CONTEXTUAL SELF-PACED LEARNING FOR WEAKLY SUPERVISED SPATIO-TEMPORAL VIDEO GROUNDING

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ABSTRACT

In this work, we focus on Weakly Supervised Spatio-Temporal Video Grounding (WSTVG). It is a multimodal task aimed at localizing specific subjects spatio-temporally based on textual queries without bounding box supervision. Motivated by recent advancements in multi-modal foundation models for grounding tasks, we first explore the potential of state-of-the-art object detection models for WSTVG. Despite their robust zero-shot capabilities, our adaptation reveals significant limitations, including inconsistent temporal predictions, inadequate understanding of complex queries, and challenges in adapting to difficult scenarios. We propose **CoSPaL** (Contextual Self-Paced Learning), a novel approach which is designed to overcome these limitations. CoSPaL integrates three core components: (1) *Tubelet Phrase Grounding (TPG)*, which introduces spatio-temporal prediction by linking textual queries to tubelets; (2) *Contextual Referral Grounding (CRG)*, which improves comprehension of complex queries by extracting contextual information to refine object identification over time; and (3) *Self-Paced Scene Understanding (SPS)*, a training paradigm that progressively increases task difficulty, enabling the model to adapt to complex scenarios by transitioning from coarse to fine-grained understanding. We demonstrate the effectiveness of CoSPaL on three benchmark WSTVG datasets, achieving a 3.9% absolute improvement on VidSTG and a 7.9% improvement on HCSTVG-v1.

1 INTRODUCTION

Spatio-temporal video grounding (STVG) is focused on identifying and localizing objects within video frames both spatially and temporally based on textual descriptions. This problem is critical for various applications, including video surveillance, autonomous driving, and general scene understanding. However, STVG presents significant challenges. Specifically, it requires not only distinguishing objects from irrelevant ones across time but also predicting the start and end timestamps of activities related to those objects. While recent works solve this problem in a fully-supervised setup (Yang et al., 2022; Jin et al., 2022; Lin et al., 2023), these approaches require extensive annotations, both temporally and spatially, which are costly and labor-intensive to acquire. Therefore, we focus on a weakly supervised setting for spatio-temporal video grounding (WSTVG), where models are trained using only video-level descriptions, eliminating the need for precise spatio-temporal annotations.

Weakly supervised learning has been studied extensively in the image domain, addressing tasks like phrase grounding Datta et al. (2019); Wang et al. (2020); Liu et al. (2021) and referral grounding Liu et al. (2019; 2022b), which locate objects in images based on text. Various methods have been explored, such as those leveraging coarse image-level labels or proposing complex mechanisms to

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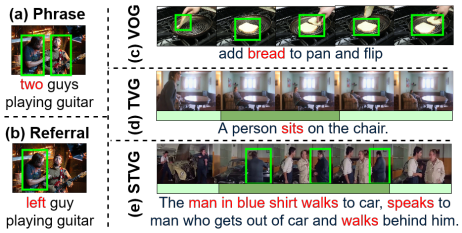

Task	PG	RG	VOG	TVG	STVG
Video	×	×	✓	✓	✓
Referring	×	✓	×	×	✓
Spatial	✓	✓	✓	×	✓
Temporal	×	×	×	✓	✓
Free-form	×	×	×	×	✓

Figure 1: **Comparison across tasks.** *(Left)* (a) Phrase grounding (PG) refers to grounding all nouns in the sentence, (b) Referral grounding (RG) makes the task harder by grounding specific subject, (c) Video object grounding (VOG) has fixed number of object categories and query template is fixed (d) Temporal video grounding (TVG) only focuses on temporal localization. Contrast to these, (e) STVG requires spatio-temporal grounding of specific subject using *free-form* query. Green denotes ground truth. Darker shade denotes temporal boundary. *(Right)* Table summarizes challenges involved in STVG against other tasks.

handle uncertainty in object localization. However, extending these approaches to videos adds a new layer of complexity due to dynamic changes in subject poses and scene context over time. As shown in Figure 1, STVG involves increased complexity compared to static image tasks, particularly when handling free-form textual queries, where models must understand and localize objects and actions described in natural language. Existing works that address WSTVG rely on computationally expensive solutions, such as hierarchical algorithms Li et al. (2023) or the inclusion of extra modality data like optical flow Chen et al. (2019b). In contrast, we propose a more streamlined and efficient approach that simplifies the process by focusing solely on visual and textual modalities.

We build upon recent progress in multimodal learning Madan et al. (2024) and leverage vision-language foundation models as our baseline, specifically adapting Grounding DINO (G-DINO) Liu et al. (2023), a model known for its strong zero-shot capabilities in image-level tasks. While this model shows promise for multimodal understanding, extending it to STVG reveals three key limitations (Table 1). First, it struggles with temporal consistency, frequently switching object focus across frames, as it lacks a clear understanding of temporal grounding. Second, despite being trained on large-scale image-text datasets, it finds it difficult to handle complex or imbalanced queries, particularly when multiple objects or activities are described simultaneously. Finally, the model's performance declines in dense scenes with numerous objects, where accurate localization becomes critical.

To address these challenges, we propose **CoSPaL**, a novel approach that enhances both spatial and temporal grounding in STVG. CoSPaL introduces three key components: (a) *Tubelet Phrase Grounding (TPG)*, which links textual queries to spatio-temporal *tubelets* (bounding boxes that span across frames), thereby improving object tracking over time. (b) *Contextual Referral Grounding (CRG)*, which fine-tunes the network's attention to accurately localize the relevant tubelet mentioned in the query, ensuring more precise object identification across both space and time. (c) *Self-Paced Scene Understanding (SPS)*, a training strategy that gradually increases task complexity, allowing the model to start with coarse predictions and refine them progressively. This structured approach significantly improves the model's adaptability and robustness in complex scenes.

