Hierarchical Local-Global Transformer for Temporal Sentence Grounding

Xiang Fang, Daizong Liu, Pan Zhou, Senior Member, IEEE, Zichuan Xu, Member, IEEE, and Ruixuan Li, Member, IEEE

Abstract—This article studies the multimedia problem of temporal sentence grounding (TSG), which aims to accurately determine the specific video segment in an untrimmed video according to a given sentence query. Traditional TSG methods mainly follow the top-down or bottom-up framework and are not end-to-end. They severely rely on time-consuming post-processing to refine the grounding results. Recently, some transformer-based approaches are proposed to efficiently and effectively model the fine-grained semantic alignment between video and query. Although these methods achieve significant performance to some extent, they equally take frames of the video and words of the query as transformer input for correlating, failing to capture their different levels of granularity with distinct semantics. To address this issue, in this article, we propose a novel Hierarchical Local-Global Transformer (HLGT) to leverage this hierarchy information and model the interactions between different levels of granularity and different modalities for learning more fine-grained multi-modal representations. Specifically, we first split the video and query into individual clips and phrases to learn their local context (adjacent dependency) and global correlation (long-range dependency) via a temporal transformer. Then, a global-local transformer is introduced to learn the interactions between the local-level and global-level semantics for better multi-modal reasoning. Besides, we develop a new cross-modal cycle-consistency loss to enforce interaction between two modalities and encourage the semantic alignment between them. Finally, we design a brand-new cross-modal parallel transformer decoder to integrate the encoded visual and textual features for final grounding. Extensive experiments on three challenging datasets (ActivityNet Captions, Charades-STA and TACoS) show that our proposed HLGT achieves a new state-of-the-art performance, demonstrating its effectiveness and computational efficiency.

Index Terms—Multi-modal representations, multimedia understanding, temporal sentence grounding, temporal transformer.

I. INTRODUCTION

TEMPORAL sentence grounding (TSG) is a fundamental but important task in multimedia understanding [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]. As shown in Fig. 1(a), given an untrimmed video, this task aims to predict a specific segment containing the activity related to the semantics of a sentence query. Traditional TSG approaches can be divided into two categories: 1) Top-down approaches [19], [20], [21], [22], [23], [24]: These methods first pre-define multiple segment proposals and align them with the query for cross-modal semantic matching. The best proposal with the highest similarity score is selected as the predicted segment. 2) Bottom-up approaches [25], [26], [27], [28], [29]: These methods directly regress the start and end boundary frames of the target segment or predict boundary probabilities frame-wisely. The predicted segment is obtained through post-processing steps that group or aggregate all frame-wise predictions. Although the above two types of works have achieved significant performances, they are not end-to-end, and still suffer from the redundant proposal generation/matching process (top-down) and complex post-processing steps (bottom-up) to refine the grounding results.

Recently, transformer-based approaches [30], [31], [32] are newly introduced to handle the TSG task in an end-to-end manner. Different from the top-down and bottom-up approaches, they capture more fine-grained interaction between the video-query input and directly output the segment predictions via the effective transformer encoder-decoder architecture [33], [34], [35], [36], [37] without using any time-consuming pre- and post-processing operation. The general transformer-based pipeline is shown in Fig. 1(b). It first simply feeds the video frames and query words into the transformer to equally align the semantics between each frame-word pair. Then, the transformer decoder with a direct set prediction [38], [39], [40] is utilized to predict a few learnable segment candidates with corresponding confidence scores. Thanks to such a simple pipeline and the multi-modal relationship modeling capabilities in a transformer, these transformer-based approaches are both effective and computationally efficient.
We design a cross-modal parallel transformer decoder with top-down and refer to a framework, which first samples have been conducted extensive experiments on three challenging frameworks, which directly re-

are newly proposed in an end-to-end manner We present a novel Hierarchical Local-Global Transformer (HLGT), which captures different levels of granularity in both video and query domains to reason the complete semantics for fine-grained grounding. To the best of our knowledge, it is the first time that a multi-level interaction network is proposed to alleviate the limitations of existing transformer-based TSG methods.

- We design a cross-modal parallel transformer decoder with a brand-new cross-modal cycle-consistency loss to encourage semantic alignment between visual and language features in the joint embedding space.
- We conduct extensive experiments on three challenging benchmarks (ActivityNet Captions, TACoS and Charades-STA) where our proposed HLGT outperforms the state-of-the-arts with clear margins, demonstrating its effectiveness and computational efficiency.

II. RELATED WORK

A. Traditional TSG Methods

As a new multimedia task introduced recently [19], [41], [42], [43], [44], temporal sentence grounding (TSG) aims to identify the start and end timestamps of the most relevant video segment from an untrimmed video with a sentence query. Most works [19], [20], [21], [22], [23], [24], [45], [46] have been proposed within a top-down framework, which first samples candidate segment proposals from the untrimmed video, then integrates the sentence query with these segments individually, and finally matches them with the query. Although these methods achieve good performances in some cases, they are severely proposal-dependent and time-consuming, which limits their applications.

Without using proposals, the latest methods [25], [26], [27], [28], [29] refer to a bottom-up framework, which directly regresses the start and end timestamps of the target segment after interacting the whole video with the query.

Although the above two types of works have achieved significant performances, they are not end-to-end. These methods might suffer from the redundant proposal generation/matching process (top-down) and complex post-processing steps (bottom-up) to refine the grounding results.

B. Transformer-Based TSG Methods

Recently, some transformer-based TSG approaches [30], [31], [32] are newly proposed in an end-to-end manner [47], [48], [49]. Different from the top-down and bottom-up approaches, they capture more fine-grained interaction between the video-query input and directly output the segment predictions via the effective transformer encoder-decoder architecture [33] without time-consuming pre- and post-processing operations. These transformer-based methods first simply feed the video frames to reduce the computational cost. By capturing both local and global granularities in the multi-modal information, our HLGT can capture the complete query semantics for more accurate video grounding.

In summary, the main contributions of our works are:

- We present a novel Hierarchical Local-Global Transformer (HLGT), which captures different levels of granularity in both video and query domains to reason the complete semantics for fine-grained grounding. To the best of our knowledge, it is the first time that a multi-level interaction network is proposed to alleviate the limitations of existing transformer-based TSG methods.
- We design a cross-modal parallel transformer decoder with a brand-new cross-modal cycle-consistency loss to encourage semantic alignment between visual and language features in the joint embedding space.
- We conduct extensive experiments on three challenging benchmarks (ActivityNet Captions, TACoS and Charades-STA) where our proposed HLGT outperforms the state-of-the-arts with clear margins, demonstrating its effectiveness and computational efficiency.
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Fig. 2. Overall pipeline of our proposed HLGT model. Given a video and a query, we first extract frame- and word-level features via the feature extractors. Then, for each modality, we generate local-level features (clip/phrase features) and global-level features via temporal transformer and feature fusion, and integrate these features based on a global-local transformer. After that, we interact the visual and textual features through a cross-modal parallel transformer, where a new cross-modal cycle consistency (CMCC) loss is designed to assist the cross-modal interaction. Finally, the boundary prediction head with feed-back networks is utilized to predict final temporal segments for accurate grounding. Best view with colors.

and query words into the transformer to equally align the semantics between each frame-word pair. Then, the transformer decoder with a direct set prediction [38] is used to predict a few learnable segment candidates with corresponding confidence scores. Based on a simple pipeline and the multi-modal relationship modeling capabilities in a transformer, this approach is more effective than traditional methods.

