VideoChat-R1: Enhancing Spatio-Temporal Perception via Reinforcement Fine-Tuning

Xinhao Li[2,1*], **Ziang Yan**[3,1*], **Desen Meng**[2], **Lu Dong**[4,1], **Xiangyu Zeng**[2,1], **Yinan He**[1]
Yali Wang[6,1], **Yu Qiao**[1,6], **Yi Wang**[†1,5], **Limin Wang**[†2,1]
[1]Shanghai AI Laboratory [2]Nanjing University [3]Zhejiang University
[4]University of Science and Technology of China [5]Shanghai Innovation Institute
[6]Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences
https://github.com/OpenGVLab/VideoChat-R1

Abstract

Recent advancements in reinforcement learning have significantly advanced the reasoning capabilities of multimodal large language models (MLLMs). While approaches such as Group Relative Policy Optimization (GRPO) and rule-based reward mechanisms demonstrate promise in text and image domains, their application to video understanding remains limited. This paper presents a systematic exploration of Reinforcement Fine-Tuning (RFT) with GRPO for video MLLMs, aiming to enhance spatio-temporal perception while maintaining general capabilities. Our experiments reveal that RFT is highly data-efficient for task-specific improvements. Through multi-task RFT on spatio-temporal perception objectives with limited samples, we develop **VideoChat-R1**, a powerful video MLLM that achieves state-of-the-art performance on spatio-temporal perception tasks without sacrificing chat ability, while exhibiting emerging spatio-temporal reasoning abilities. Compared to Qwen2.5-VL-7B, VideoChat-R1 boosts performance several-fold in tasks like temporal grounding (**+31.8**) and object tracking (**+31.2**). Additionally, it significantly improves on general QA benchmarks such as VideoMME (**+0.9**), MVBench (**+1.0**), and Perception Test (**+0.9**). Our findings underscore the potential of RFT for specialized task enhancement of Video MLLMs. We hope our work offers valuable insights for future RL research in video MLLMs.

1 Introduction

Recent advancements in the application of reinforcement learning (RL) in the domain of large language models (LLMs) have demonstrated remarkable progress. As evidenced by OpenAI-O1 [13], the implementation of test-time scaling strategies has shown substantial potential in enhancing LLMs' capacity for complex reasoning. Subsequently, DeepSeek-R1-Zero [10] revealed that even without extensive supervised fine-tuning, the strategic application of a rule-based reward system for reward modeling could effectively harness reinforcement learning to unlock exceptional reasoning and cognitive capabilities in language models.

Current research endeavors have increasingly focused on replicating DeepSeek-R1's success in multimodal large language models (MLLMs). Notably, Virgo [5] attempted to impart visual reasoning capabilities through knowledge distillation from open-source reasoning models such as DeepSeek-R1 [10], QwQ [28], and QvQ [27]. However, the predominant research direction [46, 19, 41, 3, 23, 20, 38, 43, 42, 4] emphasizes direct implementation of DeepSeek-R1's core Group Relative Policy Optimization (GRPO) combined with its rule-based reward system to enable visual reasoning in

* Equal contribution. † Corresponding authors.

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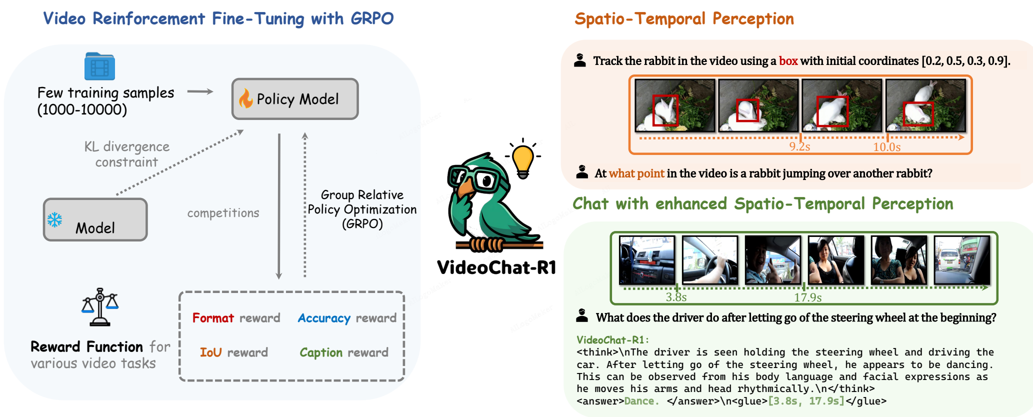


