual and linguistic features [15]...
with self-attention [16], or collecting multi-scale context from fused multi-model features [10, 17] with atrous spatial pyramid pooling (ASPP) [11, 18]. However, the former is high memory cost for computing the affinity map and may introduce redundant features, which are harmful to distinguish the referred object. The latter captures multi-scale context after two modalities are fused. The fused multi-modal features may contain heterogeneous noises from two modalities, which result in the model cannot adaptively learn the scale variations of objects. Different from these works, we argue that the multi-scale contextual information is important to facilitate the alignment of two modalities and correctly localize the referred object during the multi-modal fusion process.

In this paper, we focus on multi-scale context modeling during vision and language fusion process rather than after fused multi-modal features. Specifically, we propose a Cascaded Multi-modal Fusion (CMF) module, which can effectively aggregate multi-scale contextual information into multi-modal fusion process and encourage two modalities alignment at each position of fused feature map. The module is based on ASPP and further introduces a cascaded multi-modal fusion branch, where we iteratively fuse visual and linguistic features with atrous convolutional layers with gradually increased dilated rates. Besides, to integrate the fused multi-modal features from different layers of visual backbone for segmentation mask refining, we introduce a bi-directionally convolutional gated recurrent unit (GRU) [19] to fuse them from top-down and bottom-up paths. Finally, we conduct extensive experiments on four benchmark datasets to validate our proposed method. Experimental results show that our method outperforms most state-of-the-art methods.

2. RELATED WORK

Referring Image Segmentation (RIS). RIS aims at segmenting the object specified by a natural language expression. Hu et al. [1] made the first effort for this task via a direct concatenation of visual and linguistic features from CNN and LSTM. In order to associate visual regions with individual words and highlight features of the target object, unidirectional and bi-directional interactions between visual and linguistic features have been explored by attention mechanism [8, 7, 15, 10, 9, 17]. Multi-level feature aggregation [3, 15, 10], generative adversarial learning [20], and query reconstruction [21] were also investigated to refine multi-modal features and further improve the performance of segmentation. However, these works ignore or ineffectively model multi-scale context during multi-modal fusion process, where the context is crucial to align two modalities and accurately segment the objects with large scale variations. Different from them, our work focuses on multi-scale context modeling in an effective way during the multi-modal fusion process.

Context Modeling. Modeling the multi-scale contextual information plays a key role in semantic segmentation. PSP-
multi-modal fusion process. Thus, we propose a CMF module to fuse two modalities by taking linguistic variations and multi-scale contextual information into account.

The details of the CMF module is shown in Fig.3. Concretely, to learn more robust linguistic representation and eliminate the effect of linguistic variations, we first introduce an image-to-word attention to compute the relevance between each word and each visual region, then utilize the calculated attention matrix followed by a softmax layer to compute the weighted summation of originally linguistic features. For the i-th visual region and the j-th word, the attention matrix is calculated by:

$$A_{ij} = softmax[(W_v v_i)^T (W_h h_j)]$$

then the updated linguistic representation L for the visual feature map V is $L = \{l_i\} \in \mathbb{R}^{h \times w \times D_w}$, where $l_i$ is calculated by:

$$l_i = \sum_{j=1}^{T} A_{ij} h_j$$

To capture multi-scale contextual information, the original ASPP [11, 18] stacks multiple parallel $3 \times 3$ convolutional layers with different dilated rates and further fuses them with concatenation followed by an $1 \times 1$ convolutional layer. To effectivelly model multi-scale context and facilitate alignment of two modalities for RIS task, we introduce a cascaded fusion branch on original ASPP, as shown in Fig.3. This branch first fuses two modalities with an $1 \times 1$ convolutional layer, and then iteratively fuses two modalities using atrous convolutional layers with gradually increased dilated rates. More specifically, for the n-th fusion layer in the cascaded branch, we first concatenate the input visual feature V, spatial feature S and the fusion result $F_{n-1}$ from the $(n-1)$-th fusion layer, which can be denoted as $[V, S, F_{n-1}]$. Then we apply two linearly embedding layers (i.e., $1 \times 1$ convolutional layers) to transform the concatenated features and updated linguistic representation into the same dimension. Instead of concatenation similar to previous works [1, 2, 3], here we combine two types of features with Hadamard product followed by a non-linear projection. Finally, we feed the combined multi-modal features into a $3 \times 3$ convolutional layers with a specific dilated rate to fuse them. By introducing such a cascaded fusion module, the visual contextual information is gradually integrated into multi-modal fusion process in cascaded and parallel directions of CMF module.

3.3. Multi-level Feature Fusion and Mask Prediction

Previous approaches [3, 15, 9, 10] have shown that integrating multi-modal features from different levels of CNN can further improve the accuracy of segmentation masks. In our work, we introduce a bi-directionally convolutional GRU (Bi-ConvGRU) to progressively integrate the fused multi-modal features in bottom-up and top-down manners, which is corresponding to the two directions of forward and backward paths. The top-down manner can enhance the lower-level features with rich semantics, while the bottom-up manner can compensate spatial details for higher-level features with lower-level ones. The output of the Bi-ConvGRU is formulated as:

$$\tilde{V}_{out} = ReLU(W_p^H \tilde{H}_l + W_p^H \tilde{H} + b)$$

where $\tilde{H}$ and $\tilde{H}$ denote the last hidden states of two directions, $b$ is the bias term, and $V_{out} \in \mathbb{R}^{h \times w \times D_w}$ is the integrated multi-modal features. Finally, the same decoder layers and binary cross-entropy loss as previous works [3, 10] are adopted to predict the segmentation mask and optimize the network, respectively.

