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# PixFoundation 2.0: Do Video Multi-Modal LLMs Use Motion in Visual Grounding?

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## Abstract

Multi-modal large language models (MLLMs) have shown impressive generalization across tasks using images and text modalities. While their extension to video has enabled tasks such as video question answering and video captioning, their pixel-level visual grounding abilities are less studied. In this work, we raise the pertinent question of whether motion is used in pixel-level visual grounding and whether video MLLMs can segment objects based on natural language expressions describing their motion patterns. We identify the shortcomings in the current benchmarks, where we show that a single frame can often suffice for capturing the motion referring expression without any temporal reasoning. To address this, we introduce four motion-centric probing techniques, particularly designed for the visual grounding task, to study video MLLMs’ ability to identify true motion from a fake one and their ability to grasp the motion order. Consequently, we provide a motion-centric benchmark, MoCentric-Bench. It ensures that video MLLMs are evaluated towards leveraging the interaction between motion and language rather than being dominated by static appearance cues emphasized in existing visual grounding datasets. We further establish strong single-image baselines that are on par with or outperform prior methods. Finally, we explore simple motion-centric adaptation techniques that provide state-of-the-art performance on our MoCentric-Bench. Our motion-centric benchmark, evaluation and findings challenge future models to improve dense spatiotemporal grounding and pixel-level understanding within videos. Code and datasets will be made publicly available at <https://github.com/MSiam/PixFoundation-2.0.git>.

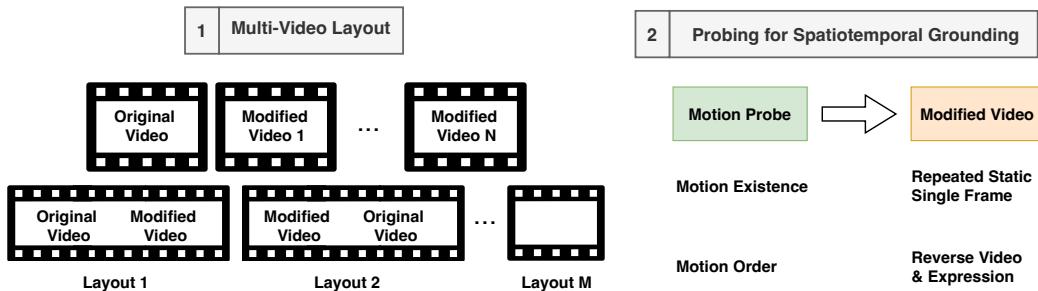
## 1 Introduction

Multi-modal large language models (MLLMs) have recently emerged as general-purpose tools that can operate on input image/video and text Liu et al. (2023); Bai et al. (2023); Wang et al. (2024); Bai et al. (2025); Liu et al. (2024); Zhu et al. (2025). They can be language guided through instructions in addition to various visual prompting techniques to produce the desired output. The extension of multi-modal large language models to operate on videos has been extensively investigated Lin et al. (2023); Maaz et al. (2023); Fu et al. (2024); Bai et al. (2025); Zohar et al. (2024); Bai et al. (2025). Nonetheless, these mainly focused on video question answering, video/region captioning or video-level grounding, i.e., determining events’ segments in seconds guided by language descriptions. However, few methods focused on *dense spatiotemporal tasks with MLLMs*, such as pixel-level visual grounding in videos that include referring video segmentation and grounded conversation generation Yan et al. (2024); Munasinghe et al. (2024); Yuan et al. (2025).

Arguably, visual grounding can be conducted on the bounding box level without resorting to the more challenging pixel-level segmentation task Bai et al. (2025); Zhu et al. (2025). Nonetheless, we believe that pixel-level tasks are a stronger direction, even if proven more challenging, because of

Table 1: **Top:** Different studies on video understanding models and benchmarks, with their respective probing techniques. Our work is the first to study dense spatiotemporal grounding, where we propose a novel probing technique that allows us to study the ability of video MLLMs to capture motion and its interaction with language, using a multi-video layout. Probing indicates a controlled change in the input to the model towards assessing certain ability or bias in a specific task. Rep: representations. OF: Optical Flow, AR: Action recognition, VS: Video segmentation without language, TL: temporal localization, STAD: spatiotemporal action detection, VidQA: video question answering, CM: caption matching, DC: direction classification. **Bottom:** Illustration of the multi-video layout probing used in our MoCentric-Bench.

Method	Year	Probing	Task
RESOUND- Li et al. (2018)	ECCV 2018	Object, Scene, People Rep. (linear probe)	AR
Scene Bias- Choi et al. (2019)	CVPR 2019	Mask Out	AR, TL, STAD
Dyn.Stat.- Kowal et al. (2022)	CVPR 2022	Shuffle, Perturb OF	AR, VS
ATP- Buch et al. (2022)	CVPR 2022	Single Frame Rep.	VidQA, Vid retrieval
Apollo- Zohar et al. (2024)	CVPR 2025	Single Frame, Text Only	VidQA
TV-Bench- Cores et al. (2024)	Arxiv 2024	Single Frame, Shuffle, Reverse, Text Only	VidQA
AOT- Xue et al. (2025)	Arxiv 2025	Reverse, Shuffle	VidQA, CM, DC.
MoCentric-Bench (ours)	2025	Single Frame, Reverse, Multi-Video Layout w/ Reverse, Multi-Video Layout w/ Single Frame	Visual Grounding



their interplay with other crucial pixel-level ones. These include depth estimation, motion estimation, tracking and prediction, all of which are closely tied to developing powerful and interpretable general-purpose embodied intelligence Szot et al. (2025). Various works emerged in studying the pixel-level visual grounding in videos Yan et al. (2024); Munasinghe et al. (2024); Yuan et al. (2025), along with the respective benchmarks pushing towards better understanding and reasoning capabilities Yan et al. (2024); Ding et al. (2023); Siam (2025). A precursor of this work, PixFoundation Siam (2025), focused on *vision-centric* benchmarking for pixel-level visual grounding and visual question answering using a paired evaluation. The goal of the study is to improve pixel-level MLLMs’ direction by providing challenging benchmarks and strong baselines. This ensures that the emerging research is in the direction of improving MLLMs’ abilities without degrading their fundamental chat capabilities.