We summarize our contributions as follows:

- We propose ***CoSPaL***, the first to solve weakly supervised spatio-temporal video grounding based on a foundation model.
- We propose *Contextual Referral grounding (CRG)* which extracts contextual information from query and enhances spatio-temporal grounding ability of the network.
- We introduce *Self-paced Scene Understanding (SPS)* training scheme that makes network robust for complex challenging scenarios.

We perform our experiments on three different benchmark datasets, ViDSTG and HCSTVG-v1 and HCSTVG-v2 demonstrating effectiveness of our proposed approach. CoSPaL outperform previous state-of-the-art methods on WSTVG task by an absolute margin of 3.9% on VidSTG and 7.9% on HCSTVG-v1.

2 RELATED WORK

Object Detection: Primary research in this area involves unimodal techniques, which use a single modality. These techniques can be broadly categorized into two groups: CNN-based methods such as FasterRCNN (Ren et al., 2017) and Bottom-Up Attention (Anderson et al., 2017), and Transformer-based methods like DETR (Carion et al., 2020) and its variants (Zhu et al., 2020; Wang et al., 2022b; Liu et al., 2022a; Cai et al., 2023; Fang et al., 2022). However, unimodal detectors are trained on limited object categories, making them unsuitable for the STVG task, which involves *free-form* queries. Recently, multimodal object detection research (Li et al., 2022; Zhang et al., 2022; Yao et al., 2022; Liu et al., 2023) has emerged, taking image and text as inputs to output bounding boxes for objects. Multimodal detection involves: a) Adaptation to open-world scenarios (Minderer et al., 2022; Feng et al., 2022; Dou et al., 2022; Zhang et al., 2022; Yao et al., 2022; Li et al., 2022), allowing detection of novel objects at test time, suitable for STVG queries, and b) Strong zero-shot grounding capabilities. These foundation models (Yan et al., 2023; Wang et al., 2023; Liu et al., 2023; Cheng et al., 2024) are trained on large-scale datasets like COCO (Lin et al., 2014) and O365 (Shao et al., 2019), showing strong zero-shot performance for various tasks, including referral grounding. G-DINO (Liu et al., 2023) outperforms previous models (Yan et al., 2023) in image referral tasks. We base our work on G-DINO. ***Different*** from existing setups, we adapt G-DINO to video settings for STVG task.

Spatio-Temporal Video Grounding: This task involves grounding spatio-temporal tubes based on textual queries, addressing spatial and temporal dimensions. Initial solutions developed for STVG use a two-stage process with separate spatial (Rohrbach et al., 2015; Yamaguchi et al., 2017; Chen et al., 2019c) and temporal grounding (Gao et al., 2017; Chen et al., 2019a). However, pre-trained object detectors have a fixed number of object categories, limiting their effectiveness for STVG tasks with free-form queries. Recent multimodal approaches (Su et al., 2021; Yang et al., 2022; Jin et al., 2022; Lin et al., 2023; Gu et al., 2024; Wasim et al., 2024) tackle this challenge in a single stage, leveraging image-based detectors (Kamath et al., 2021), video encoders, and spatio-temporal decoders (Yang et al., 2022; Wasim et al., 2024), addressing feature alignment inconsistencies (Jin et al., 2022), or utilizing static and motion cues (Lin et al., 2023; Gu et al., 2024), . These methods typically rely on frame-level bounding box annotations for training. ***Differently*** from these, our work adopts a cost-efficient approach by refraining from using spatio-temporal labels.

Weakly Supervised Learning There are some existing works on dense tasks Kumar et al. (2024); Singh et al. (2024); Kumar et al. (2023); Rana & Rawat (2023); Kumar & Rawat (2022); Rana & Rawat (2022); Dave et al. (2022); Modi et al. (2022), however, they are unimodal and on semi-supervised or active learning and can't be extended to solve weakly supervised STVG task. For grounding techniques, it can be categorized into three main classes. In images, it includes phrase and referral grounding. Phrase grounding(Rohrbach et al., 2016; Datta et al., 2019; Chen et al., 2018; Akbari et al., 2019; Gupta et al., 2020; Wang et al., 2020; Liu et al., 2021; Wang et al., 2021a) highlights objects in textual queries using margin losses (Datta et al., 2019; Chen et al., 2018), contrastive optimization (Gupta et al., 2020; Wang et al., 2020), and reconstruction (Rohrbach et al., 2016) methods. Referral grounding (Liu et al., 2019; 2022b; Jin et al., 2023) adopts reconstruction (Liu et al., 2019; 2022b) or contrastive learning (Jin et al., 2023) to ground objects. In temporal grounding for videos (Wang et al., 2021b; Chen et al., 2022; Lin et al., 2020; Zheng et al., 2022a;b), both reconstruction and contrastive methods are prominent, however recent reconstruction-based approaches (Lin et al., 2020; Zheng et al., 2022a;b) outperform contrastive ones. We employ a contrastive and reconstructive approach for spatial and temporal grounding respectively. ***Different*** from existing works, we incorporate referential capabilities in spatial and temporal grounding for videos which previous work don't. Our approach induce focusing on specific contextual knowledge to enhance mutual interaction between vision and text.

3 METHODOLOGY

Problem Formulation: In WSTVG, the input is an untrimmed video $V = (v_1, v_2, ...v_L)$ of length L frames, accompanied by a query description caption Q describing the subject and activity in the video. The task output is the spatio-temporal tubelet for the main subject, $A_R = \{a_r\}_{t_s}^{t_e}$, where a_r represents the main subject in the query, and t_s and t_e denote the corresponding starting and ending timestamps of the activity. In weakly-supervised settings, only video-level annotations are available for training, and there are no spatio-temporal labels for supervision.