Figure 1: **Overview of VideoChat-R1.** Through reinforcement learning fine-tuning using GRPO, VideoChat-R1 has powerful spatio-temporal perception capabilities and can apply these capabilities in chatting scenarios.

MLLMs. This approach has primarily concentrated on enhancing performance in multimodal tasks involving mathematical reasoning with visual inputs and spatial localization challenges.

For video understanding, from the perspective of stimulating and evaluating reasoning abilities, there is no training and evaluation corpus as suitable as math problems and coding problems in the fields of text and images. Some works [45, 31, 6] conducted concurrently with ours have validated the superiority of the GRPO algorithm over supervised fine-tuning in some specific video tasks, such as temporal grounding and video question answer. However, deeper analysis and comprehensive ablation experiments focusing on video reasoning mechanisms remain underexplored. Current research gaps include systematic evaluations of the algorithm's generalizability across diverse video-based reasoning scenarios and granular investigations into the interplay between rule-based reward systems and multimodal temporal dependencies.

Compared with video reasoning, spatio-temporal perception is a direction in which it is easier to obtain training corpora and design a rule-based reward system. Taking the enhancement of the spatiotemporal perception ability of existing video MLLMs as the core, this paper systematically and comprehensively examines the effects of Reinforcement Fine-Tuning (RFT) on various video tasks, aiming to provide critical insights for future research. Our main findings are as follows.

- ***Reinforcement fine-tuning is data-efficient for enhancing models on specific tasks without sacrificing original capabilities***. With a small amount of data, training via RFT can yield a remarkable improvement in spatio-temporal perception ability, and there is negligible impact on the performance of out-domain tasks and the original general capabilities of the model, which outperforms traditional supervised fine-tuning significantly.
- ***Through joint reinforcement fine-tuning on multiple spatio-temporal perception tasks***, we construct **VideoChat-R1**, a powerful Video MLLM that boasts state-of-the-art spatiotemporal perception capabilities while also taking into account chat abilities. We have also discovered that training on spatio-temporal perception tasks has slightly strengthened the model's spatio-temporal reasoning abilities. Compared with Qwen2.5-VL-7B, VideoChat-R1 achieves several times the performance improvement in spatiotemporal perception tasks such as temporal grounding (**+31.8**) and object track (**+31.2**). At the same time, it also achieves significant improvements on general QA benchmarks, such as VideoMME (**+0.9**), MVBench (**+1.0**), and Perception Test (**+0.9**)

2 Related work

Reinforcement Learning Enhancement for MLLMs. Recently, works like OpenAI-o1 [13] and DeepSeek-R1 [10] have made significant breakthroughs in lifting the reasoning capabilities of large language models (LLMs) through reinforcement learning (RL). These advancements [25, 10, 26] enhance their proficiency in solving complex tasks in chains, including challenging math and coding problems. For MLLMs, many efforts [46, 19, 41, 3, 23, 20, 38, 43, 42, 4] have applied RL techniques with verifiable reward mechanisms to boost visual reasoning performance. Researches in video domain remain relatively underexplored, with only a few studies [31, 45, 6] investigating how to adapt RL-based strategies to spatiotemporal reasoning. Specifically, TimeZero [31] and R1-Omini [45] respectively demonstrate the potential of GRPO in temporal grounding and sentiment analysis. Video-R1 [6] extends GRPO to facilitate implicit temporal reasoning and achieves improvements in video spatial reasoning.