Since many video-query pairs involve different levels of granularity (e.g., frame-word pairs and clip-phrase pairs), it is crucial to first capture the local query context for modeling the corresponding visual activity and then comprehend the global sentence semantics by correlating all local activities.

C. Cycle-Consistent Learning

By utilizing transitivity as the training objective, cycle-consistent learning aims to explore task correlations to regularize training [50], which is widely used in various multimedia fields, such as vision-language navigation [51], [52], text-to-image synthesis [53], [54], and image-text matching [55], [56]. For example, based on the assumption of cyclical structure, Wang et al. [57] learn visual supervision by tracking forward and backward. In the visual question answering task, Shah et al. [58] enforce consistency between the generated and the original question by using cycle-consistency for temporal video alignment. Although these methods address multi-modal tasks, they perform cycle-consistent learning only in the visual domain, which limits their applications. Thus, they cannot apply to our complex TSG task. In a broader sense, our article is the first attempt that explores cycle-consistent learning to the TSG task.

III. PROPOSED HLGT NETWORK

A. Overview

As a significant multimedia task, temporal sentence grounding (TSG) aims to localize the precise boundary \((\tau_s, \tau_e)\) of a specific segment from an untrimmed video \(V = \{v'_t\}_{t=1}^{T}\) semantically corresponding to a given query \(Q = \{q'_n\}_{n=1}^{N}\), where \(q'_n\) denotes the \(n\)-th word, \(N\) denotes the total number of words, \(\tau_s\) and \(\tau_e\) denote the start and end timestamps of the specific segment, \(v'_t\) denotes the \(t\)-th frame, \(T\) denotes the total number of frames, respectively. Recently, some transformer-based approaches [30], [31], [32] have shown their strong performance to handle the TSG task via the effective transformer encoder-decoder architecture in an end-to-end manner. However, they still suffer from the vanilla transformer design and fail to explore different levels of granularity with distinct but fine-grained semantics in both video and query. Therefore, how to effectively capture and integrate these multi-level cross-modal contexts for better grounding is an emerging issue.

In this section, we present a novel Hierarchical Local-Global Transformer (HLGT), which leverages this hierarchy information and model the interactions between different levels of granularity and multiple modalities for learning more fine-grained multi-modal representations. As shown in Fig. 2, the proposed HLGT model consists of four parts, including the multi-modal feature extractors, multi-level transformer encoder, cycle-consistent transformer decoder, and the boundary prediction head. Given the paired video-query input, we first split the video/query into the clips/phrases, and extract their internal frame- and word-level features via the multi-modal
feature extractors. Then, we capture the relationship between frame/word features within each clip/phrase based on a temporal transformer to integrate the local clip/phrase-level features. Meanwhile, we also feed the whole frames/words into another temporal transformer to encode the corresponding global representations. We fuse the local and global visual and textual tokens by two global-local transformers to learn the contextualized individual modal semantics. After that, we introduce a cross-modal parallel transformer decoder to interact the video and query features for semantic alignment in parallel. Specifically, we develop a new cross-modal cycle consistency (CMCC) loss to assist the multi-modal interaction. Then, the boundary prediction head is utilized to predict final temporal segments based on the interacted multi-modal representations. Finally, we present the details of each module.

B. Feature Extraction

Video extractor: Following [59], [60], [61], [62], for video encoding, we first sample every 16 consecutive frames as a clip with an overlap of 8 frames. Then, we use a pre-trained Resnet-152 network [63] to extract the frame-level visual features in each clip. We denote the extracted video features as \( V = \{ v_i^{T} \}_{i=1}^{T} = \{ C_i \}_{i=1}^{T/8-1} \in \mathbb{R}^{T \times D} \), where \( T \) denotes the number of frames in the total video, \( v_i \in \mathbb{R}^{1\times D} \) denotes the \( t \)-th frame, \( C_i \in \mathbb{R}^{16\times D} \) denotes the \( i \)-th clip and \( D \) denotes the visual feature dimension.

Query extractor: For query encoding, we first utilize the Glove embedding [64] to generate the word-level features. The extracted query features are denoted as \( Q = \{ q_n \}_{n=1}^{N} = \{ H_j \}_{j=1}^{J} \in \mathbb{R}^{N \times D} \), where \( N \) denotes the number of words in the whole query, \( q_n \in \mathbb{R}^{1\times D} \) denotes the \( n \)-th word feature in the query, \( J \) denotes the number of phrases in the whole query, and \( D \) denotes the textual feature dimension that is the same as the visual feature dimension in the video extractor. For the \( j \)-th phrase, \( H_j = \{ q_{k} \}_{k=1}^{K_j} \in \mathbb{R}^{K_j \times D} \), where \( q_{k} \) denotes the \( k \)-th word in the phrase and \( K_j \) denotes the number of words in the \( j \)-th phrase. Then, we follow [65] to split the given query into multiple phrases. The detailed splitting approach is as follows: to discover the potential phrase-level features, we apply 1D convolutions on the word-level features with different window sizes. At each word location, we compute the inner product of the word feature vectors with convolution filters of three kinds of window sizes, which captures three different-scale phrase features. To maintain the sequence length after convolution process, we zero-pad the sequence vectors when convolution window size is larger than one. The output of the \( n \)-th word location with window size \( s \in \{1, 2, 3\} \) is formulated by \( q_{n,s}^{p} = \tanh(\text{Conv1d}(q_{n,s+n-1}^{w}) \in \mathbb{R}^{1 \times D}) \), where Conv1d(\cdot) operates on the windowed features with \( D \) kernels. \( q_{n,s}^{p} \) is the phrase-level feature corresponding to \( n \)-th word location with window size \( s \). To find the most contributed phrase at each word location, we then apply max-pooling to obtain the final phrase-level feature \( H_j = \{ q_{k}^{p} \}_{k=1}^{K_j} \in \mathbb{R}^{K_j \times D} \) by \( q_{k}^{p} = \max(q_{k,1}^{p}, q_{k,2}^{p}, q_{k,3}^{p}), k \in \{1, 2, \ldots, K_j\} \). Thus, we can split the query into multiple phrases.

For the extracted visual features, we focus on two-level frame features in the latter reasoning: frame features in each clip and all the frame features in the whole video. Similarly, we also focus on two-level word features in the latter reasoning: word features in each phrase and all the word features in the given query.

C. Transformer Encoder

For the transformer encoder, we first feed the extracted frame/word features within each clip/phrase to a temporal transformer followed by a feature fusion module, which can fuse and generate corresponding clip-level/phrase-level features. Then, since these clip-level/phrase-level features can only learn local semantic information of the whole video/query, we also feed all the frame/word features within the whole video/query to the temporal transformer followed by a feature fusion module for learning the global semantic information. Finally, for each modality, we integrate both the global information and the local information by proposing a global-local transformer to generate more contextual features.

Temporal transformer: As shown in Fig. 2, given the extracted frame/word representations within each clip/phrase, we introduce a temporal transformer network with standard attention-blocks to learn the correlations between frames/words for latter clip/phrase-level fusion. Fig. 3 shows the details of the temporal transformer.