Table 1: Comparison of weakly-supervised G-DINO(Liu et al., 2023) with previous approaches.

Methods	VidSTG-Declarative			VidSTG-Interrogative			HCSTVG-v1		
	m_vIoU	vIoU@0.3	vIoU@0.5	m_vIoU	vIoU@0.3	vIoU@0.5	m_vIoU	vIoU@0.3	vIoU@0.5
AWGU (Chen et al., 2020)	9.0	7.9	3.1	8.6	6.9	2.9	8.2	4.5	0.8
Vis-CTX (Shi et al., 2019)	9.3	7.3	3.3	8.7	7.2	2.9	9.8	6.8	1.0
WINNER (Li et al., 2023)	11.6	14.1	7.4	10.2	12.0	5.4	14.2	17.2	6.1
W-GDINO (Liu et al., 2023)	10.6	13.0	7.8	9.8	12.1	6.7	9.0	11.6	4.6

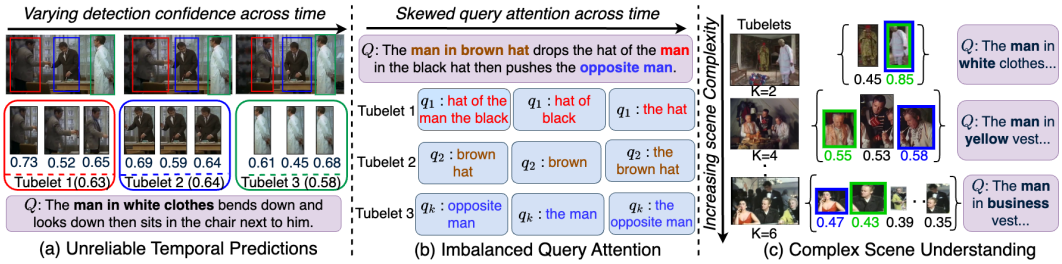

Figure 2: **Illustration of failures of W-GDINO:** (a) *Unreliable Temporal Predictions:* Foundation model predictions are inconsistent across time and switch attention between actors across time. This leads to performance degradation. (b) *Imbalanced Query Attention:* It showcases that model lacks understanding of complex queries. Across time, query which model attends to for each subject tubelet is inconsistent and doesn't match with ground truth, (c) *Complex Scene Understanding:* As the number of subjects increase, model's capability to focus on the specific subject described in query reduces. This shows it's lack of understanding of challenging scenarios. K denotes total number of subjects. Blue and red denotes predictions and green denotes ground truth in (a) and (c), and brown in (b).

3.1 Preliminaries: Grounding DINO (G-DINO)

G-DINO (Liu et al., 2023) extends closed-set object detection to open-world scenarios. It takes an image and query as input, and outputs a bounding box and confidence score. In our work, we use text input query Q and video frames $I_f = \{V_f\}_{f=1}^{T}$, with T denoting the video length. As multi-modal object detectors are image-based and STVG is a video task, we first extend G-DINO for videos. To adapt it, we run detections throughout the video, storing each subject's bounding box, confidence score, and features. Applying a tracker (Aharon et al., 2022) to these detections yields *tubelets* for each detected subject k as $\mathcal{T}_{o_k}$. K represents the total number of subjects throughout the video. This adapted model is termed weakly-supervised Grounding DINO (W-GDINO). To assess W-GDINO's performance, we accumulate and average the confidence scores of each tubelet, selecting the one with the highest score. While Table 1 demonstrates competitive performance, we observe some issues with this approach.

We attribute these issues to three major factors: *(a) Unreliable Temporal Predictions:* Figure 2 (a) shows the model's predictions are inconsistent over time due to factors like varying subject poses and similar spatial features. W-GDINO lacks spatio-temporal localization. *(b) Imbalanced Query Attention:* GDINO is trained via byte encoding scheme which breaks down the original query and then rebuild it up. Due to this, GDINO is unable to focus on a specific part of query consistently across time, as seen in Fig. 2 (b). This causes confusion about the described subject. *(c) Limitations in Complex Scene Understanding:* WSTVG datasets present challenging scenes with many objects, as shown in Fig. 2 (c). This complicates spatial and temporal associations. We propose CoSPaL to address these limitations.

3.2 Contextual Self-Paced Learning (CoSPaL)

CoSPaL consists of three key components to address the above limitations: Firstly, Tubelet Phrase Grounding (TPG) (Sec. 3.2.1) induces spatio-temporal localization capability in W-GDINO. It enables to remove unreliable temporal predictions by aligning textual and tubelet features for *spatial grounding* and textual and video features for *temporal grounding*. Second, to improve attention on relevant parts of query, we propose a novel concept of Contextual Referral grounding (CRG) module to extract fine-grained attributes that highlight the subject's contextual information. It enhances focus

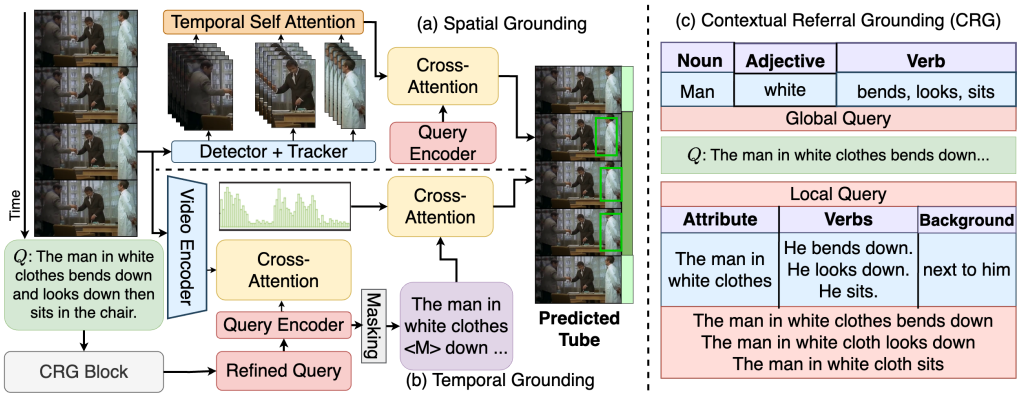

Figure 3: **Overview of CoSPaL:** TPG contains two grounding modules namely, *spatial* and *temporal*. Spatial module grounds the correct subject tubelet. Temporal module predicts the temporal action boundary via cross attention between highlighted vision features and masked query features. Contextual Referral Grounding (CRG) block shows the breakdown and generation of local (Q_{ol}) and global query (Q_{og}). Green shows predicted bounding box. Darker green shade shows predicted temporal boundary localization.