We continue this line of work and focus on *motion-centric* benchmarking. We ask the major question: “*Do video MLLMs use motion in visual grounding?*”. Various interpretability and benchmarking efforts emerged to question the developed video understanding models’ ability to capture motion information and dynamics Kowal et al. (2022, 2024); Buch et al. (2022); Zohar et al. (2024); Xue et al. (2025). One of the earliest methods Li et al. (2018) discussed representation bias as a property of datasets and how to quantify it through comparison of state-of-the-art methods to chance-level performance. However, these methods were either confined to precursors of MLLMs without language interaction or focused on simpler tasks such as video question answering or captioning. Table 1 summarizes these methods and their proposed probing techniques to identify the limitations in video understanding models and benchmarks. We propose a novel probing that is designed specifically for visual grounding. The dense spatiotemporal segmentation task within videos makes it more interesting to study the ability of video MLLMs in capturing motion information and how it interacts

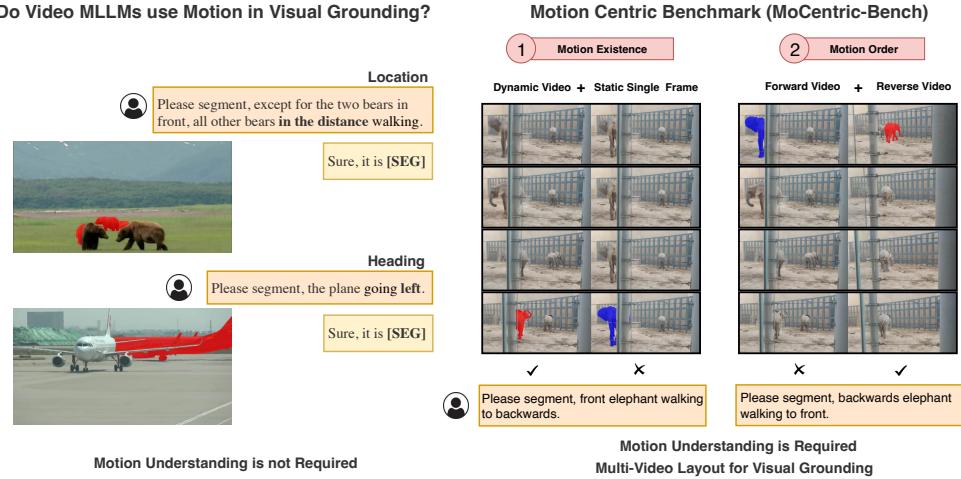


Figure 1: Our major research question: “*Do video MLLMs use motion in visual grounding?*”. **Left:** Shortcomings of the current motion referring segmentation benchmark, where the referring expression can be captured through appearance information conveyed from a single frame only without motion, e.g., using location and heading. **Right:** Our motion-centric evaluation emphasizes the use of motion information in visual grounding within videos. We propose four probing techniques specific to the visual grounding: (i) the use of a static single frame, (ii) the reverse of the video and the referred expression, (iii) multi-video layout with the original video and a static single frame side-by-side and (iv) multi-video layout with the video and its reverse. The correct and deceiving ground-truth segmentations are highlighted in red and blue, respectively.

with language. Since models can be deceived into using appearance information from one frame only, completely leaving out motion, or they can rely on multiple static keyframes across long videos rather than a proper understanding of local motion patterns or higher level dynamics within the video. As such, we provide a Motion-Centric Benchmark, MoCentric-Bench, and the accompanying baselines. We focus on two aspects: (i) identifying fake motion from a single frame vs. true motion from the dynamics in the video, and (ii) understanding the motion order and differentiating expressions describing the original motion order vs. its reverse. Our attempt highlights the problems in the current benchmarks and methods with purely empirical means. We believe our work is the initial groundwork for future research that builds motion-centric datasets within a mathematical framework that guides the data collection. Figure 1 presents the motivation of our MoCentric-Bench and shows two of the four probing techniques part of our benchmark. In summary, our contributions include: (i) We provide an empirical analysis of the shortcomings of video MLLMs benchmarks and models in identifying fake vs. true motion and understanding the motion order, within dense spatiotemporal grounding. (ii) We propose four motion-centric probing techniques for referring video segmentation that are used to synthesize datasets for both training and evaluation. (iii) We provide strong baselines using video MLLMs that outperform the state-of-the-art methods and provide supervised finetuning datasets to improve video MLLMs’ ability in understanding motion as it unfolds over time.

## 2 Related Work

**Multi-modal large language models (MLLMs) and benchmarking.** Pioneering works in multi-modal large language models such as LLaVA Liu et al. (2023/2024), Qwen-VL Bai et al. (2023) and InternVL Chen et al. (2024b) have driven significant development towards the creation of general-purpose models. Consequent works built upon these developments to equip MLLMs with better spatial and temporal understanding emerged Wang et al. (2024); Bai et al. (2025); Chen et al. (2024a); Zhu et al. (2025); Lai et al. (2024); Rasheed et al. (2024); Zhang et al. (2024a,b); Munasinghe et al. (2024); Yan et al. (2024); Zohar et al. (2024). Some of these methods can perform visual grounding in either images or videos on the bounding box level or pixel-level Lai et al. (2024); Rasheed et al. (2024); Zhang et al. (2024a,b); Munasinghe et al. (2024); Yan et al. (2024). One of the major drivers behind these developments is the evaluation benchmarks that push the limit on



Figure 2: Qualitative analysis of our proposed automatic keyframe selection from five examples that show a single frame can be sufficient to convey the motion expression without any motion involved. It is mainly conveyed through the use of static cues such as the heading, object type, or position. Expressions of each example are as follows: (a) “jump to the left then jump back”, (b) “dog playing with monkey”, (c) “puppy that overwhelms another puppy”, (d) “cow shaking head and looking at us.” (e) “The little cat walking from behind to the front”. Groundtruth segmentation highlighted in red.

these models and ensure improved performance, in addition to studies that interpret their behaviour. There is an abundance of standard benchmarks used to evaluate MLLMs Yue et al. (2024); Yu et al. (2016); Kazemzadeh et al. (2014); Fang et al. (2024); Fu et al. (2024). Concurrent work studying video MLLMs Zohar et al. (2024) has shown the bias within such evaluation benchmarks towards using a single image or textual input only instead of fully evaluating the use of temporal information. Nonetheless, the majority of previous works on video MLLMs benchmarking focused on simpler tasks, e.g., video question answering. Our work focuses on the visual grounding task with carefully designed probing techniques for the task.