For ease of description, we first introduce the notation of a standard transformer (called TRM). Considering that transformer architecture contains multi-head self-attention blocks for multi-inputs correlating and updating, we define TRM as:

\[
\text{TRM}(Q, K, V) = \text{FFN}\left(\text{Softmax}\left(\frac{QK^T}{\sqrt{D}}V\right)\right),
\]

where FFN is the feed forward network; \( D \) is the feature dimension of the multi-head block; \( Q, K \) and \( V \) are the individual query, key and value in TRM respectively, and they are computed by:

\[
Q = W_1 Z, \quad K = W_2 Z, \quad V = W_3 Z,
\]

where \( W_1, W_2 \) and \( W_3 \) are the embedding weight matrices; \( Z \) denotes any sequence (e.g., \( C_i, H_j, Q \) and \( V \)) as the input of TRM.

Then, in each modality, all the temporal transformers share the same weight. In the visual branch, if the input of the temporal transformer is the frame-level clip feature \( C_i \), and we denote its corresponding output as \( \tilde{C}_i \), which is obtained by:

\[
\tilde{C}_i = \text{TRM}(QC_i, KC_i, VC_i),
\]

where \( QC_i, KC_i, VC_i \) are the query, key and value in the clip-based temporal transformer respectively. To obtain the frame-level video representation \( \widehat{V} \), we employ the same temporal transformer on the whole video, and its output is \( \widehat{V} = \text{TRM}(QV, KV, VV) \).

Similarly, in the textual branch, if the input of the temporal transformer is \( H_j \), its output is \( H_j = \text{TRM}(QH_j, KH_j, VH_j) \), which is the word-level phrase representation. Likewise, the word-level query representation is \( Q = \text{TRM}(QQ, KK, QQ) \).

In the TSG task, both video and query naturally represent at different levels of granularity: a video/query is composed of several clips/phrases, and each clip/phrase contains multiple

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frames/words. These frames/words in each clip/phrase only contain partial visual/textual information of the specific clip/phrase, which is only the local representation for the given video/query. To obtain the global representation of the given video/query, we also feed all the frame/word features to the temporal transformer to obtain the global visual feature $v_{\text{global}} \in \mathbb{R}^{1 \times D}$ and the global textual feature $q_{\text{global}} \in \mathbb{R}^{1 \times D}$.

**Feature fusion:** To integrate these frame/word features within each clip/phrase, we introduce a feature fusion module based on an attention-aware approach. For any sequence $Z$, the corresponding attention matrix $A$ is calculated by:

$$A = \text{Softmax} \left( W_4 \text{Gelu} \left( W_5 Z^T + b_1 \right) + b_2 \right)^T,$$

where $W_4$ and $W_5$ are two learnable transformation weight matrices; $b_1$ and $b_2$ are two biases; Gelu$(\cdot)$ is the activation function GELU.

Each element in $A$ denotes the pixel-wise attention score whether the frame/word contents contribute to the clip-/phrase- (or video-/query) level semantics. It helps to highlight the foregrounds and filter out the backgrounds for better representation learning. Thus, based on matrix $A$, we can obtain the fused feature $\tau$ by:

$$\tau = \sum_{s=1}^{S} A_s \odot \hat{Z}_s,$$

where $\odot$ is element-wise multiplication; $s$ is the frame/word number in the clip/phrase (or video/query); $\hat{Z}$ is the output of temporal transformer with the input of $Z$; $A_s$ and $\hat{Z}_s$ are the $s$-th attention column of $A$ and $\hat{Z}$, respectively.

In the visual branch, for the $i$-th clip, $C_i = \{ \hat{v}_r \}_{r=i-7}^{i+8}$ is the input of the attention-aware feature fusion module. Based on (4) and (5), we fuse all the frame features in $C_i$ into the clip-level feature $\tau_i \in \mathbb{R}^{1 \times D}$. Similarly, we also fuse all the frame features in the whole video into the global visual feature $\bar{v}_{\text{global}}$.

For the textual branch, we obtain phrase-level features by fusing the word-level features in the phrase. For instance, we fuse all the word feature in the $j$-th phrase $\hat{H}_j$ into the phrase-level feature $\hat{h}_j \in \mathbb{R}^{1 \times D}$ based on (5). Besides, we obtain the global textual feature $\bar{q}_{\text{global}}$ by fusing all the word features in the given query.

**Global-local transformer:** In each modality, the above generated global features (video- or query-level) and local features (clip- or phrase-level) are at different levels. To effectively integrate these cross-level features for more fine-grained feature fusion, we propose a global-local transformer shown in Fig. 3. Specifically, the global-local transformer contains two modules: local transformer $\text{TRM}_{\text{Local}}$ and global transformer $\text{TRM}_{\text{Global}}$. Both the visual branch and the textual branch have the same global-local transformer architecture. For each modality, the local transformer $\text{TRM}_{\text{Local}}$ is used to learn the short-term interactions between low-level semantics (adjacent dependency between clips/phrases). The global transformer $\text{TRM}_{\text{Global}}$ aims to model the long-term interactions between local and global representations (global dependency between clip-video or phrase-query).

For $\text{TRM}_{\text{Local}}$, its core components include: a multi-head attention, a feed-forward layer and a normalization layer. Following [67], we append the positional embedding (PE) by using sine function $\sin(\cdot)$ and cosine function $\cos(\cdot)$ of different frequencies:

$$PE_i[2j] = \sin \left( \frac{i \cdot 10000^{2j/\varsigma}}{10000^{2j/\varsigma}} \right),$$

$$PE_i[2j+1] = \cos \left( \frac{i \cdot 10000^{2j/\varsigma}}{10000^{2j/\varsigma}} \right),$$

where $\varsigma$ is the frequency of the network and $j$ is the position. These positional embeddings provide the transformer with the sense of absolute position.
where \(2j \) and \(2j + 1\) are the even and odd indices of the positional embedding; \(PE_t\) denotes the positional embedding of the \(t\)-th position, and \(c\) is the dimension of \(PE_t\). Therefore, the output of the local transformer is:

\[
O^v_{\text{local}} = \frac{8}{T-8} \sum_{i=1}^{T/8-1} \text{TRM}_{\text{Local}} \left( Q_{\pi_i}, K_{\pi_i}, V_{\pi_i} \right), \tag{8}
\]

\[
O^q_{\text{local}} = \frac{1}{J} \sum_{j} \text{TRM}_{\text{Local}} \left( Q_{\pi_j}, K_{\pi_j}, V_{\pi_j} \right), \tag{9}
\]

where \(O^v_{\text{local}}\) is the visual output of the local transformer and \(O^q_{\text{local}}\) is the textual output of the local transformer.

The keys/values in \(\text{TRM}_{\text{Global}}\) are from the output of the normalization layer in \(\text{TRM}_{\text{Local}}\), the query is the matrix from the global representation, and we feed both global representation and local representation as input to the multi-head attention block to learn the cross-level correlating and updating. As a result, the TRM block in the global transformer (\(\text{TRM}_{\text{Global}}\)) generates attention features to the global representation conditioned on the local representation. We set \(Q_{\pi_i} = \text{TRM}_{\text{Local}} \left( Q_{\pi_i}, K_{\pi_i}, V_{\pi_i} \right), K_{\pi_i} = \{\pi_i\}_{i=1}^{T/8-1}, V_{\pi_i} = \{\pi_i\}_{i=1}^{T/8-1}\). Thus, the corresponding output of the global transformer is:

\[
O^v_{\text{global}} = \text{TRM}_{\text{Global}} \left( Q_{\pi_{\text{global}}}, K_{\pi_{\text{local}}}, V_{\pi_{\text{local}}} \right), \tag{10}
\]

\[
O^q_{\text{global}} = \text{TRM}_{\text{Global}} \left( Q_{\pi_{\text{global}}}, K_{\pi_{\text{local}}}, V_{\pi_{\text{local}}} \right), \tag{11}
\]

where \(O^v_{\text{global}}\) is the visual output of the global transformer and \(O^q_{\text{global}}\) is the textual output of the global transformer. Similar to the local transformer, we also add a feed-forward layer and a normalization layer to encode \(O^v_{\text{global}}\) and \(O^q_{\text{global}}\). Finally, for each modality, we concatenate the local and global representations to generate the final fine-grained visual/textual features as follows:

\[
f^v = \text{concat} \left( O^v_{\text{local}}, O^v_{\text{global}} \right), \tag{12}
\]

\[
f^q = \text{concat} \left( O^q_{\text{local}}, O^q_{\text{global}} \right), \tag{13}
\]

where \(f^v\) is the final visual feature and \(f^q\) is the final textual feature.