Spatio-Temporal Perception of MLLMs. Spatio-temporal perception is one of the most core capabilities of video understanding models. Despite the significant progress that Video Multimodal Large Language Models (video MLLMs) [15, 21, 16, 32, 44, 33, 18, 12, 1] have recently made in general understanding tasks such as video question answering and captioning, MLLMs' video performance still lag behind humans (event classical vision expert models) notably. Merlin [39] and TimeSuite [40] introduce spatio-temporal data augmentation for MLLM's temporal abilities, at the cost of general performance. VideoChat-TPO [36] enhances fine-grained spatio-temporal perception in videos by introducing task-specific heads using substantial training costs.

3 Methodology

We first briefly review the Group Relative Policy Optimization (GRPO) [25]. Then, we demonstrate how we design and leverage the spatio-temporal rewards for GRPO to enhance video MLLMs.

3.1 Preliminary of Group Relative Policy Optimization

Group Relative Policy Optimization (GRPO) [25] is a variant of Proximal Policy Optimization (PPO) [24] in reinforcement learning. By comparing groups of candidates responses directly, GRPO eliminates dependency on a critic model and significantly lowers training resources. Given an input question q, GRPO first generates G distinct candidate responses $o = \{o_1, \ldots, o_G\}$ through policy sampling. The MLLM serves as the reward function to get the corresponding scores $\{r_1, \ldots, r_G\}$. GRPO computes their mean and standard deviation for normalization and determines the quality of these responses:

$$A_i = \frac{r_i - \mathrm{mean}(\{r_i\}_{i=1}^{G})}{\mathrm{std}(\{r_i\}_{i=1}^{G})}, \tag{1}$$

where A_i represents the relative quality of the i-th answer. GRPO encourages the model to favor better answers with a high score within the group. The final training objective also considers preventing the optimized policy π_θ from deviating far from the original MLLM parameters π_{ref} by adding a KL-divergence term$\mathrm{D}_{\mathrm{KL}}(\cdot|\cdot)$ to :

$$\max_{\pi_\theta} \mathbb{E}_{o\sim\pi_{\theta_{\mathrm{old}}}(p)} \Big[\sum_{i=1}^{G} \frac{\pi_\theta(o_i)}{\pi_{\theta_{\mathrm{old}}}(o_i)} \cdot A_i - \beta\, \mathrm{D}_{\mathrm{KL}}\Big(\pi_\theta \,\|\, \pi_{\mathrm{ref}}\Big)\Big], \tag{2}$$

where β is a regularization coefficient, preventing excessive deviation from the reference policy during optimization.

3.2 Spatio-Temporal Rewards of Video MLLM in GRPO

We explore how to use GRPO to enhance the performance of Video MLLM in video-language understanding. We consider the five most common types of video related tasks: temporal grounding, object tracking, video question answering, captioning, and quality assessment in our experiments.

Format reward. To enable the model to output responses in the format we desire. For example, we expect the model to enclose its thought process with <think>...</think> and the answer with <answer>...</answer>, we designed a format reward R_{format} for each task. We use regular expression matching to determine whether the model adheres to our specified format:

$$R_{\mathrm{format}} = \begin{cases} 0, & \text{if output matches format,} \\ 1, & \text{if output doesn't match format.} \end{cases} \tag{3}$$

IoU reward in spatio-temporal perception. For the spatio-temporal perception such as temporal grounding and object tracking, it requires the Video MLLM to output the time interval in the video that is associated with the content of a given textual query. Evidently, we can use the Intersection over Union (IoU) between the predicted interval by the model and the ground-truth interval as the reward function. This reward function effectively characterizes the accuracy of the interval predicted by the model.

$$R_{\text{IoU}} = \frac{|\mathcal{I}_{\text{pred}} \cap \mathcal{I}_{\text{gt}}|}{|\mathcal{I}_{\text{pred}} \cup \mathcal{I}_{\text{gt}}|}, \tag{4}$$

where $\mathcal{I}_{\text{pred}}$ and $\mathcal{I}_{\text{gt}}$ are the predicted and the ground truth of time intervals or detection boxes, respectively.