**Video segmentation.** The general task of video segmentation takes as input a video clip and outputs segments within the video based on the definition for the objects of interest that can either be: (i) based on semantic categories (i.e., video semantic segmentation) Miao et al. (2021), (ii) within foreground/background segmentation framework relying on saliency or tracking (i.e., video object segmentation) Karim et al. (2023), (iii) based on language (i.e., referring video segmentation) Munasinghe et al. (2024); Yan et al. (2024); Wu et al. (2022); Ding et al. (2023). We focus on referring video segmentation that relies on a referring expression describing the object/s of interest to be segmented within an input video. One track of methods focused on emphasizing motion in referring video segmentation Ding et al. (2023). However, our work shows the shortcomings in the aforementioned benchmarks, and we show that state-of-the-art methods and our proposed baselines that surpass them fail in our motion-centric evaluation.

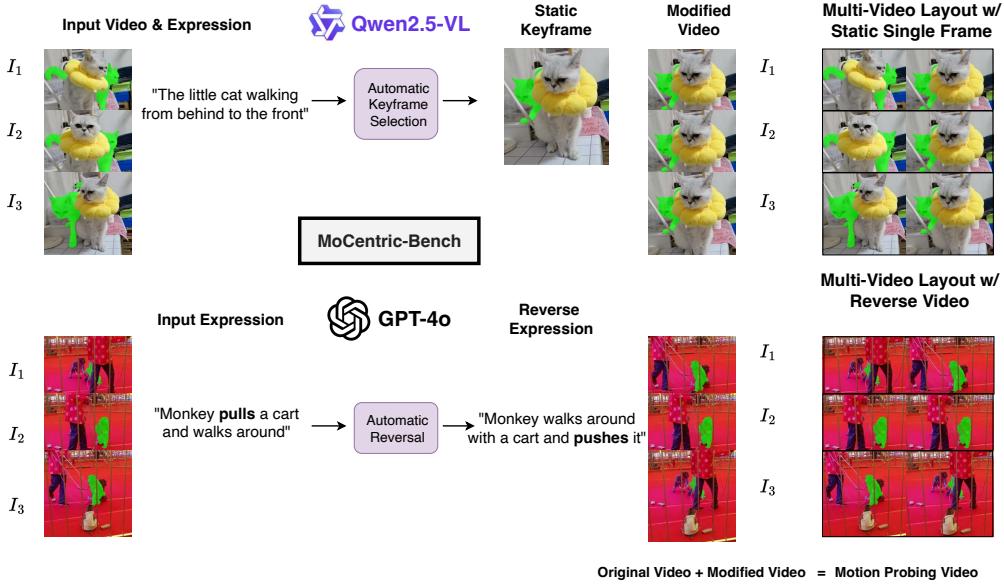
### 3 Method

In this section, we summarize the shortcomings in the current video visual grounding benchmarks and video MLLMs. Visual grounding can be manifested in various tasks, including referring segmentation and grounded conversation generation. In this work, we focus on the former to provide initial evidence on these shortcomings. Then we describe our motion-centric probing and the respective benchmark. We also propose strong baselines that do not use the full spatiotemporal information, yet they are competitive with state-of-the-art video MLLMs for visual grounding.

#### 3.1 Shortcomings in Video MLLMs and Visual Grounding Benchmarks

While there have been previous works focusing on establishing single-image baselines for video-language understanding on coarse-level tasks Buch et al. (2022), (e.g., video question answering), we are the first to explore this within dense spatiotemporal grounding tasks. We focus on referring video segmentation and emphasize both standard and motion referring expressions Ding et al. (2023). We argue that the majority of referring expressions can be identified using strong single-image baselines that do not have an understanding of temporal information. While motion referring expressions may seemingly use motion, we show that such expressions can still be identified from one static frame.

Figure 2 shows five examples that can be sufficiently identified with static information without the use of temporal information, thus showing a weakness in the current evaluation benchmarks. In Figure 2a, 2d, 2e, we show examples that can be identified from one frame, where the direction, heading or the object’s location in the referred expression can be deduced from one static frame. Moreover, in certain scenarios, stating the object category can be sufficient to ground the object without motion, e.g., Fig. 2b with only one dog in the scene. As such, we propose a motion-centric probing and



**Figure 3: MoCentric-Bench:** The mechanism for creating our motion-centric benchmark. **Top:** We rely on an automatic keyframe selection to identify the best static frame (i.e., keyframe) to convey the motion referring expression and use it to deceive video-MLLMs as fake motion. The output modified video is the repeated keyframe and can be paired with the original video in various layouts to deceive their grounding mechanisms. We show that state-of-the-art models can easily be deceived with these static keyframes. **Bottom:** We use GPT-4o to perform an automatic motion referring expression reversal to match the respective reverse of the video. The output modified video and expression can similarly be paired with the original video to deceive video-MLLMs’ grounding mechanisms in their ability to differentiate the original (forward) from the reverse of the video. Ground-truth segmentation of the fake/true referred object is highlighted in green.

evaluation to study the shortcomings in video MLLMs with respect to capturing the true motion. Our experiments confirm these limitations in prior benchmarks and methods, where our probing techniques consistently reduce performance by roughly half across various settings. Additionally, we propose quantitative means to analyze the properties existing in the referring expressions and input videos that can drive better evaluation for the use of motion beyond a single image.