**D. Transformer Decoder**

After obtaining the fine-grained visual and textual features \(f^v\) and \(f^q\), we need a transformer decoder to handle these cross-modal interactions. Supposing we need to predict \(M\) segment candidates, as the additional input, segment queries \(S = \{s_h^M\}_{h=1}^{30}, [68], [69]\) are utilized to learn a possible segment by aligning the semantics between \(f^v\) and \(f^q\). Based on \(S\), we develop a cross-modal parallel transformer to integrate these features from different modalities in parallel. To further assist the multi-modal semantic alignment and interaction, we also design a new cross-modal cycle consistency loss in this decoder for supervision.

**Cross-modal parallel transformer:** Given the visual features \(f^v\), we employ several linear layers on it to generate a set of video-specific key \(K_{f^v}\) and video-specific value \(V_{f^v}\). Similarly, we can also obtain the query-specific key \(K_{f^q}\) and query-specific value \(V_{f^q}\) as:

\[
K_{f^v} = f^v W^k_6, V_{f^v} = f^v W^v_6, \tag{14}
\]

\[
K_{f^q} = f^q W^k_7, V_{f^q} = f^q W^v_7, \tag{15}
\]

where \(W^k_6, W^v_6, W^k_7\) and \(W^v_7\) are learnable parameters. Based on the modality-specific key and value, we design a modality-specific attention module to fuse multi-modal features by two parallel branches (i.e., two MultiAtt modules) in Fig. 3, where MultiAtt is the standard Multi-head Attention module [33], [70], which is defined as:

\[
\text{Att}_v = \text{MultiAtt} \left( S, K_{f^v}, Q_{f^v} \right), \tag{16}
\]

\[
\text{Att}_q = \text{MultiAtt} \left( S, K_{f^q}, Q_{f^q} \right), \tag{17}
\]

where \(\text{Att}_v\) is the attention output in the visual branch and \(\text{Att}_q\) is the attention output in the textual branch, \(S\) denotes the enhanced segment queries by the self-attention operation. To model fine-grained cross-modal interaction, we integrate these two attentions as follows:

\[
O_{\text{cross}} = \text{Att}_v \oplus \text{Att}_q, \tag{18}
\]

where \(\oplus\) denotes the additive sum with learnable weights. \(\text{Att}_v\) is the sum with learnable weights in the visual branch, and \(\text{Att}_q\) is the sum with learnable weights in the textual branch. Note that the main computational cost of the cross-modal parallel transformer is matrix multiplication (i.e., "matmul" in Fig. 3). Based on (17) and (18), we can calculate the visual attention and the textual attention in parallel, which improves the computational efficiency.

**Cross-modal cycle consistency:** In the TSG task, a phrase often corresponds to a specific clip. To enforce better semantic alignment between clips and phrases, we design a new cross-modal cycle-consistency loss during cross-modal interaction. In general, if a clip and a phrase are identified as semantically aligned, their representations are nearest neighbors in the learned common spaces. After obtaining clip-level features \(\{\tau_i\}_{i=1}^{T/8-1} \in \mathbb{R}^{T/8-1 \times D}\) or phrase-level features \(\{\bar{\tau}_j\}_{j=1}^{J} \in \mathbb{R}^{J \times D}\), we design a cross-modal cycle-consistency constraint for better cross-modal alignment.

In the TSG task, since the phrases \(\{\bar{\tau}_j\}_{j=1}^{J}\) in given sentence follow a temporal order, we first find the visual soft nearest neighbor (i.e., the most relevant clip) \(\tau_i \in \mathbb{R}^{1 \times D}\) by:

\[
\tau_i = \sum_{r=1}^{T/8-1} \frac{\exp \left( -||\bar{\tau}_j - \tau_i||^2 \right)}{\sum_{t=1}^{T/8-1} \exp \left( -||\bar{\tau}_j - \tau_t||^2 \right)} \tau_r, \tag{19}
\]

where \(\exp \left( -||\bar{\tau}_j - \tau_i||^2 \right) / \sum_{t=1}^{T/8-1} \exp \left( -||\bar{\tau}_j - \tau_t||^2 \right)\) is used to compute the similarity score of phrase \(\tau_j\) and any clip \(\tau_i\).

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Then, we cycle back from $\tau_i$ to phrase sequence $\{\tilde{h}_j\}_{j=1}^J$ by calculating the soft phrase location as follows:
\[
p = \sum_{j=1}^J \frac{\exp \left(-||\tilde{h}_j - \tau_i||^2\right)}{\sum_{\xi=1}^M \exp \left(-||\tilde{F}_\xi - \tau_i||^2\right)}.
\]  

(20)

To learn semantically consistent representations, we penalize deviations from cycle-consistency for sampled clips and phrases based on the following loss function:
\[
L_{CMCC} = e^{-\cos(p, j)},
\]

(21)

where $\cos(p, j)$ denotes the cosine similarity of $p$ and $j$.

Finally, by minimizing (21), we can make the source location $j$ and the soft destination location $p$ as close as possible. If $p = j$, the clip $\tau_i$ and the phrase $\tilde{h}_i$ are semantically corresponding; if $p \neq j$, we can obtain the nearest neighbor of $\tau_i$ by minimizing (21).

E. Boundary Prediction

After obtaining $O_{cross}$ by (18), we utilize multiple feed-forward networks to obtain a series of fixed-length boundary predictions $Y = \{\tilde{y}_h\}_{h=1}^M$, where $\tilde{y}_h = (\tilde{b}_h; \tilde{d}_h)$ contains the $h$-th predicted segment coordinate $\tilde{b}_h \in [0, 1]^2$ and the corresponding confidence score $\tilde{d}_h \in [0, 1]$. We denote the ground truth as $Y = \{y_h\}_{h=1}^M$, which contains the ground-truth segment coordinate $\tilde{b}_h \in [0, 1]^2$.

Based on the fixed-length boundary predictions and ground-truth boundary, we design the boundary prediction loss:
\[
L_{\text{boundary}}(\tilde{y}_h; y_h) = \lambda_{cl} \cdot \frac{||b - \tilde{b}_h||_1 + \lambda_{IoU} |\mathcal{C}_{IoU}(b, \tilde{b}_h) - \tilde{d}_h|}{2},
\]

(22)

where $\lambda_{cl}$ and $\lambda_{IoU}$ are weighting parameters; $\mathcal{C}_{IoU}(\cdot, \cdot)$ is a scale-invariant generalized intersection over union. By minimizing (22), we can determine the optimal prediction segment slot from multiple boundary predictions. Assuming that the $\mu$-th slot is optimal, we denote the corresponding optimal prediction as $\tilde{y}_\mu$.