on the subject in context (Sec. 3.2.2). Finally, since STVG is challenging and matching queries with numerous scene subjects is difficult, we introduce self-paced scene understanding (SPS). It progressively increases task difficulty to adapt the network for complex scenarios and enhance the network's discriminative ability over time (Sec. 3.2.3). An overview of CoSPaL is shown in Fig. 3.

3.2.1 Tubelet Phrase Grounding (TPG)

TPG adapts W-GDINO to solve *spatial* and *temporal* grounding jointly. The *spatial grounding* module leverages word-level representations to enhance the alignment between textual and tubelet features. Meanwhile, the *temporal grounding* module optimizes the correspondence between video and textual features to accurately predict the start and end timestamps of the activity described in the caption. Following previous works in weakly supervised grounding (Datta et al., 2019; Gupta et al., 2020; Wang et al., 2020; 2021a) we incorporate a visual encoder to extract features from pre-trained object detectors and video encoders and a language encoder (Devlin et al., 2019; Pennington et al., 2014) to provide rich textual representations of query.

Visual encoder: We extract object level representations $f_{o_k} = F_o(o_k) \in \mathbb{R}^{K\times 256}$ from G-DINO (based on DETR (Carion et al., 2020)), where, F_o is object encoder model, and, o_k denotes k^{th} detected subject. We link these detections via a tracking (Aharon et al., 2022) algorithm to generate subject tubelets for subject k, $\mathcal{T}_{o_k} = \{o_{k_t}\}_{t=s}^{e}$ where s and e denotes starting and ending timestamp of the subject in the video. Tubelet features for a video is represented by $\mathcal{F}_T = \{f(\mathcal{T}_{o_k})\}_{k=1}^{K} \in \mathbb{R}^{T\times K\times 256}$, where K denotes number of objects present in a video. For video features, we utilize a video encoder, F_v (e.g. I3D (Carreira & Zisserman, 2017)) to get clip-level features, $f_c = F_v(\{V_t\}_{t=1}^{C}) \in \mathbb{R}^{C\times 1024}$. C denotes the number of clips in the video.

Query encoder: We pass the query Q through a language encoder (F_l), BERT (Devlin et al., 2019), to get word level embeddings $\mathcal{F}_W = \{f_{w_m}\}_{m=1}^{N} \in \mathbb{R}^{N\times 768}$, where $f_w = F_l(\{q_m\}_{m=1}^{N})$. N denotes total words in query.

Spatial Grounding Module highlights the correct tubelet. We use a multimodal contrastive learning optimization to highlight the relation between words and tubelet. The insight is that to find the maximal mutual information shared between two modalities, they first need to be projected into the same space. We start with subject tubelet features in a video ($\mathcal{F}_t$). The features are extracted from DETR; thus, the features do not have any interaction amongst them temporally. To establish connection between them and enhance the features temporally, we apply a temporal self-attention block (`TSA`) to generate updated tubelet features, $\tilde{\mathcal{F}}_T = \texttt{TSA}(\mathcal{F}_T)$. This helps the network to highlight frames which provide more contextual information. For example, if the query description is "man in brown coat...", `TSA` give higher weights to the frame when the actor's coat is visible rather than noisy frames (frames with zoomed in faces, partial body, challenging poses, figure shown in

supplementary). We project ($\tilde{\mathcal{F}}_T$) for each actor into a shared space by applying cross-attention block to highlight subjects mentioned in the query ($\mathcal{F}_w$). $\tilde{\mathcal{F}}_T$ is used as key and value pairs, and, $\mathcal{F}_W$ is query. We use simple feed-forward MLP layers to project key and query features. We calculate the similarity (SIM) between individual word f_w and tubelet feature $f_{\tilde{T_k}}$ as $\texttt{SIM}(f_{w_m}, f_{\tilde{T_k}}) = (\texttt{MLP}_\texttt{q}(f_{w_m})^T \texttt{MLP}_\texttt{k}(f_{\tilde{T_k}}))/\sqrt{d}$, where $\texttt{MLP}_\texttt{q}$ and $\texttt{MLP}_\texttt{k}$ denote MLP layers for key and query features. Using the features projected into the same space, we calculate aggregated attention for the video with all tubelets T, $\texttt{A}_\texttt{T}$ with each word as $\texttt{A}_\texttt{T}(f_T, f_{w_m}) = \sum_{k=1}^{K} \texttt{softmax}(f_{\tilde{T_k}}, f_{w_m})\texttt{MLP}_\texttt{v}(f_{\tilde{T_k}})$, where $\texttt{softmax}$ is defined in Eq. 1.

$$\texttt{softmax}(f_{T_k}, f_{w_m}) = \frac{exp(\texttt{SIM}(f_{w_m}, f_{\tilde{T_k}}))}{\sum_{k'=1}^{K} exp(\texttt{SIM}(f_{w_m}, f_{\tilde{T_k'}}))} \tag{1}$$