### 3.2 A Motion-Centric Benchmark

**Motion-Centric Probing.** We describe two motion probes: (i) *Motion Existence*: probing video-MLLMs to inspect if they can identify true motion across the video vs. fake motion from one repeated static single frame, and (ii) *Motion Order*: probing video-MLLMs for their ability to ground the expression and differentiate it from its reverse and vice versa. Figure 3 describes the two major motion probes and how we construct their respective modified video and referring expressions. Each one results in a modified video that can either be used directly or within a multi-video layout that includes both the original and the modified one. This results in four probing techniques: (i) single frame, (ii) reverse video, (iii) multi-video layout with single frame and (iv) multi-video layout with reverse video. These can help inspect the video-MLLMs’ true ability in motion and video understanding within a visual grounding framework.

In the motion existence probe, the automatic selection of the keyframe is the crucial step to approximate the motion expression with only one static frame. Towards that, we use a multi-modal large language model that has the capability of coarse video grounding, i.e., identifying the events’ segments in seconds guided by language descriptions without spatial grounding. In our case, we use Qwen2.5-VL and prompt it to identify the expression using the following: "Given the query: <EXP>, when does the described content occur in the video? Output the first and last seconds for this action in JSON format." The output is further processed to identify the temporal window of frames with the middle frame labelled as the

keyframe capturing this motion. Figure 2 shows five example keyframes selected with their motion referring expression. We use the retrieved keyframes to create a video containing both the static keyframe in addition to the original video as shown in Figure 3 (top). In the motion order probe, the crucial step is to reverse the motion referring expression to match the reversal of the video. Towards that, we prompt GPT-4o using the following: "Taken an input motion referring expression as <EXP> corresponding to an original video, can you convert it to the motion expression describing what will occur in the reverse version of the same video? Output the new expression only." This is followed by manual inspection of the reverse motion referring expressions with their respective reverse videos to discard examples that can not be sufficiently differentiated from the original motion using the expression. Figure 3 (bottom) shows an example of the automatic reversal for the motion expression from "pulling" to "pushing". Additional examples are provided in Appendix A.

**Strong baselines and adaptation.** We establish strong single-image baselines for referring video segmentation using powerful MLLMs that can visually ground objects on the region level. Models such as Qwen2.5-VL Bai et al. (2025) and InternVL3 Zhu et al. (2025) have emerged that show strong capabilities in visually grounding objects and outputting their corresponding bounding boxes. We build two baselines that are biased to the static information conveyed from a single image. The first baseline relies on the MLLM output, followed by using SAM 2.0 Ravi et al. (2024) to generate the output segmentation for the corresponding referring expression (MLLM + SAM 2.0). We use the following prompt: "Locate the <EXP>, output its bbox coordinates using JSON format." and use the first frame in the video. In cases where the model's response can not be parsed into a bounding box, we allow the model to use the first frame from the beginning of the video that provides a bounding box response. The second baseline follows a similar procedure, but instead of using the first frame, it uses the keyframe in the input video that can have the referred expression (MLLM + SAM 2.0<sup>†</sup>). The keyframe is retrieved following the previous method in the motion-centric probing. The last baseline can not capture the full spatiotemporal information in the video. It is rather an intermediate baseline between full spatiotemporal and coarse temporal grounding. It identifies the object within the video on the coarse level, but for the pixel-level grounding, it only uses one static keyframe, followed by propagating the segmentation in the video using SAM 2.0.

We also provide a simple adaptation of the strongest concurrent work, Sa2VA Yuan et al. (2025). We hypothesize that the reason behind the models' inability to identify true vs. fake motion or the forward vs. the reverse motion is tied to a vision encoder that has a weak ability to understand the dynamics and motion in the video. It is worth noting that Sa2VA is designed to handle the first five frames of the video through the MLLM, aside from the segmentation propagation that goes through the whole video. Nonetheless, the first few frames can give an initial evidence for the vision encoder and LLM to differentiate the true from the fake motion and visually ground the motion referring expression, if it is finetuned to handle such challenging cases. Thus, we perform a motion-centric low-rank adaptation Hu et al. (2022) of the vision encoder and use our supervised finetuning data. Specifically, following our motion-centric probing, we create synthetic referring video segmentation data using our multi-video layout. Refer to Appendix A for more details.

## 4 Experimental Results

### 4.1 Experimental Setup

**Datasets and metrics.** We use established referring video segmentation datasets in our supervised finetuning, including RefDAVIS17 Pont-Tuset et al. (2017), the motion referring expression dataset MeVIS Ding et al. (2023), referring YouTubeVOS Seo et al. (2020), the reasoning VOS dataset Yan et al. (2024) and the motion-centric variants we synthesize from MeVIS. For the evaluation, we evaluate on the provided *validation* split of RefDAVIS17 that includes 30 videos, while for MeVIS, we use two splits: the *val\_u* subset, which includes 50 videos with their corresponding ground-truth available and the *val* subset that includes 140 videos that do not have their ground-truth publicly available but can be evaluated upon using MeVIS evaluation server<sup>1</sup>. Finally, we evaluate on our constructed motion-centric variants of MeVIS *val\_u*, as detailed in Sec. 3.2, which are: (i) *Single frame*, (ii) *val\_u & Single frame*, (iii) *Reverse* and (iv) *val\_u & Reverse*. The *Reverse* variants of MoCentric-Bench include 32 videos and 152 segmentation-motion expression pairs. While the *Single*

<sup>1</sup><https://codalab.liisn.upsaclay.fr/competitions/15094>

Table 2: **State-of-the-art Comparison** of our strong single-image baselines and our adapted Sa2VA with respect to the state-of-the-art methods on RefDAVIS’17 and MeVIS *val* subset. Our baselines are mostly biased to the static information, yet surpass previous methods. Backbone MLLMs include, LLaVA Liu et al. (2023), ChUniVi Jin et al. (2024), VEn.: vision encoders for CLIP and InternVideoV2 used in VideoGLAMM, Phi3: Phi3-mini Abdin et al. (2024), IVL2/2.5: InternVL2/2.5 Chen et al. (2024a), Q2.5VL: Qwen2.5-VL Bai et al. (2025). Our baselines include the use of a base MLLM to output a potential bounding box in the first frame/keyframe followed by SAM 2.0 (S2).  $\dagger$ : indicates the use of the automatic keyframe selection.  $*$ : adapted variant of Sa2VA w/ supervised LoRA tuning of the vision encoder. Best and second-best results are bolded and underlined, respectively.

