GAUSSIAN KERNEL-BASED CROSS MODAL NETWORK FOR SPATIO-TEMPORAL VIDEO GROUNDING

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ABSTRACT

Spatial-Temporal Video Grounding (STVG) is a challenging task which aims to localize the spatio-temporal tube of the interested object semantically according to a natural language query. Most previous works not only severely rely on the anchor boxes extracted by Faster R-CNN, but also simply regard the video as a series of individual frames, thus lacking their temporal modeling. Instead, in this paper, we are the first to propose an anchor-free framework for STVG, called Gaussian Kernel-based Cross Modal Network (GKCMN). Specifically, we utilize the learned Gaussian Kernel-based heatmaps of each video frame to locate the query-related object. A mixed serial and parallel connection network is further developed to leverage both spatial and temporal relations among frames for better grounding. Experimental results on VidSTG dataset demonstrate the effectiveness of our proposed GKCMN.

Index Terms— anchor-free, Gaussian kernel, spatial-temporal video grounding

1. INTRODUCTION

Video grounding with natural language is a fundamental but challenging problem due to its vast potential applications in visual-language understanding. Generally, it could be categorized into three different classes: spatial grounding [1, 2, 3, 4], temporal grounding [5, 6, 7, 8] and spatio-temporal grounding [9]. Among them, Spatial-Temporal Video Grounding (STVG) is substantially more challenging as it needs to not only model the complicated multi-modal interactions for semantics alignment, but also retrieve both spatial location and temporal duration of the target activity. As shown in Fig. 1, STVG aims to localize the spatio-temporal tube of the queried object according to the given textual description.

Most previous spatial or temporal video grounding technologies [10, 11, 12] are designed to tackle the grounding problems by directly detecting the foreground objects of each video frame for objects correlation learning [11, 12], or by regressing the temporal segment boundary in the video [10].

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pose the first anchor-free model GKCMN for spatio-temporal video grounding, which utilizes Gaussian kernels to highlight the foremost region of target semantics; (2) We design a mixed convolutional network to capture both temporal and spatial information; (3) We demonstrate the effectiveness of the GKCMN model by evaluating on the VidSTG dataset.

2. METHOD

Given an untrimmed video $V$ and a sentence $S$, the STVG task aims to retrieve a spatio-temporal tube $U$ in video $V$, which corresponds to the semantic of sentence $S$. The framework of our proposed GKCMN is illustrated in Fig. 2.

2.1. Encoder

**Video Encoder.** To encode the video frames, we utilize a pre-trained 3D network [13] to extract its last convolutional layer features as $V = \{v_t\}_{t=0}^{T-1}$, where $T$ denotes the frame number, $v_t \in \mathbb{R}^{d \times H \times W}$ represents the $t$-th frame 2D feature, $d$ is visual feature dimension, $H$ and $W$ are the height and width of input frames, and $r_h, r_w$ are scaling factors.

**Sentence Encoder.** For sentence encoding, we first extract word-level features via the Glove [14] embedding, and then employ a self-attention module [15] to capture the self-dependencies among words. We further utilize a Bi-GRU [16] to learn their sequential features and denote the final sentence feature as $S = \{s_n\}_{n=0}^{N-1}$, where $s_n \in \mathbb{R}^L$ represents the $n$-th word feature, and $D$ is word feature dimension.

**Cross-model Interaction.** We first repeat the textual tensor $S_r = \text{repeat}(S)$ to the same shape with visual tensor, and obtain the multi-modal matrix by fusing $V$ with $S_r$. Next, the cross-modal interacted feature $F_{f2}$ is obtained by:

$$F_{f1} = g(VW_{c1}) \cdot g(S_rW_{s1}),$$

$$F_{f2} = \text{concat}(g(F_{f1}W_{f2}), g(VW_{c2})), \quad (1)$$

where $g(\cdot)$ is the non-linear activation function, $W_{c1}, W_{s1}, W_{f2}$ and $W_{c2}$ are learnable parameters. In following process, we utilize $F_{f2} \in \mathbb{R}^{D' \times T \times L_x \times L_y}$ as the input fusion feature to extract spatio-temporal relationships.