$\texttt{MLP}_\texttt{v}$ is MLP layers to project value features and $\texttt{softmax}(f_{T_k}, f_{w_m})$ indicates normalized attention scores. Word features are used as query since the context in the caption is present in the scene, but the reverse may not be true. Lastly, to optimize the learning for spatial module, we apply multimodal InfoNCE loss shown in Eq. 2 to induce discriminative learning in the projection layers to pull regions with higher attention closer and push away negative tubelets farther. To get the compatibility function for loss, we update the $\texttt{A}_\texttt{T}$ as $\texttt{A}_\texttt{T} = \texttt{MLP}_\texttt{v}{}^T(f_{w_m})\texttt{A}_\texttt{T}$. We pick negative tubelets ($f_T^{'}$) within the batch.

$$\mathcal{L}_s = -\sum_{m=1}^{N} \left(\log \frac{exp(\texttt{A}_\texttt{T}(f_{T_k}, f_{w_m}))}{\sum_{k'=1,(k'\neq k)}^{K} exp(\texttt{A}_\texttt{T}(f_{T_{k'}}, f_{w_m})))} \right) \tag{2}$$

Temporal Grounding Module provides temporal boundary for activity mentioned in query. The limitation of the spatial grounding module is its inability to provide start and end timestamps for actions, which reduces its adaptability for the WSTVG task. We incorporate a reconstruction-based approach based on its effectiveness for temporal grounding(Lin et al., 2020; Yang et al., 2023; Zheng et al., 2022a;b). The main idea is to enforce semantic consistency between video and query. Firstly, original query highlights key segments in video. Then, original query is masked and use the highlighted visual segments features to regenerate masked query features. This enforces the video features semantically correspond to query features at test time. Fig. 3 (b) shows outline for the CRG module.

Since temporal grounding requires understanding of action, and features from the object detector contain only image-level information, we therefore acquire clip-level features f_c from the video encoder model. We take cross attention (CA) between original query features (f_q) to get highlighted visual features as $f_c^{'} = \texttt{CA}(f_q, f_c)$. Key and value pairs come from the visual features and query comes from the caption. Then, the original query is passed through a masking module $\mathcal{M}$ which looks into specific part-of-speech (POS) tags of the query and mask out noun/adjectives/verb to generate the masked query, $\tilde{q}$. We use a transformer decoder (DEC) to regenerate the probability distribution of masked query as $\mathcal{P}(\tilde{q}_{w_m}|f_c^{'}, \tilde{q}_{[0:m-1]}) = \texttt{DEC}(\texttt{CA}(f_c^{'}, \tilde{q}))$, where, $\mathcal{P}$ denotes probability distribution for m^{th} word $\tilde{q_w}$. The reconstruction loss ($\mathcal{L}_t$) to train the model is the difference between regenerated and original query distribution shown in equation 3, where N denotes total number of words.

$$\mathcal{L}_t = -\sum_{m=1}^{N} log\mathcal{P}(q_w|f_c^{'}, \tilde{q}_{[0:m-1]}) \tag{3}$$

3.2.2 Contextual Referral Grounding (CRG)

Analyzing the original query Q, we observe that it contains descriptions of background objects/scene. It also contains information about attributes and actions related to those objects. In equation 2, spatial loss $\mathcal{L}_s$ applies a summation across similarity with all words. This leads to confusion for the network regarding which tubelet is actually the target tubelet (*referral subject*). CRG addresses this by leveraging referral subject's attributes to improve attention over objects sharing common information with the query. The *intuition* is that referral subject-related attributes further enhance grounding capability.

We refine this information from *free-form* text query by decomposing query Q into three sub-parts: a) Referral tubelet and its attributes (Q_{oa}), b) Referral tubelet action verbs (Q_{ov}), and, c) background

information (Q_b). We generate new queries, Q_o that describes *referral* tubelet using Q_{oa} and Q_{ov}. This helps the network associate attributes and actions with correct tubelets ($\mathcal{T}_{o_k}$). Additionally, for a more fine-grained aspect, we look into noun-adjective-verb word features corresponding to referral from generated (Q_o) and original query (Q). These features contain relevant information in relation to the whole caption. Thus, we call these referral features as Q_{og}, since they contain global knowledge, and earlier query Q_o as Q_{ol} since they contain local knowledge in relation to the original query. Fig. 3 (c) illustrate the process of generation of Q_{ol} and Q_{og}. The updated spatial loss ($\tilde{\mathcal{L}}_s$) is shown in equation 4, where $f_{w\langle Q_{og}:Q_{ol}\rangle}$ denotes words from updated queries.

$$\tilde{\mathcal{L}}_s = -\sum_{m=1}^{N}\left(\log\frac{exp(\mathtt{A_T}(f_{T_k}, f_{w\langle Q_{og}:Q_{ol}\rangle_m}))}{\sum_{k'=1,(k'\neq k)}^{K} exp(\mathtt{A_T}(f_{T_{k'}}, f_{w\langle Q_{og}:Q_{ol}\rangle_m}))}\right) \tag{4}$$

Similarly, for temporal localization module, existing works (Chen et al., 2022; Wang et al., 2021b; Lin et al., 2020) lacks referential capabilities. Thus, we update original query with these local queries such that attention is more concentrated on beginning and ending timestamps relevant to the referral subject. Eq. 5 shows updated reconstruction loss ($\tilde{\mathcal{L}}_t$).

$$\tilde{\mathcal{L}}_t = -\sum_{m=1}^{N} log\mathcal{P}(q_{w\langle Q_{og}:Q_{ol}\rangle}|f_c^{'}, \tilde{q}_{[0:i-1]\langle Q_{og}:Q_{ol}\rangle}) \tag{5}$$

3.2.3 Self-paced Scene understanding (SPS)

STVG is inherently complex, particularly when dealing with videos lacking explicit spatio-temporal labels and containing multiple subject tubelets. The primary challenge lies in maximizing correlation between query and subject features, especially when their number increases significantly. To address this, we introduce a self-paced curriculum learning (SPL) strategy (Wang et al., 2022a; Soviany et al., 2022) to enhance optimization. This approach incrementally increases task complexity, beginning with simpler scenarios and progressively introducing more difficult ones as the model improves. By gradually exposing the model to more challenging cases, SPL ensures better convergence and robustness in learning complex spatio-temporal relationships.