Method	Venue	Backbone/Base MLLM	RefDAVIS-17			MeVIS		
			$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$	$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$
ReferFormer	CVPR 2022	VideoSwin-B	58.1	64.1	61.1	29.8	32.2	31.0
LMPM	ICCV 2023	Swin-T	-	-	-	34.2	40.2	37.2
LISA	CVPR 2024	LLaVA-7B	62.2	67.3	64.8	35.1	39.4	37.2
TrackGPT	Arxiv 2023	LLaVA-7B	63.2	59.4	67.0	37.6	42.6	40.1
VISA	ECCV 2024	ChUniVi-7B	66.3	72.5	69.4	40.7	46.3	43.5
VidGLAMM	CVPR 2025	VE+Phi3-3.8B	65.6	73.3	69.5	42.1	48.2	45.2
Sa2VA	Arxiv 2025	IVL2-8B	-	-	75.2	-	-	46.9
Sa2VA	Arxiv 2025	IVL2.5-8B	-	-	75.9	-	-	<b>51.5</b>
MLLM+S2	(ours) 2025	Q2.5VL-7B	67.4	73.5	70.5	41.3	47.7	44.5
MLLM +S2 $\dagger$	(ours) 2025	Q2.5VL-7B	<u>68.7</u>	<u>74.7</u>	71.7	<u>43.5</u>	<u>50.2</u>	46.9
Sa2VA*	(ours) 2025	IVL2.5-8B	<b>71.9</b>	<b>80.7</b>	<b>76.3</b>	<b>47.6</b>	<b>54.8</b>	<u>51.2</u>

*frame* variants have 50 videos and 793 segmentation and motion expression pairs. We use the standard evaluation metrics for the region similarity,  $\mathcal{J}$ , the contour accuracy,  $\mathcal{F}$ , and their average,  $\mathcal{J} \& \mathcal{F}$ .

**Compared methods.** We compare our strong baselines<sup>2</sup> with respect to state-of-the-art referring video segmentation methods, including the prior ones that relied on masked modelling from the RoBERTa model, such as ReferFormer Wu et al. (2022) and LMPM Ding et al. (2023). Additionally, we compare against recent ones that rely on the power of large language models with autoregressive modelling in LISA Lai et al. (2024), TrackGPT Zhu et al. (2023), VISA Yan et al. (2024), VideoGLAMM Munasinghe et al. (2024) and Sa2VA Yuan et al. (2025). For the motion-centric evaluation, we focus specifically on the best models in each category, which have their codes and weights publicly available (i.e., LMPM, VideoGLAMM and Sa2VA), in addition to our strong baselines and our motion-centric adapted Sa2VA. Note that the results for our motion-centric adapted Sa2VA is the average of two training runs.

## 4.2 Strong Baselines Evaluation

In this section, we show that our baselines already provide state-of-the-art performance, surpassing previous methods (i.e., LISA and VISA) and one of our concurrent works (i.e., Video GLAMM), while being competitive with the most recent concurrent work, Sa2VA. Table 2 shows results across two benchmarks, including the motion referring expression segmentation dataset. It clearly shows that the simple baseline, MLLM + SAM 2.0, which does not incorporate any temporal information in the identification of the referred expression, surpasses VideoGLAMM, which is one of the state-of-the-art methods, on RefDAVIS17. While our strongest baseline, MLLM + SAM 2.0 $\dagger$ , outperforms VideoGLAMM on both benchmarks and is competitive with concurrent work from Sa2VA.

This confirms that our single-image baselines, which perform the visual grounding on a single frame, establish strong results that can be safely used for our motion-centric probing and evaluation. While our baselines rely on a stronger base multi-modal large language model than some of the previous methods, they are only meant to motivate the motion-centric evaluation and identify their shortcomings on our proposed benchmark and the corresponding analysis of the referring expressions.

<sup>2</sup>The Arxiv version results have some differences from the NeurIPS submission without changes to the conclusions. This is due to an implemented fix to the string parsing from Qwen2.5-VL, a fix to the flipping that makes it more challenging for the multi-video layout setting in addition to improvements to the keyframe selection.

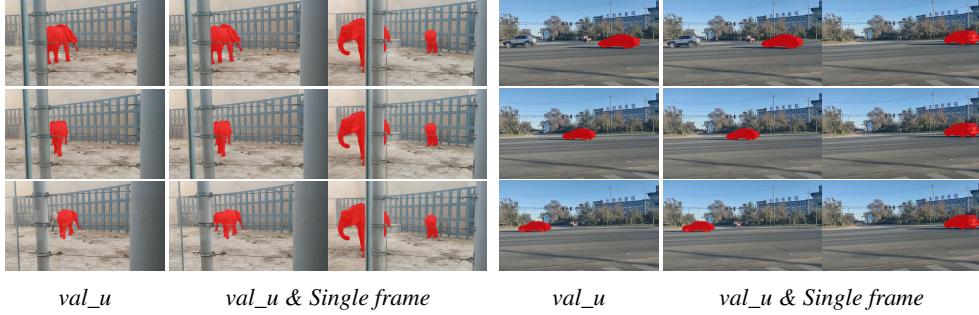


Figure 4: **Qualitative analysis** comparing the original MeVIS *val\_u* set performance vs. the motion-centric one that incorporates an additional static keyframe to the video to confuse video MLLMs, *val\_u & Single frame*. Predictions of our strongest baseline, Qwen2.5-VL + SAM 2.0 $\dagger$  are highlighted in red. Motion referring expressions for the examples are as follows: (i) first column is “elephants moving”, (ii) second column is “black one that turns and goes left”.