4. EXPERIMENTS

4.1. Experiment Settings

Datasets and Protocols. We perform experiments on four benchmark datasets, including ReferIt [23], G-Ref [24], UNC [25] and UNC+ [25]. The ReferIt contains 130,525 expressions for 96,654 regions in 19,994 images, the categories of regions are objects or stuff (e.g., “sky”, “wall”). The G-Ref consists of 26,711 images with 104,560 expressions for 54,822 objects. The average length of expressions (8.4 words) in this dataset is much longer than that of other three datasets. The UNC contains 142,209 expressions for 50,000 objects in 19,994 images. The UNC+ is composed of 141,564 expressions for 96,654 regions in 19,894 images, the categories of regions are objects or stuff (e.g., “sky”, “wall”).

Implementation Details. Similar to [2, 3], the commonly used DeepLab ResNet-101 [11], which is pre-trained on Pascal VOC [26], is utilized as our CNN backbone to extract different level visual features. This backbone is fixed during training and testing. The input images are resized to $320 \times 320$. For language encoding, we first keep the maximum length of each expression as 20. The network is trained using Adam optimizer with an initial learning rate of $2.5e^{-4}$ and a weight decay of $5e^{-4}$. We apply a polynomial decay with power of 0.9 to the learning rate. For the feature dimensions, we set $D_v = D_w = 1000, D_o = 500$.

4.2. Comparison with the State-of-the-arts

We conduct experiments on four benchmark datasets and compare the corresponding results with previous methods in Table 1. Note that the symbol “$*$” denotes the segmentation
results of the corresponding method are post-processed with DenseCRF [27]. It can be observed that the performance of our method outperforms all previous methods on UNC and UNC+. Compared with the best method BRINet, our method achieves 0.68%, 1.33% and 0.5% improvement on val, testA and testB sets of UNC. 1.05%, 0.98% and 0.09% improvement on val, testA and testB sets of UNC+. In particular, the expression of UNC+ does not include location words, the experimental results show that our method is robust to align the semantics of objects between two modalities. Since G-Ref describes an object with a long expression, ReferIt contains stuff categories, they are more challenging than UNC and UNC+. Although our method does not establish complex interactions between two modalities like [9, 17, 10], the performance of our method also outperforms most state-of-the-art methods on G-Ref and ReferIt. Thus, the integration of multi-scale context information is helpful to align two modalities and improve segmentation accuracy of objects.

### 4.3. Ablation Study

Table 2: Ablation study on the UNC val set with the visual feature \( V_3 \) (post-processed by DenseCRF).

| Method          | \( P@0.5 \) | \( P@0.6 \) | \( P@0.7 \) | \( P@0.8 \) | \( P@0.9 \) | IoU  |
|-----------------|-------------|-------------|-------------|-------------|-------------|------|
| LSTM-CNN (2016) [1] | 48.82       | 36.47       | 25.25       | 12.25       | 1.67        | 46.87|
| RIN (2017) [2]   | 51.95       | 43.11       | 32.74       | 19.28       | 4.11        | 50.12|
| DCLSTM (2020) [7] | 54.62       | 44.20       | 30.77       | 16.02       | 2.56        | 50.50|
| BRINet (2019) [10]| 65.53       | 57.46       | 46.85       | 30.42       | 7.28        | 56.76|
| Baseline        | 48.15       | 38.56       | 28.11       | 16.58       | 3.81        | 48.13|
| Baseline + ATTN  | 50.54       | 41.20       | 30.13       | 17.74       | 4.36        | 49.50|
| Baseline + ATTN + ASPP | 61.48 | 53.61 | 43.47 | 28.49 | 7.41 | 55.30|
| CMF Module      | 68.60       | 62.35       | 52.35       | 36.40       | 10.23       | 59.05|

In order to verify the effectiveness of our CMF module, we first conduct ablation studies without Bi-ConvGRU on UNC val set. As [1, 2, 3], we take \( V_3 \) from Res5 as the visual feature and fuse it with the linguistic feature. Here we consider three variants of CMF module: (1) Baseline: Following [1, 3], this model uses the last hidden state of LSTM as the holistic representation of an expression. We use Hadamard product followed by a convolutional layer with filter size 1 to fuse two modalities. (2) Baseline + Attention (ATTN): This model uses visual feature as a guidance to adaptively learn a robust linguistic representation with an attention mechanism. (3) Baseline + ATTN + ASPP: This model introduces an original ASPP model on the fused multi-modal feature, similar to [17, 10]. The experimental results are summarized in Lines 5-8 of Table 2. It can be observed that CMF module brings 10.92% improvement on baseline model, and brings 3.75% improvement compared with using original ASPP.

5. CONCLUSIONS

We have proposed an effective cascaded multi-modal fusion (CMF) module for referring image segmentation. It stacks multiple atrous convolutional layers in parallel and further introduces a cascaded branch to fuse visual and linguistic features using these layers with gradually increased dilated rates. The model can iteratively integrate multi-scale context and facilitate the alignment of two modalities during multi-modal fusion process. We perform experiments on four benchmark datasets and achieve state-of-the-art performance.
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