SPL utilizes a student-driven difficulty scheme. Firstly, we analyze the scenes where model gets confused and then devise training accordingly. Thus, we emulate SPL in two stages: *(a) Difficulty Measure:* We measure difficult based on the scene complexity. Fig. 2 (c) shows drop in attention values on correct subject as the scene gets complex. and *(b) Training scheduler:* Based on our difficulty measure, we design the training schedule of each curriculum step by setting the upper bound on number of tubelets per video. We increase this upper bound by a factor and keep including more challenging videos with each stage and finally include all videos in last stage. This facilitates both spatial and temporal grounding module in terms of coarse-to-fine understanding of scenes. In the beginning, the network has lower discriminative power so it can understand easy (coarse) scenes better, and with time we keep increasing the difficulty and the network's ability to understand complex scenes (fine) improves.

4 Experiment Details

Datasets: For our experiments, we show results on three benchmark datasets, namely VidSTG(Zhang et al., 2020), HCSTVG-v1 (Tang et al., 2020) and HCSTVG-v2 (Tang et al., 2020). VidSTG distribution comprises of 99,943 videos-sentence pairs, out of which 44,808 are declarative and 55,135 are interrogative. The total number of videos are 10,303 and it contains 80 different type of object categories. Training, validation and test contains 80,684, 8,956 and 10,303 distinct video-sentence pairs respectively and the amount of unique videos for each distribution is 5,436, 602 and 732 respectively. HCSTVG-v1 contains 4500 videos for training and 1160 videos for testing with sentence description referring to human attributes/actions. HCSTVG-v2 dataset extends version 1 to 16,544 videos. The dataset is divided into 10,131 training, 2,000 validation and 4,413 testing videos. Since test set is not available, we evaluate and show results on validation set following previous works (Yang et al., 2022; Lin et al., 2023; Gu et al., 2024).

Implementation details: We divide this into three parts: (a) Detection And Tracking: We utilize G-DINO(Liu et al., 2023) with 0.4 threshold for both phrase and box threshold. We run the detector

Table 2: Comparison with existing state-of-the-art methods on HCSTVG-v1 and v2 datasets.

Methods	HCSTVG - v1				HCSTVG - v2			
	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5
Fully-Supervised								
STGVT [TCSVT20] (Tang et al., 2020)	-	18.2	26.8	9.5	-	-	-	-
STVGBert [ICCV21] (Su et al., 2021)	-	20.4	29.4	11.3	-	-	-	-
TubeDETR [CVPR22] (Yang et al., 2022)	43.7	32.4	49.8	23.5	53.9	36.4	58.8	30.6
STCAT [NeurIPS22] (Jin et al., 2022)	49.4	35.1	57.7	30.1	-	-	-	-
CSDVL [CVPR23] (Lin et al., 2023)	-	36.9	62.2	34.8	58.1	38.7	65.5	33.8
CG-STVG [CVPR24] (Gu et al., 2024)	52.8	38.4	61.5	36.3	60.0	39.5	64.5	36.3
VGDINO [CVPR24] (Wasim et al., 2024)	-	38.3	62.5	36.1	-	39.9	67.1	34.5
Weakly-Supervised								
AWGU [ACMMM20] (Chen et al., 2020)	-	8.2	4.5	0.8	-	-	-	-
Vis-CTX [CVPR19] (Shi et al., 2019)	-	9.8	6.8	1.0	-	-	-	-
WINNER [CVPR23] (Li et al., 2023)	-	14.2	17.2	6.1	-	-	-	-
W-GDINO (Ours-Baseline)	18.0	9.0	11.6	4.6	23.3	9.9	13.3	5.6
CoSPaL (Ours)	**41.2**	**22.1**	**31.8**	**19.6**	**48.6**	**22.2**	**31.4**	**18.9**
	(+23.2)	(+7.9)	(+14.6)	(+13.5)	(+25.3)	(+12.3)	(+18.1)	(+13.3)

every 5th frame and extract features from the last decoder layer. We use BoTSORT tracker(Aharon et al., 2022) algorithm to generate tubes; (b) TPG: We sample 32 frames equally indexed to get tubelet features. We extract video clip level features using I3D (Carreira & Zisserman, 2017) model. (c) CRG and SPS: We use GPT-3.5 to extract *quantifier* and *phrases* from original caption for CRG. We show more details and examples in supplementary. For SPS, we incorporate three stages of training with upper bound on four, seven and all tubelets. The model is trained for 10 epochs with 5 iterations over the dataset through each sub-phrases. More details about hyperparameters are present in supplementary.

Inference: We infer the subject with highest attention from spatial localization module to get the tubelet $\hat{a}$. Temporal localization module predicts the start and end temporal bounds $\hat{a}_{t_s}^{t_e}$ for the predicted tubelet.