Accuracy reward in classification. Discriminative tasks, such as multiple-choice video question answering and classification, aim to determine whether the model's prediction is consistent with the answer to the question. Therefore, we define:

$$R_{\text{accuacy}} = \begin{cases} 0, & \text{if } A_{\text{pred}} \neq A_{\text{gt}} \\ 1, & \text{if } A_{\text{pred}} = A_{\text{gt}}, \end{cases} \tag{5}$$

where A_{pred} and A_{gt} denote the predicted and the ground truth answers, respectively.

Recall reward in video captioning. For tasks like video captioning with open-ended outputs, it is impossible to simply compare and determine the gap between the generated caption and the ground truth caption. Therefore, we use a LLM as a "judge" to provide a reward score. In order to reduce the uncertainty of the evaluation criteria for the LLM, we first make the LLM decompose the ground truth and predicted captions into events list. Specifically, we utilize Qwen2.5-72B [37] to extract the events in the description and judge whether the events in a ground truth description can be entailed by the description predicted by the model. We calculate the event recall score as the ratio of events in a ground truth description that are entailed by the predicted description, and set different rewards according to the event recall score:

$$R_{\text{recall}} = \text{Recall}_{\text{event}}(C_{\text{pred}}, C_{\text{gt}}), \tag{6}$$

where C_{pred} and C_{gt} represent the predicted and the ground truth captions, respectively.

By combining the above reward functions, we explored how to utilize GRPO to enhance the performance of Video MLLM in various tasks. The specific details can be found in the Section 4.

3.3 Enhance Spatio-Temporal Perception of Video MLLM through GRPO

Reward fuction. We adopt different combinations of reward functions for training in different tasks. Specifically, for the temporal grounding and object tracking task, $R_{\text{st}} = R_{\text{format}} + R_{\text{IoU}}$. For the multi-choice QA and video quality assessment, $R_{\text{qa}} = R_{\text{format}} + R_{\text{accuacy}}$. For the multi-choice QA with glue (e.g. Grounding QA), $R_{\text{gqa}} = R_{\text{format}} + R_{\text{IoU}} + R_{Acc}$. For the video caption, $R_{\text{cap}} = R_{\text{format}} + R_{\text{Caption}}$.

Training data. For the temporal grounding task, we use the training set of Charade - STA [8] (5,338 samples) for training. For the object tracking task, training is conducted on the GoT - 10k [11] dataset, which has 9,335 samples. For the QA and grounding QA tasks, the validation set of NExTGQA [34] (3,358 samples) is used for training. For video captioning, FIBER-1k [35] (1,000 samples) is adopted for training. For video quality assessment, we use the quality assessment task from VidTAB [17] under the 100-shot setting, with 200 samples for training. Finally, for the training of VideoChat-R1, we perform joint training on three spatio-temporal perception-related tasks: temporal grounding, object tracking, and grounding QA. In total, 18,031 samples are used for training.

4 Experiments

Implementation details. The main experiments are all conducted based on Qwen2.5-VL-7B [1] (except for the video captioning, for which Qwen2-VL-7B [30] is used).

Benchmarks. We employ MVBench [16], Perception Test [22], VideoMME [7] for evaluation of general video understanding. Given that the majority of videos in our training set are short-length, we only use the short subset of VideoMME in testing. For the temporal grounding task, we use the test set of Charade-STA [8] for in-domain testing and the test set of ActivityNet-Grounding [14] as out-domain test data. For the object tracking task, testing is done using the GoT-10k [11] dataset. For the QA and grounding QA tasks, the test set of NExTGQA [34] is used for testing. And we use Dream-1k [29] and VidTAB-QA [17] for the video captioning and video quality access.