Table 3: **MoCentric-Bench** results based on the synthesized multi-video layout variants of MeVIS dataset *val\_u* subset, using the original videos with the respective static single keyframe that shows fake motion (i.e., *val\_u & Single frame*), the reverse of the video and expression (i.e., *Reverse*) and the multi-video layout for both the original videos and their respective reverse (i.e., *val\_u & Reverse*).  $\dagger$ : indicates the use of the automatic keyframe selection.  $\star$ : adapted variant of Sa2VA w/ supervised LoRA tuning of the vision encoder. It clearly shows a strong drop in performance for all the models, including our baselines from *val\_u* to *val\_u & Single frame*, similarly between the *Reverse* and *val\_u & Reverse*. It shows that the state-of-the-art methods and our single-image baselines can not differentiate true from fake motion and do not understand the motion order. Best results are bolded.

Method	<i>val_u</i>			<i>val_u &amp; Single frame</i>			<i>Reverse</i>			<i>val_u &amp; Reverse</i>		
	$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$	$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$	$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$	$\mathcal{J}$	$\mathcal{F}$	$\mathcal{J} \& \mathcal{F}$
LMPM	34.2	40.2	37.2	18.2	26.9	22.6	31.8	38.1	35.0	18.0	25.4	21.7
VidGLAMM	43.6	52.7	48.2	18.1	25.1	21.6	49.4	58.4	53.9	28.7	39.3	34.0
Sa2VA	-	-	58.9	23.5	33.5	28.5	55.9	66.4	61.1	31.0	42.9	37.0
MLLM+S2	47.9	56.2	52.0	21.4	31.6	26.5	44.0	53.0	48.5	21.4	30.2	25.8
MLLM+S2 $\dagger$	54.0	60.9	57.4	23.0	33.2	28.1	49.5	57.3	53.4	26.1	36.1	31.1
Sa2VA $\star$	<b>55.9</b>	<b>65.0</b>	<b>60.5</b>	<b>25.8</b>	<b>36.3</b>	<b>31.1</b>	<b>60.3</b>	<b>69.9</b>	<b>65.1</b>	<b>35.1</b>	<b>48.8</b>	<b>42.0</b>

Additionally, our adapted variant, Sa2VA $\star$ , either slightly outperforms the original Sa2VA or provides on-par performance. We demonstrate that the real benefits from our adaptation will be captured during the motion-centric evaluation, as shown in the following section.

### 4.3 MoCentric-Bench Results

In this section, we focus on the motion-centric evaluation, where we show that both the state-of-the-art methods and our strong baselines still fall short in identifying true vs. fake motion and in understanding the motion order. Table 3 shows the evaluation on the *val\_u* set of MeVIS and the corresponding motion-centric variants. Across all the methods, there is a clear degradation of around half the original performance on the standard videos (i.e., *val\_u* or *Reverse*) vs. the multi-video layout ones that are quite challenging for visual grounding (i.e., *val\_u & Single frame* or *val\_u & Reverse*). It highlights the major shortcoming in state-of-the-art visual grounding video MLLMs, where most of the methods do not have a proper understanding of motion and are mostly biased to information conveyed from a single frame. Moreover, when looking at the gap between the multi-video layout and its respective original video across both Sa2VA and our motion-centric adapted variant, Sa2VA $\star$ , we notice improvement with around 1%, where our motion-centric adaptation slightly reduces this gap. However, there is still plenty of room to improve this result through developing MLLMs that are both vision and motion centric in their core, beyond simple adaptation mechanisms. Additional results for the *Single frame* only and ablation on the frame selection are provided in Appendix B.

**Qualitative analysis.** Figure 4 shows the qualitative analysis for our strongest baseline, MLLM + SAM 2.0 $\dagger$ , which relies on identifying the keyframe and then propagating the information across the video. Even with the strongest baseline, the models tend to segment the objects based on static