2.2. The Mixed Convolutional Network

We construct spatio-temporal relationships in terms of depth and width by the serial connection network and the parallel connection network, respectively.

**Serial Connection Network.** For any 3D signal $F_{f2}$, we reshape it into the 2D batches and learn the spatial characteristics of each frame by 2D convolutional blocks. Next, we use 3D convolution to learn the timing sequential relationship between each activity. Therefore, the output of the serial connection network $M_{ser}$ can be formulated as:

$$M_{ser} = K^3 \otimes \text{reshape}(K^2 \otimes \text{reshape}(F_{f2})), \quad (2)$$

where $\otimes$ represents the convolution operation, $K^i$ means the $i$-dimension kernel.

**Parallel Connection Network.** Similarly, we utilize parallel structures to learn and fuse stationary and temporal information via 2D and 3D CNN blocks.

$$M_{par} = K^3 \otimes F_{f2} + \text{reshape}(K^2 \otimes \text{reshape}(F_{f2})). \quad (3)$$

**Mixed Convolutional Network.** Our Mixed Convolutional Network combines series and parallel connections with a residual structure. As shown in Fig. 2, we fuse the original feature maps $F_{f2}$, serial features $M_{ser}$ and temporal residual features $M^3$ via a triple-parallel structure. Then we have:

$$M_{mix} = K^3 \otimes F_{f2} + M_{ser} + F_{f2}. \quad (4)$$

2.3. Spatial Location Head

We construct a Gaussian kernel-based spatial location head to predict bounding boxes of queried object. Firstly, we upsample $M_{mix}$ to obtain $M_{up} \in \mathbb{R}^{D' \times T \times L_x \times L_y}$ for spatial localization scaling, where $L$ is the feature map size.
Gaussian Kernels. We deem the video frames as a series of heatmaps with the queried object as the center of the heat source, and utilize Gaussian kernels to describe the probability distribution of the object’s position as shown in Fig. 3.

Given annotated boxes \( \{b_t\}_{t=0}^{T-1} \), firstly we linearly map it to the feature map scale \( L \). For each re-scaled box \( b'_t \), we find the center coordinates \((x_t, y_t)\). Then, the heatmap \( h_t \in [0, 1]^{T \times L \times L} \) using Gaussian kernel is given by:

\[
h_t(x, y) = \exp\left(-\frac{(x-x_t)^2 + (y-y_t)^2}{2\sigma^2}\right),
\]

where \( \sigma \) determines the size of kernels.

Point Localization. In this step, our aim is to learn the predicted heatmaps \( \{h_t\}_{t=0}^{T-1} \) supervised by the Gaussian kernel-based one. The peak of the Gaussian distribution of key points is regarded as the positive sample while other pixels are regarded as the negative sample. We modify focal loss [17] as:

\[
\mathcal{L}_{loc}^s = \frac{-1}{M_{foc}} \sum_{t, x, y} \left( (1 - h_{txy})^\alpha \log(h_{txy}), \quad \text{if } h_{txy} > \gamma 
\right) + \left( (1 - h_{txy})^\beta \hat{h}_{txy}^n \log(1 - \hat{h}_{txy}), \quad \text{else} \right)
\]

where \( M_{foc} \) stands for the number of annotated boxes, \( \alpha \) and \( \beta \) are hyper-parameters of the focal loss, \( \gamma \) is our modified hyper-parameter which determines the number of positive samples.

Size Regression. Then, a size regression head is employed to define the object size. Each pixel in the annotation box is treated as a regression sample. Given the predicted distances \( \{s_t\}_{t=0}^{T-1} \in \mathbb{R}^{T \times 4 \times L \times L} \) and ground truth \( \{s_t\} \), we decode the predicted boxes \( \{b_t\} \) and corresponding annotated boxes \( \{b_t\} \). Then, GIoU is used as loss for bounding box regression:

\[
\mathcal{L}_{reg}^s = \frac{1}{M_{sou}} \sum_{(t, x, y) \in a_t} \text{GIoU}(\hat{h}_{txy}, b_t),
\]

where \( M_{sou} \) represents the number of regression samples, i.e., the number of the pixel \((t, x, y)\) in annotation area \( a_t \).