4.1 Evaluation of VideoChat-R1

Method	Charades-STA			ActivityNet			NExTGQA		GoT		VideoMME	MVBench	Peception Test
	mIoU	R@0.5	R@0.7	mIoU	R@0.5	R@0.7	mIoU	acc	Overlap	R@0.5	Short-Avg	Avg	Val
Baseline													
Qwen2.5-VL-7B	29.0	24.2	11.1	21.1	15.8	7.5	15.4	59.5	12.6	1.1	71.3	66.9	69.1
SFT on specific tasks													
+SFT w/ Charades-STA	46.3	45.0	25.3	20.6	16.7	7.9	-	-	-	-	N/A*	N/A*	N/A*
+SFT w/ GoT	-	-	-	-	-	-	-	-	41.8	29.5	59.2	58.6	58.5
+SFT w/ NextQQA	-	-	-	-	-	-	28.2	64.8	-	-	60.1	59.2	60.7
GRPO on various tasks													
VideoChat-R1	**60.8**	**71.7**	**50.2**	**36.6**	**33.4**	**17.7**	32.4	**70.6**	**43.8**	**38.2**	72.2	**67.9**	**70.0**
VideoChat-R1-thinking	59.9	70.6	47.2	35.5	33.3	16.7	**36.1**	69.2	43.3	33.9	**74.2**	66.2	69.6

Table 1: **Results of VideoChat-R1 on various Video Benchmarks.** * indicates that the model has suffered from overfitting and is unable to answer the question properly. Since the number of input pixels is fixed during our evaluation, the baseline results are slightly lower than those reported in their origin paper [1].

As shown in Table 1, after training with GRPO on spatio-temporal perception datasets, both VideoChat-R1 and VideoChat-R1-thinking significantly outperform the performance of Qwen2.5-VL and that of models fine-tuned through SFT for a single specific task across various spatiotemporal perception benchmarks and the general understanding benchmark VideoMME. This validates the effectiveness of our approach, which leverages multiple spatiotemporal perception datasets and RFT for enhancing spatiotemporal perception.

Meanwhile, we observe that for spatio-temporal perception tasks, engaging in thinking processes does not necessarily lead to performance gains. However, for tasks such as QA and VideoMME, which may require complex reasoning, conducting inferences during testing can result in notable performance improvements.

4.2 Ablation Studies and Discussions

Method	Epochs	Training Prompt		Test Prompt		Charades-STA (in domain)				ActivityNet (out domain)				VideoMME
		Think	Answer	Think	Answer	mIoU	R@0.3	R@0.5	R@0.7	mIoU	R@0.3	R@0.5	R@0.7	Short-Avg
Vision Experts														
FlashVTG [2]	-	-	-	-	-	-	-	70.3	49.9	-	-	-	-	-
InternVideo2-6B [32]	-	-	-	-	-	-	-	70.0	49.0	-	-	-	-	-
SG-DETR [9]						-	-	71.1	52.8	-	-	-	-	-
MLLMs														
Qwen2.5-VL-7B	-	-	-		✓	29.0	44.7	24.2	11.1	21.1	28.3	15.8	7.4	71.3
(baseline)	-	-	-	✓	✓	28.1	41.8	23.4	11.1	17.7	22.7	13.4	7.7	71.3
+ SFT	1		✓		✓	46.3	63.9	45.0	25.3	20.6	30.2	16.7	7.9	N/A*(-71.3)
	3		✓		✓	34.6(+6.5)	51.7	36.3	20.6	17.3(-3.8)	26.1	10.0	3.9	N/A*(-71.3)
+ GRPO	1		✓		✓	58.7	80.9	67.7	45.4	31.9	46.3	28.8	14.1	72.6
	1	✓	✓	✓	✓	59.3(+31.2)	81.7	70.4	46.0	30.7(+13.0)	45.0	27.5	12.9	73.6(+2.3)
	3	✓	✓	✓	✓	61.3(+33.2)	83.1	72.8	51.5	34.3(+16.6)	50.4	32.2	16.2	70.9(-0.4)

Table 2: **Results of Temporal Grounding Task.** * indicates that the model has suffered from overfitting and is unable to answer the question properly.

Method	GoT			VideoMME
	Average overlap	R@0.5	R@0.7	Short-Avg
Qwen2.5-VL-7B	12.6	1.1	0	71.3
+SFT	41.8	29.5	3.9	59.2
+GRPO	42.5(+29.2)	30.6(+29.5)	3.9(+3.9)	71.4(+0.1)

Table 3: **Results of Object Tracking.** We use 8 frames as input for training and evaluation.