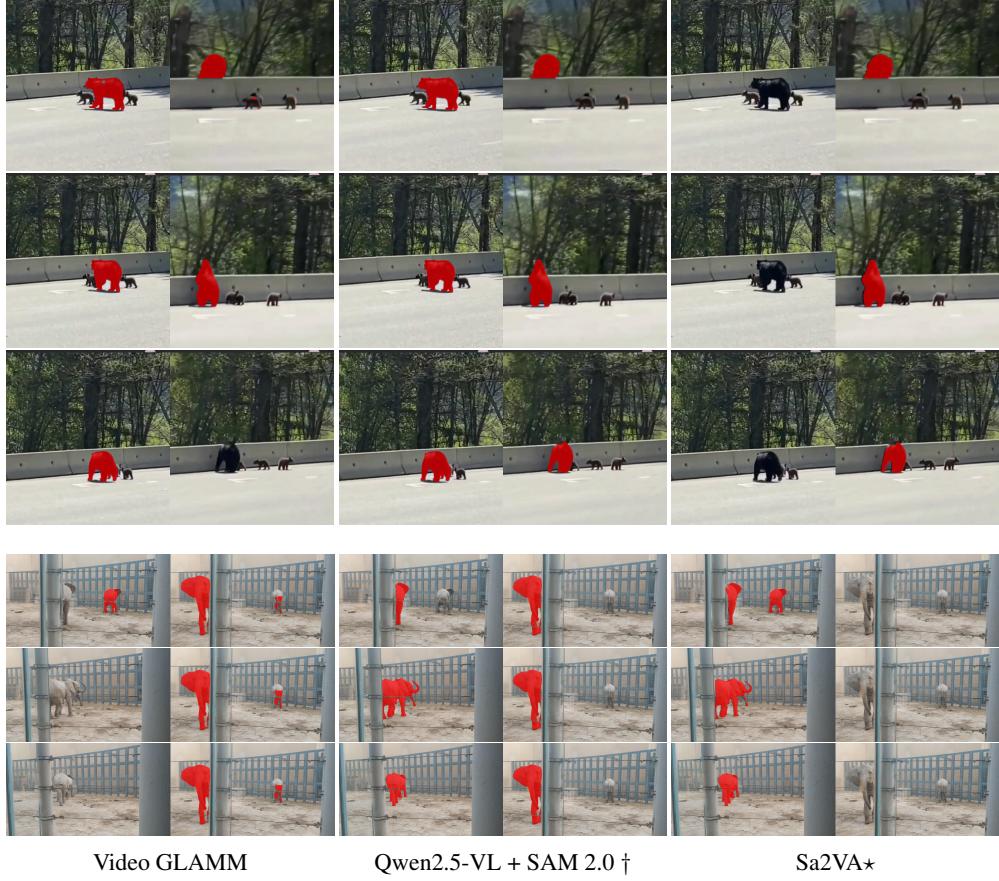


Figure 5: **Qualitative ablation on MoCentric-Bench** comparing our strongest baseline, Qwen2.5-VL + SAM 2.0 †, our adapted motion-centric model, Sa2VA\*, and concurrent work from VideoGLAMM. **Top three rows:** multi-video layout w/ *Reverse*, expression is “bear landing from a jump backward over a barricade and walking backward”. **Bottom three rows:** multi-video layout w/ *Single frame*, expression is “The elephant walking to the left”.

Table 4: Differentiating the properties of the two major groups of referring expressions based on analysing the false positives in the static frame. The first group has less than 2% false positives in the static keyframe and as such we refer to as the Dynamic group. While the second group has more than 2% false positives and is referred to as the Static group. The differences are automatically generated using GPT-4o by parsing the referring expressions from each group.

Motion Group	Static Group
<ul style="list-style-type: none"> <li>- Richer in dynamic verb phrases</li> <li>- Describes multi-step actions</li> <li>- Shows how actions unfold in context</li> <li>- Captures transitions and directional movement</li> </ul>	<ul style="list-style-type: none"> <li>- More abstract or static at times</li> <li>- Static poses</li> <li>- Less about sequences, more about simple states or high-level summaries</li> </ul>

cues in the referred expression. Hence, in the two examples provided “elephants” and “black car” were segmented regardless of their motion, where the right-hand side has the static keyframe without any motion. Furthermore, we show a qualitative ablation of our strongest baseline and our motion-centric adapted model, Sa2VA\*, compared to our concurrent work, VideoGLAMM, in Figure 5 on MoCentric-Bench (*val\_u* & *Single frame* and *val\_u* & *Reverse*). It shows two example sequences with three frames each, where our motion-centric adapted model, Sa2VA\*, has a better ability to differentiate the static frame from the dynamic video and to differentiate the forward from the reverse motion than other methods.

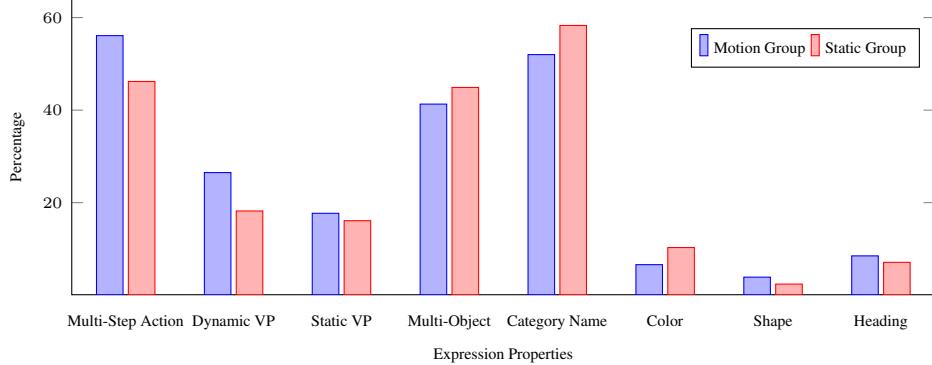


Figure 6: Fine-grained analysis on the properties of the two major groups of referring expressions which are the Motion and Static groups. VP: verb phrase.

**Analysis on the referring motion expressions.** In order to study the type of referred expression that can be misleading beyond the visual contextual information, we use our strongest baseline, Qwen2.5-VL + SAM 2.0<sup>†</sup>, and compute the false positives in the static frame within our motion-centric evaluation (i.e., *val\_u* & *Single frame*) per video and referred expression. We then split the expressions into two major groups: the ones that resulted in less than 2% false positive segmentation in the static frame, and the ones that have higher than 2%. In the total of 793 pairs of segmentation and motion expressions, we find that almost half of the expressions, at 380 out of 793, are in the second group (i.e., group with more false positives in the static frame). It shows the major concern with the original MeVIS benchmark evaluation vs. our motion-centric evaluation. Furthermore, we prompt GPT-4o with the referred expressions from the two groups and inquire “Which group captures better motion expressions?”. The answer includes a differentiation between the two groups’ characteristics as summarized in Table 4 and a correct identification that Group 1 (i.e., Motion Group), captures motion expressions better.

We take another step to study both the motion and static cues conveyed from the referred motion expressions from the identified two groups. Towards that, we use GPT-4o to identify eight main properties in each of the referring expressions through prompting it with the following: (i) “Does the following expression have a multi-step action: <EXP>?”, (ii) “Does the following expression have a multi-object interaction: <EXP>?”, (iii) “Does the following expression have a rich dynamic verb phrase: <EXP>?”, (iv) “Does the following expression include color: <EXP>?”, (v) “Does the following expression include shape: <EXP>?”, (vi) “Does the following expression describe heading or direction: <EXP>?”, (vii) “Does the following expression have a verb indicating static position: <EXP>?” and (viii) “Does the following expression have the subject as an identifiable category: <EXP>?”. We show the percentage of expressions within each group that received a response “yes” from GPT-4o for the previous properties, highlighting the differences between both the motion and static groups in Figure 6. It shows that the motion group is mainly differentiated from the static one with multi-step actions and more dynamic verb phrases. While the static verb phrases in the static group are on par with the motion ones. On the other hand, three main properties differentiate the static vs. motion group of referred expressions, which are the multi-object interactions, the use of the category name and the color. Such properties provide static cues in the referred expression that make a single image sufficient to segment the object.