Evaluation Metrics: We show performance on metrics used by previous approaches (Yang et al., 2022; Jin et al., 2022), namely mean average spatio-temporal localization (m_vIoU) and temporal localization (tIoU). vIoU and tIoU is calculated as $\frac{1}{|S_u|}\sum_{t\in S_i}\text{IoU}(\hat{b_t}, b_t)$ and $\frac{|S_i|}{|S_u|}$ respectively, where S_i and S_u implies intersection and union between the predicted timestamp by the model and the ground truth timestamp. $\text{IoU}(\hat{b}_t, b_t)$ calculates the spatial overlap between the predicted bounding box $\hat{b}_t$ and ground truth bounding box b_t at frame t. m_vIoU is calculated by averaging over vIoU for all the videos in test set. vIoU@R indicates scores for samples whose mean vIoU is greater than R. We show for two values 0.3 and 0.5 following previous works(Yang et al., 2022; Li et al., 2023).

5 Results and Analysis

Comparison with weakly-supervised baselines: In Tables 2 and 3, we compare our approach with previous weakly-supervised approaches. On HCSTVG-v1 dataset, we beat AWGU and Vis-CTX on all metrics by a margin of 14-15% at mean vIoU score. We outperforms the recent approach, WINNER(Li et al., 2023) by a margin of 8%. Looking closely at different IoUs, we outperform previous SOTA at 0.3 by 2x and at 0.5 by 3x. Against W-GDINO, CoSPaL outperforms it by a margin of 5.4% and 12.4% on m_vIoU and tIoU respectively. VidSTG is an extremely challenging large-scale dataset. This is also evident by the gain made by fully-supervised approaches in recent years which is less than 2%. CoSPaL outperforms previous weakly approach by 4.4% on declarative and 3.3% on interrogative settings. At higher metrics 0.3 and 0.5, our approach achieves a gain of 4-6%.

Comparison with fully-supervised baselines: We also compare our approach with fully supervised approaches (Tables 2 and 3). On VidSTG dataset, the proposed approach beats a few of the fully-supervised approaches which are combination of spatial and temporal grounding (Gao et al., 2017) modules. On HCSTVG-v1 dataset, we outperforms STGVT and SVGBert on all metrics. Against recent approaches(Yang et al., 2022; Jin et al., 2022; Lin et al., 2023), our approach is within 10% for

Table 3: Comparison with existing state-of-the-art methods on VidSTG dataset.

Methods	Declarative Sentences				Interrogative Sentences			
	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5
Fully-Supervised								
Groun-R [ECCV16] (Rohrbach et al., 2015)	-	9.8	11.0	4.1	-	9.3	11.4	3.2
STPR [CVPR17] (Yamaguchi et al., 2017)	34.6	10.1	12.4	4.3	33.7	10.0	11.7	4.4
WSSTG [ACL19] (Chen et al., 2019c)	-	11.4	14.6	5.9	-	10.7	13.9	5.3
STGRN [CVPR20] (Zhang et al., 2020)	48.5	19.8	25.8	14.6	46.9	18.3	21.1	12.8
STVGBert [ICCV21] (Su et al., 2021)	-	24.0	30.9	18.4	-	22.5	26.0	16.0
TubeDETR [CVPR22] (Yang et al., 2022)	48.1	30.4	42.5	28.2	46.9	25.7	35.7	23.2
STCAT [NeurIPS22] (Jin et al., 2022)	50.8	33.1	46.2	32.6	49.7	28.2	39.2	26.6
CSDVL [CVPR23] (Lin et al., 2023)	-	33.7	47.2	32.8	-	28.5	39.9	26.2
CG-STVG [CVPR24] (Gu et al., 2024)	51.4	34.0	47.7	33.1	49.9	29.0	40.5	27.5
VGDINO [CVPR24] (Wasim et al., 2024)	52.0	34.7	48.1	34.0	50.8	29.9	41.0	27.6
Weakly-Supervised								
AWGU [ACMMM20] (Chen et al., 2020)	-	9.0	7.9	3.1	-	8.6	6.9	2.9
Vis-CTX [CVPR19] (Shi et al., 2019)	-	9.3	7.3	3.3	-	8.7	7.2	2.9
WINNER [CVPR23] (Li et al., 2023)	-	11.6	14.1	7.4	-	10.2	12.0	5.4
W-GDINO (Ours-Baseline)	28.7	10.6	13.0	7.8	29.1	9.8	12.1	6.7
CoSPaL (Ours)	**41.1**	**16.0**	**20.1**	**13.1**	**38.9**	**13.5**	**16.4**	**10.2**
	(+12.4)	(+4.4)	(+6.0)	(+5.3)	(+9.8)	(+3.3)	(+4.3)	(+3.5)

Table 4: **Ablation on TPG (upper) and SPS (lower)** on different factors and stages of training. S & T denotes spatial and temporal grounding module, TSA denotes temporal attention.

S	TSA	T	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5
✓			26.2	13.5	17.7	7.3
✓	✓		27.3	13.9	18.6	6.9
✓		✓	35.2	18.0	26.3	14.1
✓	✓	✓	37.6	19.2	28.8	15.3

Stages	m_tIoU	m_vIoU	vIoU@0.3	vIoU@0.5
I	34.1	17.7	26.0	14.4
II	36.2	18.5	27.0	14.8
III	38.2	20.1	28.5	17.6

Table 5: **Ablation study** on proposed sub-modules. We show the effectiveness of each module and their combinations. First row shows W-GDINO performance.

TPG	CRG	SPS	tIoU	m_vIoU	vIoU@0.3	vIoU@0.5
			18.0	9.0	11.6	4.6
✓			37.6	19.2	28.8	15.3
	✓		35.8	20.2	30.5	17.6
✓	✓		37.8	21.0	31.7	16.8
✓		✓	38.2	20.1	28.5	17.6
	✓	✓	38.1	21.1	30.7	18.4
✓	✓	✓	41.2	22.1	31.8	19.6
			(+23.2)	(+13.1)	(+20.2)	(+15.0)

mean tIoU and within 15% at m_vIoU on both HCSTVG-v1 and v2. Fully-supervised approaches utilizes ground truth information to optimize the network, whereas our approach does not.