Temporal Grounding and Object tracking. As shown in Table 2 and Table 3, fine-tuning Qwen2.5-VL using GRPO significantly improves the performance of temporal grounding and object tracking tasks. Additionally, it slightly enhances the performance on the general understanding benchmark VideoMME. Even when training for more epochs, GRPO is less prone to overfitting compared to SFT. Instead, it can continuously improve the performance of temporal grounding, eventually surpassing the performance of previous expert models. Moreover, stimulating the model's thinking ability provides some benefits for both temporal grounding and VideoMME tasks.

Video Question Answer. As shown in Table 4, for the video question answering task, we selected the multi-choice QA task, which is easy to evaluate, for our experiments. Additionally, we explored the grounding QA task. In this task, when answering questions, the model is required to simultaneously provide the temporal cues on which its answers are based. Using merely a little over three thousand training data samples, we found that GRPO demonstrated remarkable fine-tuning capabilities. Not only did it lead to a substantial improvement in the performance of the NExTGQA task, but it also brought about a noticeable enhancement in the VideoMME task. We noticed that, unlike the previous strongly spatiotemporal perception tasks such as temporal grounding, thinking played a significant role in the QA task. Meanwhile, the glue signals also provided some assistance for relatively complex video understanding tasks like VideoMME.

Method	Training Prompt			Test Prompt			NExTGQA		VideoMME
	Think	Answer	Glue	Think	Answer	Glue	mIoU	acc	Short-Avg
Direct Output									
Qwen2.5-VL-7B					✓		-	41.7	71.3
(baseline)					✓	✓	15.4	59.5	-
+ SFT		✓			✓		-	65.1	60.2
		✓	✓		✓	✓	28.2(+12.8)	64.8(+5.3)	60.1(-11.2)
+ GRPO		✓			✓		-	70.1	71.7
		✓			✓	✓	16.2	70.2	71.7
		✓	✓		✓	✓	35.1(+19.7)	68.7(+9.2)	72.0(+0.7)
Chain-of-thought Output									
Qwen2.5-VL-7B				✓	✓		-	47.7	73.0
				✓	✓	✓	20.2	53.3	72.2
+ GRPO	✓	✓		✓	✓		-	68.8	74.7
	✓	✓	✓	✓	✓	✓	32.9(+12.7)	66.9(+13.6)	75.3(+3.1)

Table 4: **Results of Multi-Choice Video QA.**

Video Caption and Video Quality Assessment. For the Video Caption and Video Quality Assessment tasks, we found that GRPO still demonstrated its advantages over SFT. Surprisingly, although the reward we designed for the Caption task was not entirely rigorous and reasonable, it still enabled the model to achieve significant improvements in metrics on the Dream-1k benchmark.

Method	Dream-1k			VidTAB-QA
	F1	Precision	Recall	Accuracy
Baseline	30.6	33.8	27.9	70.7
+ SFT	31.4	32.6	30.2	71.7
+ GRPO	38.2(+7.6)	45.4(+11.6)	33.1(+5.2)	72.6(+1.9)

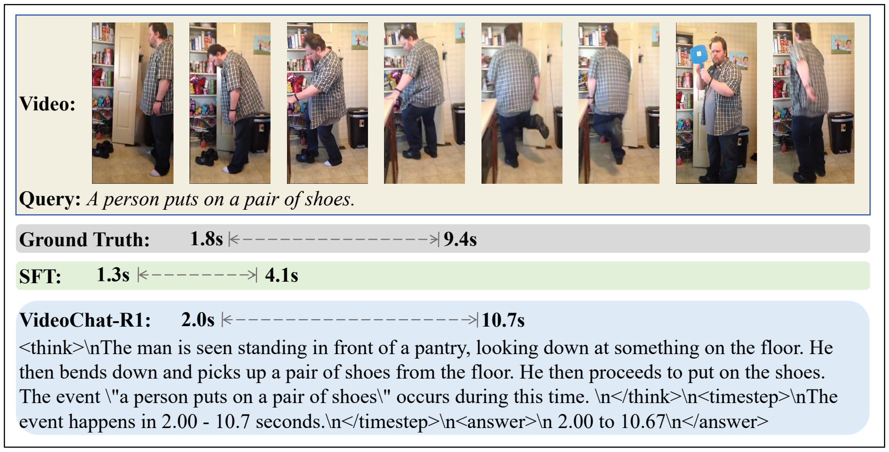
Table 5: **Results of Video Caption and Video Quality Access.**

Muti-task Co-training. As shown in Table 6, we found that mixed training of different spatiotemporal perception tasks using GRPO can yield a synergistic improvement effect. Training with the multiple tasks achieves nearly the best results across all benchmarks. This reveals the potential of GRPO for larger-scale and multi-task collaborative training in the future.