Thus, the final loss is as follows:
\[
L_{\text{final}} = L_{CMCC} + \lambda_f L_{\text{boundary}}(\tilde{y}_\mu; y_h),
\]

(23)

where parameter $\lambda_f$ is utilized to control the balance.

Inference: The inference process of our proposed HLGT is very simple. Without predefined threshold values or time-consuming post-processing processes, we generate the predicted segment boundary in only one forward pass. The predicted segment with the highest confidence score will be selected as the final predicted segment.

IV. EXPERIMENTS

A. Datasets and Evaluation Metric

We conduct experiments on three challenging benchmark datasets: ActivityNet Captions [71], Charades-STA [41] and TACoS [72].

ActivityNet Captions: ActivityNet Captions [71] contains 20 k untrimmed videos with 100 k language descriptions from YouTube [73]. These videos are mainly about complicated human activities in daily life. These videos are 2 minutes on average, and these annotated video segments have much larger variation, ranging from several seconds to over 3 minutes. Since the test split is withheld for competition, following the public split [41], we use 37421, 17505, and 17031 query-video pairs for training, validation, and testing respectively.

Charades-STA: Built upon the Charades [74] dataset, Charades-STA [41] contains 6672 videos and involves 16128 video-query pairs, which pays attention to daily life indoors activities. It is collected for video action recognition and video captioning, and contains 6672 videos and involves 16128 video-query pairs. Following [41], [75], we utilize 12408 video-query pairs for training and 3720 pairs for testing.

TACoS: Collected by [72] for video grounding and dense video captioning tasks, TACoS consists of 127 long videos, which are mainly about cooking scenarios. It consists of 127 videos on cooking activities with an average length of 4.79 minutes. In video grounding task, it contains 18818 video-query pairs. For fair comparisons, we follow the same split of the dataset as [41], which has 10146, 4589, and 4083 video-query pairs for training, validation, and testing respectively.

Evaluation metric: Following [28], we adopt “R@n, IoU=m” proposed by [76] for the metric, which calculates the ratio of at least one of top-$n$ selected segments having an intersection over union (IoU) larger than $m$. The larger metric means the better performance. In our experiments, we utilize $n \in \{1, 5\}$ for all datasets, $m \in \{0.5, 0.7\}$ for ActivityNet Captions and Charades-STA, $m \in \{0.3, 0.5\}$ for TACoS.

B. Implementation Details

Following [59], [60], [61], [62], for video encoding, we define continuous 16 frames as a clip and each clip overlaps 8 frames with adjacent clips. Then, we use a pre-trained Resnet-152 network [63] to extract the frame-level visual features in each clip. Since some videos are overlong, we follow [77] to uniformly downsample frame-feature sequences to $T = 256$. For query encoding, we utilize the Glove embedding [64] to embed each word to 300-dimension features. For both visual and textual branches, we set the hidden state size as 1024 and the attention head as 8 in all the transformer and attention blocks. We train the whole model for 80 epochs with the batch size of 64 and the early stopping strategy. The hyperparameters $\lambda_{cl}$, $\lambda_{IoU}$ and $\lambda_f$ are set to 0.8, 0.5 and 0.2 respectively according to empirical study. We perform the parameter optimization by Adam optimizer [78] with leaning rate $3 \times 10^{-4}$ for ActivityNet Captions and Charades-STA and $2 \times 10^{-4}$ for TACoS, and linear decay of the leaning rate and gradient clipping of 1.0. Our method is implemented by using PyTorch on the machine with eight NVIDIA Tesla V100 GPUs.

C. Comparison With State-of-The-Arts

Compared methods: We compare the proposed HLGT with state-of-the-art TSG methods on three datasets. These methods are grouped into three categories by the viewpoints of top-down,
bottom-up and transformer-based methods. To make a fair comparison with these TSG methods, following [79], we cite their results from corresponding works:

i) Top-down approach: CTRL [41], ACRN [80], QSPN [81], SCRM [22], BPNet [82], CMIN [21], 2D-TAN [23], DRN [83], FIAN [45], CBLN [84]. These methods first sample multiple candidate video segments, and then directly compute the semantic similarity between the query representations with segment representations for ranking and selection.

ii) Bottom-up approach: CBP [85], GDP [25], LGI [27], VSLNet [28], IVG-DCL [86], ACRM [3]. These methods directly predict the start and end timestamps of the target segment by regression.

iii) Transformer-based approach: VIDDGTR [32], De-VLTrans-MSA [31], GTR [30]. Different from the above top-down and bottom-up approaches, they capture more fine-grained interaction between the video-query input and directly output the segment predictions via the effective transformer encoder-decoder architecture without using any time-consuming pre- and post-processing operation.

Comparison on ActivityNet Captions: We compare our proposed HLGT with the state-of-the-art top-down, bottom-up, and transformer-based TSG methods on the ActivityNet Captions dataset in Table I, where our HLGT reaches the best performance over all the metrics. Particularly, compared with the best top-down approach CBLN, our HLGT achieves 7.56%, 6.65%, 4.87% and 4.02% improvements on all the metrics, respectively. Our HLGT also obtains an even larger improvement over the best bottom-up method IVG-DCL in metrics R@1, IoU = 0.5 and R@1, IoU = 0.5, and brings the improvements by 7.78% and 3.05% in terms of R@1, IoU = 0.5, respectively. Compared to the best bottom-up method VIDDGTR by 2.73% and 2.88% absolute improvement in terms of R@1, IoU = 0.5 and R@5, IoU = 0.5, respectively.

Comparison on Charades-STA: As shown in Table I, we also compare our proposed HLGT with the state-of-the-art top-down, bottom-up, and transformer-based TSG methods on the Charades-STA dataset. Obviously, our HLGT beats all the other methods over all evaluation metrics. Compared to the best top-down method CBLN, our HLGT outperforms it by 4.18% and 4.17% absolute improvement in terms of R@1, IoU = 0.5 and R@5, IoU = 0.5, respectively. Compared to the best bottom-up method ACRM, our HLGT improves the performance by 7.78% and 3.05% in terms of R@1, IoU = 0.5 and R@1, IoU = 0.7, respectively. Besides, our HLGT beats the best transformer-based method De-VLTrans-MSA by 2.73% and 2.88% absolute improvement in terms of R@1, IoU = 0.5 and R@5, IoU = 0.5, respectively.

Comparison on TACoS: To further compare our proposed HLGT with the state-of-the-art top-down, bottom-up, and transformer-based TSG methods, we present the results in Table I. We can find that HLGT still outperforms all the other TSG methods in terms of all the metrics. Compared to the best top-down method CBLN, our HLGT outperforms it by 10.35%, 11.52%, 9.1% and 12.7% in terms of all metrics, respectively. HLGT also beats the best bottom-up method ACRM and brings the improvements by 10.54% and 12.13% in terms of R@1, IoU = 0.3 and R@1, IoU = 0.5, respectively. Compared to the best transformer-based method De-VLTrans-MSA, HLGT brings the improvements of 1.60% and 1.43% in terms of R@1, IoU = 0.3 and R@5, IoU = 0.3, respectively.