5.1 Ablation Study

Effectiveness of TPG sub-modules: Firstly, we look into our base model, TPG. From Table 4, we observe that temporal grounding module plays a significant role. It boosts the standalone score of spatial grounding module on all metrics. mean tIoU and vIoU scores is boosted by a margin of 9% and 4.5% respectively. At 0.3 score boosts by a margin of 10% and almost 2x at vIoU@0.5. Temporal attention block improves score by 1% additionally on mean vIoU.

Impact of SPS stages: Table 4 demonstrates the importance of progressive learning. Increasing the difficulty with each indeed helps the network become more discriminative. We observe gains of 3% and 4% on mean vIoU and tIoU respectively.

Effectiveness of SPS and CRG: We analyze each sub-module in our proposed approach in Table 5. Firstly, our proposed TPG outperforms W-GDINO on all metrics. On the main metric, our method outperforms it by 10%. The context refinement grounding aspect standalone boosts the score by 11% on top of Weakly-GDINO and 1% on TPG module. This shows the impact that contextual referral matters and focus in on attributes related to *referral subject* helps. When TPG and CRG are combined, that is we utilize different referral phrases and noun-adjective-verb pairs, we observe further improvement in performance by 0.8%. Introducing SPS on TPG and CRG standalone, shows a gain of 0.9% on m_vIoU in both. This indicates that the network adapts well when the difficulty of the task is increased

Figure 4: **Qualitative analysis:** Green: ground truth; red:W-GDINO, and blue: CoSPaL (darker shade represents temporal detection boundaries). W-GDINO suffers from temporal localization and imbalanced attention focusing on different subjects throughout the video. CoSPaL overcomes these limitations and has better overlap with GT in both scenarios.

progressively. Using both SPS and CRG with TPG performs the best (last row). It boosts the performance on top of TPS+CRG by a margin of 1.1% on mean vIoU and 3.4% on m_tIoU. Against TPG, the addition of proposed sub-modules improves the performance by 2.9% and 3.6% on m_vIoU and m_tIoU respectively. Looking specifically at higher IoU at 0.5, SPS boost the performance by a margin of 2.3, 0.8 and 2.8 on TPG, CRG, and TPG+CRG. This shows substantial evidence that SPS helps both spatial and temporal grounding module increasing its discriminative ability with task complexity.

Impact of detector backbones: Table 6 shows CoSPaL outperforms WINNER with Faster R-CNN Anderson et al. (2018) backbone for fair comparison. Comparing across backbones, DETR outperforms Faster R-CNN by a margin of 6% at m_vIoU on HCSTVG-v1.

Table 6: Comparison against detector backbones.

Methods	Detector	m_vIoU	vIoU@0.3	vIoU@0.5
WINNER	Faster-RCNN	11.6	14.1	7.4
CoSPaL	Faster-RCNN	16.4	23.7	11.1
CoSPaL	DETR	**22.1**	**31.8**	**19.6**

Computational Efficiency: Fig. 5 shows CoSPaL is computationally efficient against all fully-supervised approaches. The main reason is the use of a frozen backbone whereas fully-supervised approaches finetune the whole backbone end-to-end. Against ours, fully-supervised training time is 2-4x with 2.5x-6.5x more GPU memory requirement. We use single gpu against 8 in CSDVL(Lin et al., 2023), 16 in TubeDETR(Yang et al., 2022) and 32 in STCAT(Jin et al., 2022) and CG-STVG(Gu et al., 2024). In terms of total memory (number of GPUs $\times$ GPU memory), our approach uses only 1-3% against fully-supervised approaches.

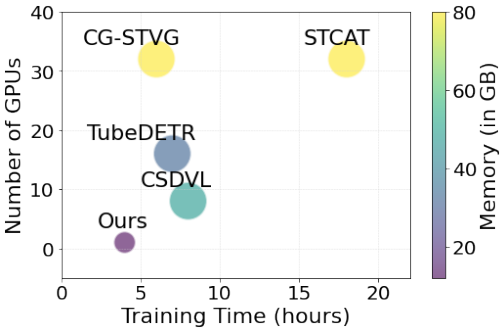

Figure 5: Comparison on computational efficiency against fully supervised approaches.

Qualitative Analysis: In Fig. 4, we show the effectiveness of our approach qualitatively. W-GDINO struggles with grounding the right actor as well as provides inaccurate temporal bounds, whereas our approach spatio-temporally grounds the actor better. More examples are shared in supplementary.

6 Conclusion

In this work we focus on Weakly Supervised spatio-temporal video grounding (WSTVG), aiming to localize specific objects based on textual queries without relying on labeled data. As a first step, we provide an extension of G-DINO for WSTVG task, and observe several challenges and limitations. To address these, we introduce *Contextual Self-Paced Learning* for Weakly Supervised Spatio-temporal Grounding *(CoSPaL)*. It employs *Tubelet Phrase Grounding (TPG)* module to enhance spatio-temporal prediction coherency in localization and introduces the *Contextual Referral Grounding (CRG)* module for extracting contextual information from textual queries, improving object localization precision. Additionally, the *Self-Paced Scene Understanding (SPS)* training scheme progressively increases task complexity, enhancing the network's robustness in challenging scenarios. We evaluate the proposed approach on three benchmark datasets, surpassing existing methods and demonstrating its effectiveness.

7 ACKNOWLEDGMENTS

This research is based upon work supported in part by the Office of the Director of National Intelligence (Intelligence Advanced Research Projects Activity) via 2022-21102100001 and the National Science Foundation under Grant No. 2239292. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of ODNI, IARPA, or the US Government. The US Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein. The authors would like to thank Aisha Urooj Khan (Lunit) and Rohit Gupta (UCF CRCV) for helpful discussions on weakly supervised grounding and multimodal aspects.

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