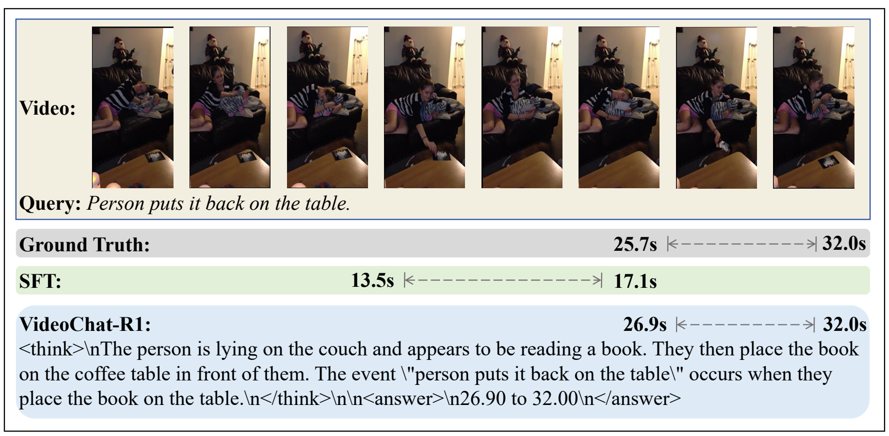
GRPO vs. SFT. It can be observed that across various types of tasks, GRPO outperforms SFT. Whether it is in terms of the performance on in-domain tasks, out-domain tasks, or the preservation

Method	Charades-STA			ANet			NExTGQA		GoT		VideoMME
	mIoU	R@0.5	R@0.7	mIoU	R@0.5	R@0.7	mIoU	acc	Overlap	R@0.5	Short-Avg
Qwen2.5-VL-7B	29.0	24.2	11.1	21.1	15.8	7.5	15.4	59.5	12.6	1.1	71.3
+GRPO w/ STA	59.3	70.4	46.0	30.7	27.5	12.9	31.4	61.2	27.8	12.9	**72.6**
+GRPO w/GQA	36.0	33.5	15.5	24.9	20.6	10.7	35.1	68.7	36.1	26.7	72.0
+GRPO w/ GoT	28.7	25.1	9.6	20.1	16.2	6.8	15.6	60.5	42.5	30.6	71.4
+GRPO w/ STA-GQA	59.8	69.7	47.0	33.7	31.0	16.0	**35.7**	67.7	36.5	28.9	72.2
+GRPO w/ STA-GQA-GoT	**60.8**	**71.7**	**50.2**	**36.6**	**33.4**	**17.7**	32.4	**70.6**	**43.8**	**38.2**	72.2

Table 6: **Results of Cotraining on Spatio-Temporal Tasks.**



(1)



(2)

Figure 2: **Examples on temporal grounding task.** VideoChat-R1 gives a more accurate time interval after thinking.

of the original general performance, our experimental results demonstrate that GRPO is a promising fine-tuning approach. We will leave the large-scale comparison for future research.

Chain-of-thought vs. Direct Output. Based on the video tasks and experiments we have explored, which focus on spatiotemporal perception, the output of the chain of thought has not demonstrated obvious advantages. In some cases, it is even inferior to the direct output. We believe that how to define appropriate video reasoning tasks and evaluation methods remains to be explored. The existing training data is insufficient to activate the model to output truly effective video reasoning chains.

4.3 Qualitative Results

As shown in Figure 2 and 3, we provide visualizations of VideoChat-R1's outputs for the temporal grounding and video QA tasks. Note that VideoChat-R1 possesses strong spatiotemporal perception.