Efficiency comparison: We further evaluate the efficiency of our proposed HLGT by fairly comparing its inference speed (QPS) with state-of-the-art methods on the challenging ActivityNet Captions dataset in Fig. 4. HLGT can process more than $6 \times 10^3$ queries per second, which shows that our HLGT can efficiently process these challenging multi-modal data. Compared with other state-of-the-art methods, our HLGT runs faster and achieves better grounding performance. Particularly, our HLGT
TABLE II
MAIN ABLATION STUDIES OF OUR PROPOSED HLGT ON ALL THREE DATASETS, WHICH INVESTIGATES FEATURE EXTRACTION, TRANSFORMER ENCODER, TRANSFORMER DECODER, AND BOUNDARY PREDICTION

| Model | Feature Extraction | Transformer Encoder | Transformer Decoder | Boundary Prediction | ActivityNet Captions | TACoS | Charades-STA |
|-------|--------------------|---------------------|---------------------|---------------------|----------------------|-------|-------------|
|       | Local | Global | Local | Global | $L_{GMCC}$ | $L_{boundary}$ |  R@1, IoU=0.5 |  R@1, IoU=0.7 |  R@5, IoU=0.5 |  R@5, IoU=0.7 |
| i     | ×     | ×      | ×     | ×      | ×           | ×                   | 44.95 | 28.37 | 75.08 | 60.72 |
| ii    | ✓     | ×      | ✓     | ×      | ×           | ×                   | 46.83 | 30.21 | 78.92 | 63.14 |
| iii   | ×     | ✓      | ✓     | ✓      | ×           | ×                   | 47.56 | 29.33 | 79.31 | 62.05 |
| iv    | ✓     | ✓      | ✓     | ✓      | ×           | ×                   | 50.64 | 30.12 | 81.34 | 63.18 |
| v     | ✓     | ✓      | ✓     | ✓      | ✓           | ✓                   | 52.61 | 31.07 | 82.56 | 64.32 |
| Full  | ✓     | ✓      | ✓     | ✓      | ✓           | ✓                   | 55.68 | 34.25 | 84.19 | 67.43 |

**Main ablation study:** We first conduct the main ablation study to examine the effectiveness of all the modules in our model, including multi-level feature extractions (local and global), multi-level transformer encoders (local and global), the transformer decoder and the boundary predict module. The ablation results are reported in Table II: 1) Model i is the baseline model without temporal transformer and feature fusion, where we directly employ these frame- and word-level features for grounding. 2) For each modality, Model ii only uses the local features and ignores the global features for grounding. 3) On the contrary, Model iii only utilizes the global features for grounding. 4) As for Model iv, we use both local and global features for grounding. 5) In Model v, we add the CMCC loss to Model iii. 6) Model Full is our full HLGT.

From Table II, we can find that: i) Model Full performs the best and Model i the worst. ii) Compared to Model i, Model ii and iii achieve the improvement by 1.18% and 2.61% respectively in terms of “R@1, IoU = 0.5” on the ActivityNet Captions dataset. It shows that local and global features can be used to align visual and textual representations. iii) Compared to Model ii and iii, Model iv improves the performance by 1.49% and 1.82% respectively in terms of “R@1, IoU = 0.7” on the Charades-STA dataset. It is because both local and global features are significant to learn the full visual/textual representation. iv) As for Model v, it outperforms Model iv by 2.23% in terms of “R@5, IoU = 0.5” on the TACoS dataset. It is because our cross-modal cycle consistency can encourage semantic alignment between visual and language features in the joint embedding space for video grounding. v) Compared to Model v, Model Full achieves the performance improvement by 1.36% in terms of “R@1, IoU = 0.7” on Charades-STA.

Fig. 4. Efficiency in terms of R@1, IoU = 0.5 and query per second (QPS, i.e., the number of localized queries per second) on ActivityNet Captions.

is 5.24% better than transformer-based method VIDTR with 38.71% faster speed, which shows the effectiveness and efficiency of our HLGT. Our satisfactory performance attributes to: i) Our cross-modal parallel transformer is able to process visual features and textual features in parallel, which effectively reduces the time consumption of processing multi-modal features. ii) For each modality, our global-local transformer can learn the interactions between the local and global semantics for better multi-modal reasoning and more accurate video grounding. Therefore, our HLGT will have wider real-world multimedia applications, due to its efficiency and effectiveness on the challenging large-scale ActivityNet Captions dataset.

### D. Ablation Study

To examine the effectiveness of each component in our HLTG, we perform in-depth ablation studies on three challenging datasets: ActivityNet Captions, Charades-STA and TACoS.
Training process of different ablation models: Following [87], we try to analyze the training process and grounding performance of different ablation models. Fig. 5 shows the experimental results. We can obtain the following representative observations: i) On each epoch, HLGT(full) outperforms other ablation models, which demonstrates the effectiveness of each module. For example, compared to the second-best model HLGT(v), HLGT(full) improves the performance by 3.27%. ii) HLGT(full) converges faster than ablation models, which shows that our full model is more efficient on time-consuming. For instance, HLGT(full) converges within 14 epochs, while HLGT(i) converges after 18 epochs. Thus, our full HLGT can process these challenging datasets more efficiently.

Analysis on different visual feature extractor network: Most of previous methods use pre-trained C3D or I3D to obtain the visual features. However, both C3D and I3D only obtain the clip-level features not the frame-level features. Different from them, we utilize a Resnet-152 network to obtain the fine-grained frame-level feature. In this subsection, we conduct an ablation study to analyze the performance of our used Resnet-152 network. Table III shows the results, where the plain transformer is the baseline network. Obviously, our proposed HLGT on the Resnet-152 network performs better than other clip-level pre-trained feature extractor network (C3D and I3D). Specifically, compared to HLGT(C3D), our used HLGT(Resnet-152) significantly improves the grounding performance by 0.39%, 0.41%, 0.42% and 0.30% over all metrics. The satisfactory performance improvement illustrates the effectiveness of our used Resnet-152 network.

Effect of different transformers: To examine the effect of our transformers (i.e., three designed transformers in Fig. 3), we replace our designed transformers with some state-of-the-art transformer modules. For this ablation study, we consider two aspects: different transformer modules on TACoS and different transformer layers on Charades-STA. Table IV shows the experimental results.

In our experiments, we utilize a transformer module from "option" to replace a transformer module (①, ② and ③) in our HLGT with freezing our remaining two transformer modules.

![Image](https://example.com/image.png)
our cross-modal parallel transformer achieves performance improvement by 1.12% in terms of “R@1, IoU = 0.5”. The satisfactory performance of our transformers shows the effectiveness of our transformers, each of which contributes to the model performance.

About the impact of different transformer layers, it shows that for each component, the multi-layer transformer only performs marginally better than the single-layer transformer with the higher computational cost (smaller VPS and larger Para.) of transformer operations. An interesting finding is that the multi-layer global-local transformer can bring more improvement than the other two transformers. It is because the global-local transformer can effectively integrate multi-grained features, which improves the grounding performance. For the temporal transformer and the cross-modal parallel transformer, “layer = 1” achieves similar performance compared to “layer = 3” but significantly decreases the computation (Para.). Therefore, for all the transformers, we set “layer = 1”, which is the suggested value on our TSG task.

Impact of segment queries: To investigate the effectiveness of segment queries on the transformer decoder, we conduct the ablation study on the Charades-STA dataset. As shown in Table V, with segment queries, our HLGT achieves the significant performance improvement. Specifically, compared with the first option (wo./ segment queries), the second option (w/ segment queries) improves the performance by 0.43%, 0.36%, 0.13% and 0.24% over all metrics, respectively. The significant performance improvement shows the effectiveness of our used segment queries.