2.4. Temporal Location Head
Taking the multi-modal features \( M_{mix} \) as input, we put it to a temporal location head to attain the temporal boundaries as is shown in Fig. 4.

Embedding Layer. First, three different kinds of 3D convolution layers are deployed with the kernel size 1, 3 and 5 respectively to learn differentiated time-length features. Then a 3D convolution layer and an average pooling layer are placed after the above layers. Next, we use a self-attention module to enhance the inner relation in terms of time sequence.

Score Confidence Head. This head is implemented as a Bi-GRU and a 1D convolution layer. We estimate the IoU \( i \in [0, 1] \) between the generated temporal tubes and the corresponding ground truth, and confidence scores are the value of the IoUs. Then a threshold \( c \) is defined to set the score of the tubes to zero where \( i < c \). We utilize a smooth \( l_1 \) loss for confidence evaluation, given by:

\[
\mathcal{L}_{con}^t = \frac{1}{N_c} \sum_{n=1}^{N_c} \mathcal{L}_1(i_n, \hat{i}_n),
\]

where \( \mathcal{L}_1 \) is the smooth \( l_1 \) loss, \( N_c \) and \( \hat{i}_n \) stand for the number of tubes and the \( n \)-th predicted IoU score.

Boundary Regression Head. Similarly, we use a Bi-GRU and a 1D convolution layer to implement the boundary regression head. Every tube that has the potential to be selected owns an offset \( \delta_k = (\delta_s, \delta_c) \). With the ground truth \((t_s, t_c)\) and the predicted tube \((\hat{t}_s, \hat{t}_c)\), we know that \( \delta_s = t_s - \hat{t}_s \) and \( \delta_c = \hat{t}_c - t_c \). Then we compute the smooth \( l_1 \) distance by:

\[
\mathcal{L}_{reg}^t = \frac{1}{N_c} \sum_{k=1}^{N_c} \mathcal{L}_1(\delta_k, \hat{\delta}_k).
\]

Therefore, the total loss is a multiple loss combing the above four loss functions as:

\[
\mathcal{L} = \alpha_1 \mathcal{L}_{loc}^s + \alpha_2 \mathcal{L}_{reg}^t + \alpha_3 \mathcal{L}_{con}^s + \alpha_4 \mathcal{L}_{reg}^t,
\]

where \( \alpha_1, \alpha_2, \alpha_3, \alpha_4 \) are balanced parameters for loss.

3. EXPERIMENTS
Dataset. We evaluate our method on a large-scale spatio-temporal video grounding dataset VidSTG [9], which contains 5,563, 618 and 743 untrimmed videos in the training, validation and testing sets respectively.
In this paper, we propose a novel anchor-free cross-modal network GKCMN for STVG task. The main contributions of our work are: 1) we propose a Gaussian kernel-based anchor-free architecture for STVG task, 2) we develop a mixed convolutional network to capture cross-modal features in both temporal and spatial aspects, 3) experimental results on VidSTG dataset show the superiority of our method. In order to eliminate the influence of temporal grounding on the overall spatio-temporal grounding, we conducted a separate experiment by giving the temporal ground truth as shows in Table 2. Here, we can clearly observe that the proposed GKCMN outperforms the other anchor-based methods and achieves a comparable result with STGRN. It is worth noting that our Gaussian kernel design has greatly improved the accuracy of spatial localization compared with BM.

Ablation Study. For ablation study, we verify the contribution of each part of our proposed GKCMN with the center-based scheme. More specifically, we modify our complete model to five settings: w/o SC, w/o PC, w/o MN, w/o TA, w/o SK, which represents the removal of the serial connection, the parallel connection, the complete mixed convolutional network, the self-attention module, and the replacement Gaussian kernel with single point localization, respectively.

The ablation results are shown in Table 3. We can find that every ablation model has precision reduction compared with the full model, which manifests each above component provides a positive contribution.

4. CONCLUSION

In this paper, we propose a novel anchor-free cross-modal network GKCMN for STVG task. The main contributions of our work are: 1) we propose a Gaussian kernel-based anchor-free architecture for STVG task, 2) we develop a mixed convolutional network to capture cross-modal features in both temporal and spatial aspects, 3) experimental results on VidSTG dataset show the superiority of our method.

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