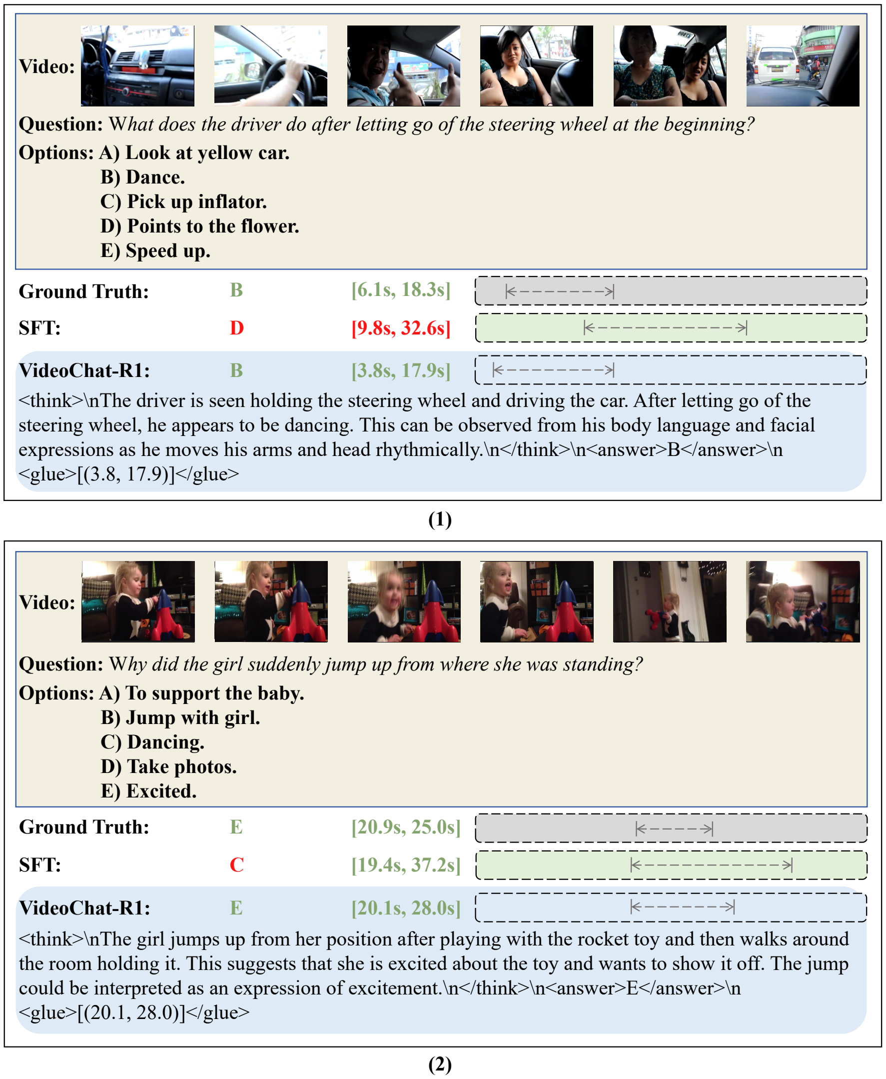


Figure 3: **Examples on Video QA task.** It can be seen that VideoChat-R1 can not only answer questions correctly but also provide relatively accurate reference time periods (glue).

Additionally, its thought process exhibits a certain degree of logic. However, due to the limitations of the tasks, compared with the thought processes for math problems in the text and image domains, the thought process of VideoChat-R1 is still rather simplistic and rudimentary.

5 Conclusions

In this work, we systematically investigate the role of reinforcement fine-tuning (RFT) with Group Relative Policy Optimization (GRPO) in enhancing video-centric multimodal large language models (MLLMs). Our experiments demonstrate that RFT is a highly data-efficient paradigm for task-specific improvements, enabling VideoChat-R1—a model trained with limited samples via multi-task RFT—to achieve state-of-the-art performance on spatio-temporal perception tasks while preserving general chat capabilities and exhibiting emergent spatiotemporal reasoning. We believe our work can present relevant insights for future research efforts in reinforcement learning of video MLLMs.

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