Impact of shared weight: To analyze the impact of shared weight in temporal transformer and feature fusion components, we conduct an ablation study on the Charades-STA dataset. For the setting of unshared weight, we assign an independent weight to each temporal transformer and feature fusion component. As shown in Table VI, by introducing the shared weight approach, our HLGT can significantly improve the grounding performance. Compared to the setting of unshared weight, for the temporal transformer, our setting of shared weight achieves the performance improvement by 0.37% in terms of “R@1, IoU = 0.5”. As for the feature fusion, our setting improves the performance by 0.49 % in terms of “R@1, IoU = 0.5”. The improvement shows the effectiveness of the shared weight in temporal transformer and feature fusion components.

Choices for CMCC loss: Cross-modal cycle consistency (CMCC) is a significant assistance to enforce the cross-modal interaction. We compare our proposed CMCC loss ($L_{CMCC}$ in (21)) with three following popular loss functions: 1) L1 loss $L_1 = ||p − j||^2_1$; 2) L2 loss $L_2 = ||p − j||^2_2$; 3) cosine similarity loss $L_3 = −\cos(p, j)$. Table VII reports the results on all the datasets. Obviously, $L_{CMCC}$ dramatically improves grounding performance than other losses, which illustrates the effectiveness of our $L_{CMCC}$. Especially, compared to the second-best loss $L_3$, our proposed CMCC loss improves the performance by 1.68% in terms of “R@5, IoU = 0.5” on the TACoS dataset. Therefore, we choose the CMCC loss as the final loss of our cross-modal cycle consistency.

Influence of clip duration: As shown in Table VIII, we further investigate the influence of the clip duration. Obviously, with the increase of the duration, the variation of the performance follows a general trend, i.e., rises at first and then starts to decline. It is because shorter clip will guide a meaningful action to be split into different clips, which limits our model’s understanding of the video. In addition, longer clip will have multiple actions gathered into a clip, leading to incorrect understanding of the video.

### Table V

**Ablation Study on Segment Queries on Charades-STA**

| Option          | R@1, IoU=0.5 | R@1, IoU=0.7 | R@5, IoU=0.5 | R@5, IoU=0.7 |
|-----------------|--------------|--------------|--------------|--------------|
| wo/ Segment Queries | 64.88 | 41.02 | 94.37 | 64.48 |
| w/ Segment Queries | 65.31 | 41.38 | 94.50 | 64.72 |

### Table VI

**Ablation Study on Shared Weight on Charades-STA**

| Component | Option          | R@1, IoU=0.5 | R@1, IoU=0.7 | R@5, IoU=0.5 | R@5, IoU=0.7 |
|-----------|----------------|--------------|--------------|--------------|--------------|
| Temporal Transformer | Unshared Weight | 64.94 | 41.02 | 94.18 | 64.57 |
| Feature Fusion | Unshared Weight | 64.82 | 40.99 | 94.02 | 64.26 |
| Temporal Transformer | Our Shared Weight | 65.31 | 41.38 | 94.50 | 64.72 |
| Feature Fusion | Our Shared Weight | 65.31 | 41.38 | 94.50 | 64.72 |

### Table VII

**Choices for Cross-Modal Cycle Consistency on All Three Datasets**

| Loss | R@1, IoU=0.5 | R@1, IoU=0.7 | R@5, IoU=0.5 | R@5, IoU=0.7 |
|------|--------------|--------------|--------------|--------------|
| $L_1$ | 60.14 | 37.57 | 90.42 | 61.31 |
| $L_2$ | 63.95 | 38.14 | 91.18 | 62.70 |
| $L_3$ | 64.18 | 40.71 | 93.56 | 63.21 |
| Our $L_{CMCC}$ | 65.31 | 41.38 | 94.50 | 64.72 |

### Table VIII

**Influence of Clip Duration on ActivityNet Captions**

| Clip Duration | R@1, IoU=0.5 | R@1, IoU=0.7 | R@5, IoU=0.5 | R@5, IoU=0.7 |
|---------------|--------------|--------------|--------------|--------------|
| 4 frames | 54.81 | 33.26 | 83.48 | 67.14 |
| 8 frames | 55.12 | 33.80 | 83.94 | 67.28 |
| 16 frames | 55.68 | 34.25 | 84.19 | 67.43 |
| 32 frames | 55.30 | 34.13 | 83.98 | 67.30 |

### Table IX

**Complexity Comparison on ActivityNet Captions**

| Method | R@1, IoU=0.7 | Time | Memory (batch size) |
|--------|--------------|------|---------------------|
| CMIN | 23.88 | 0.08s | 3692M (64) |
| 2D-TAN | 26.34 | 0.57s | 10572M (16) |
| CBLN | 27.60 | 0.18s | 10184M (64) |
| Our HLGT | 34.25 | 0.23s | 10259M (64) |

“Time” means the average time to localize one sentence.
video. Obviously, the optimal clip duration is 16 frames, where all variants obtain the best performance.

Computational complexity of our HLGT: We further evaluate the computational complexity of our model, we give an in-depth study in terms of inference time and memory. As shown in Table IX, the “time (s/sample)” denotes the average time to localize one sentence in a given video, “memory (M)” denotes the size of parameters. Compared with state-of-the-art works (2D-TAN and CBLN), our HLGT achieves better grounding performance (R@1, IoU = 0.7) with much faster processing speeds (time) and similar parameters sizes (memory). Compared with CMIN, our HLGT outperforms it with a large margin. This attributes to: 1) For multi-step feature fusion, 2D-TAN uses many convolutional layers, which contains a great amount of parameters and are cost time. 2) CBLN utilizes multiple global and local windows to extract multi-level contexts in the given video, thus requiring more parameters. 3) Although CMIN has smaller model size than other methods, it performs the worst. With the similar model size, our HLGT beats CBLN with a large margin. Compared to 2D-TAN, our model performs better and much more efficient. Overall, the experimental results show the superiority of our HLGT in terms of both effectiveness and efficiency.

Analysis of the hyperparameters: To achieve the best performance, we analyze the impact of three hyperparameters: \( \lambda_{k_1} \), \( \lambda_{1oU} \) and \( \lambda_f \). Table X shows the experimental results. It can be observed that, with the increase of \( \lambda_{k_1} \), \( \lambda_{1oU} \) and \( \lambda_f \), their performance follows a general trend, i.e., rises at first and then starts to decline. The optimal values of \( \lambda_{k_1} \), \( \lambda_{1oU} \) and \( \lambda_f \) are 0.8, 0.5, and 0.2 respectively, where all the hyperparameters obtain the best performance. Therefore, in our article, we set \( \lambda_{k_1} = 0.8 \), \( \lambda_{1oU} = 0.5 \) and \( \lambda_f = 0.2 \).

Performance of different datasets: To analyze the generalization ability of our HLGT, we test its running speed on different datasets. Table XI shows its performance on three datasets. On the one hand, although these datasets are under different scales, our HLGT has a similar parameter scale for different datasets, which shows that HLGT can deal with different types of datasets with little or no model changes. On the other hand, on the ActivityNet Captions and TACoS datasets, HLGT has the similar running speed (VPS). On the ActivityNet dataset, our HLGT deals with 190.76 videos per second, while it processes 196.54 videos on the TACoS dataset per second. It is because ActivityNet Captions and TACoS have similar average video length. The Charades-STA dataset has shorter video length, which leads to larger VPS.

E. Visualization

To investigate the grounding results of our HLGT, we provide two qualitative examples of HLGT and VIDGTR in Fig. 6. We can observe that HLGT achieves more precise localization than the state-of-the-art method VIDGTR. The main reason is that VIDGTR only focuses on the frame-level visual features for encoding and ignores higher-level features (video- and clip-level features), which fails to capture the subtle cross-modal multi-granularity details and understand the complicated background visual content. Different from VIDGTR, HLGT can learn multi-level cross-modal interaction (clip-phrase and video-query interaction), thus capturing more fine-grained visual contexts for more accurate grounding.

| \( \lambda_{k_1} \) | ActivityNet Captions | Charades-STA | TACoS |
|---|---|---|---|
| 0.4 | 53.82 | 31.69 | 82.94 | 65.07 | 61.33 | 39.17 | 92.49 | 61.93 | 46.52 | 37.28 | 66.49 | 55.70 |
| 0.6 | 55.01 | 32.98 | 83.72 | 66.15 | 62.95 | 40.86 | 93.01 | 62.99 | 48.27 | 38.04 | 68.15 | 57.13 |
| 0.8 | 55.68 | 34.25 | 84.19 | 67.43 | 65.31 | 41.38 | 94.50 | 64.72 | 49.33 | 39.17 | 69.06 | 58.94 |
| 1 | 54.13 | 32.76 | 83.04 | 65.91 | 63.49 | 41.25 | 92.48 | 63.10 | 49.12 | 38.76 | 67.65 | 57.09 |

| \( \lambda_{1oU} \) | ActivityNet Captions | Charades-STA | TACoS |
|---|---|---|---|
| 0.3 | 63.25 | 31.68 | 81.05 | 64.30 | 61.89 | 38.72 | 91.37 | 61.04 | 46.21 | 36.28 | 66.09 | 55.32 |
| 0.4 | 54.16 | 33.72 | 82.64 | 65.75 | 63.82 | 39.67 | 93.51 | 63.28 | 48.39 | 37.50 | 67.82 | 56.73 |
| 0.5 | 55.68 | 34.25 | 84.19 | 67.43 | 65.31 | 41.38 | 94.50 | 64.72 | 49.33 | 39.17 | 69.06 | 58.94 |
| 0.6 | 55.14 | 32.78 | 82.95 | 66.03 | 63.12 | 40.84 | 92.87 | 62.34 | 47.52 | 38.25 | 67.31 | 57.93 |

| \( \lambda_f \) | ActivityNet Captions | Charades-STA | TACoS |
|---|---|---|---|
| 0.1 | 54.07 | 33.85 | 83.69 | 66.02 | 64.17 | 40.02 | 92.11 | 63.02 | 48.15 | 38.06 | 67.92 | 56.32 |
| 0.2 | 55.68 | 34.25 | 84.19 | 67.43 | 65.31 | 41.38 | 94.50 | 64.72 | 49.33 | 39.17 | 69.06 | 58.94 |
| 0.3 | 54.87 | 33.72 | 83.05 | 66.31 | 64.07 | 40.18 | 93.04 | 63.18 | 47.30 | 37.95 | 68.01 | 57.37 |
| 0.4 | 52.10 | 31.74 | 82.06 | 64.18 | 62.50 | 38.42 | 91.03 | 61.84 | 46.35 | 36.72 | 66.51 | 55.40 |

| Table XI | Video Per Second (VPS) and Parameters (Para.) on All Three Datasets |
|---|---|---|---|
| Dataset | Domain | VPS | Para. |
| ActivityNet Captions | Open | 190.76 | 119 |
| Charades-STA | Indoor | 257.38 | 114 |
| TACoS | Cooking | 196.54 | 116 |
Query: He washes the cucumber in the sink and puts it on the plate.

| GT | VDGCTR | VIDCTR | HLGCTR | HLGCTV |
|----|--------|--------|--------|--------|
| 56.63s | 55.31s | 55.82s | 54.78s | 55.96s |

Query: The woman and the man arm wrestle.

| GT | VDGCTR | VIDCTR | HLGCTR | HLGCTV |
|----|--------|--------|--------|--------|
| 20.08s | 20.08s | 60.43s | 87.35s | 59.08s |

Query: A person is running into the room holding a pillow.

| GT | VDGCTR | VIDCTR | HLGCTR | HLGCTV |
|----|--------|--------|--------|--------|
| 1.80s | 1.05s | 2.83s | 1.35s | 1.67s |

Fig. 6. Qualitative results sampled from all three datasets (top: TACoS, middle: ActivityNet Captions, bottom: Charades-STA).

V. CONCLUSION

In this article, we proposed a novel Hierarchical Local-Global Transformer (HLGT) for temporal sentence grounding, which leverage this hierarchy information and model the interactions between multiple levels of granularity and different modalities for learning more fine-grained multi-modal representations. Experimental results on three challenging datasets (ActivityNet Captions, Charades-STA and TACoS) validate the effectiveness of our HLGT. In the future, we will apply HLGT to other tasks/datasets [93], [94] to further improve its generalization. Meanwhile, we also will introduce HLGT in the weakly-supervised manner to explore how to use more unannotated data in supervised manner.

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Xiang Fang received the M.E. degree from the School of Computer Science and Technology, Huazhong University of Science and Technology (HUST), Wuhan, China, in 2020. He is currently a Remote Intern with the School of Cyber Science and Engineering, HUST. His research interests include multimodal learning, data mining, and machine learning.

Daizong Liu received the B.S. degree in information engineering from the Wuhan University of Technology, Wuhan, China, in 2018, and the M.S. degree in electronic information and communication of Huazhong University of Science and Technology, Wuhan, in 2021. He is currently working toward the Ph.D. degree with the Wangxuan Institute of Computer Technology of Peking University, Beijing, China. His research interests include 3D adversarial attacks and multi-modal learning.

Pan Zhou (Senior Member, IEEE) received the Ph.D. degree with the School of Electrical and Computer Engineering, Georgia Institute of Technology (Georgia Tech), Atlanta, GA, USA, in 2011. He is currently a Full Professor and Ph.D. Advisor with Hubei Engineering Research Center on Big Data Security, School of Cyber Science and Engineering, Huazhong University of Science and Technology (HUST), Wuhan, China. His current research interest includes: security and privacy, Big Data analytics, machine learning, and information networks. He received the Rising Star in Science and Technology of HUST in 2017, and the Best Scientific Paper Award in the 25th International Conference on Pattern Recognition (ICPR) 2020. He is currently an Associate Editor for IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING.

Zichuan Xu (Member, IEEE) received the B.Sc. and M.E. degrees in computer science from the Dalian University of Technology, Dalian, China, in 2008 and 2011, respectively, and the Ph.D. degree in computer science from the Australian National University, Canberra, ACT, Australia, in 2016. From 2016 to 2017, he was a Research Associate with the Department of Electronic and Electrical Engineering, University College London, U.K. He is currently a Professor with the School of Software, Dalian University of Technology. He is also a Xinghai Scholar in Dalian University of Technology. His research interests include mobile edge computing, serverless computing, network function virtualization, Internet of Things, and algorithm design.

Ruixuan Li (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in computer science from the Huazhong University of Science and Technology, Wuhan, China, in 1997, 2000, and 2004, respectively. He is currently a Professor with the School of Computer Science and Technology, Huazhong University of Science and Technology. He was a Visiting Researcher with the Department of Electrical and Computer Engineering, University of Toronto, Toronto, ON, Canada, from 2009 to 2010. His research interests include cloud computing, Big Data management, and machine learning. He is a member of ACM.