## 5 Conclusion

In conclusion, we have shown the shortcomings in both the visual grounding methods and the benchmarks used in their evaluation when considering motion. We propose a novel benchmark that is motion-centric to probe the models’ ability to understand motion existence and its order. Additionally, we propose two strong single-image baselines that are competitive with the state of the art. Finally, we propose a motion-centric adaptation that outperforms the current state-of-the-art approaches. For our future work, we plan to explore building datasets based on real-world settings faced by robotics and UI control agents, while taking a mathematical approach for a motion-centric dataset collection that avoids the previously discussed shortcomings. Towards that, we plan to explore a

chain-of-thought probing akin to the linear probing in the RESOUND work, with focus on three applications: autonomous driving, robot manipulation and video GUI control.

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Table 5: Examples of the original motion expression of the forward motion and the respective reverse motion expression for the video in reverse.

Exp. #	Forward Motion Expression	Reverse Motion Expression
1	turn and walk away from us	turn and walk towards us
2	the elephant walking to the left	the elephant walking to the right
3	the moving pair of elephants.	the pair of reversing elephants
4	the individual providing food to the lizard	the individual taking food away from the lizard
5	the elephant pressing its nose against the other elephant’s back	the elephant moving its nose away from the other elephant’s back
6	the aircraft moving towards us	the aircraft moving away from us
7	Man pushing bicycle around in a circle	man pulling bicycle around in a circle in reverse
8	the two model airplanes in motion	the two model aircraft in reverse movement
9	dog walking then turn around	dog turning around then walking backward
10	the male child going to embrace the small dog	the male child moving away from the small dog after an embrace

Table 6: Additional results. **Left:** Evaluation on the *Single frame* MeVIS variant showing the mean intersection over union for the modified background class,  $\mathcal{J}_{Bg}$ . **Right:** Ablation study on the frame selection mechanism.

Method	$\mathcal{J}_{Bg}$	Method		
		$\mathcal{J}$	$val\_u$	$\mathcal{J} \& \mathcal{F}$
LMPPM	5.5			
VideoGLAMM	8.8			
MLLM + SAM 2.0	13.2	First Frame	47.9	56.2
MLLM + SAM 2.0†	13.1	Last Frame	49.2	57.5
		KeyFrame	<b>54.0</b>	<b>60.9</b>
				<b>57.4</b>

## A Additional Implementation Details

**Synthetic motion-centric datasets.** For the multi-video layout, we create three main layouts that are used across the different variants, which are: (i) *Layout 1*: (One Video) modified video, *Layout 2*: (Split Screen) - (Left) original video + (Right) modified video, (ii) *Layout 3*: (Split Screen) - (Left) modified video + (Right) original video. For both the motion existence and motion order probes, we synthesize based on MeVIS *val\_u* and *train* subsets following these three layouts. For the motion existence, the modified video is the repeated static keyframe, while for the motion order, the modified video is the reverse one. For the reverse probing we show examples of the reverse motion expressions automatically generated using GPT-4o in Table 5. We only use 32 videos and 152 segmentation and motion expression pairs, since some of the expressions in the original MeVIS dataset could not be reversed in a manner that makes it differentiated from the original expression. As such, they were removed from the evaluation to avoid ambiguities

**Training details.** For the motion-centric adaptation of Sa2VA we follow a similar procedure to Sa2VA training but instead we add the motion-centric synthetically generated MeVIS training subset with the static keyframe following layout two and three. We set the LoRA finetuning hyperparameters with rank  $r=128$  and  $\alpha = 256$ , this is conducted for the vision encoder. We use the trained Sa2VA weights as “ByteDance/Sa2VA-8B” that are provided in HuggingFace as the initialization for our model, then finetune the vision encoder with a learning rate of  $4 \times 10^{-5}$ . We use a dataset ratio of 1:1 during the sampling from both the original MeVIS training set and our motion-centric synthetic one. For the motion-centric synthetic one, we randomly sample the layout during training from the aforementioned layouts.

**Inference details.** For our two baselines, we use the following weights for Qwen2.5-VL that are available from HuggingFace “Qwen2.5-VL-7B-Instruct”. For the motion-centric probing and to avoid any spatial bias that might exist in Qwen2.5-VL, we rather prompt the models with layout two and three for the same video; one that has the static key-frame on the left side and another on the

right side. Then we use the combination of both predictions for the SAM 2.0 initialization and merge the outputs from the original and flipped variants. Throughout all the experiments, we use an A6000 GPU in the training and the evaluation of all the models discussed.

## B Additional Ablation Studies

We provide additional results for the *Single frame* videos, which only include the static keyframe repeated following our first layout. However, since the ground truth in this case is background only and there is no foreground segmentation, we rather compute the mean intersection over union for the background instead. To prevent the domination of background pixels in our metrics, we rather use the original groundtruth segmentation mask with the foreground and label these pixels as background; we call these pixels the modified background. Then we compute the mean intersection over union only for these modified background segments, and the original background pixels are rather ignored. This metric,  $\mathcal{J}_{Bg}$ , provides a better measure to evaluate the false positives appearing in that static keyframe. Table 6 (Left) shows multiple methods failing with extremely low mean intersection over union, which confirms the shortcomings in video MLLMs in understanding that this is a video of a static frame that has no motion. The major shortcoming in this MoCentric-Bench variant is that it can prefer models that simply predict all background, which can provide seemingly higher mean intersection over union than other methods that are not biased to the background class. Hence, we believe our design for the multi-video layout provides a better benchmark that is carefully designed for the visual grounding task to probe video MLLMs’ ability to differentiate fake from true motion.

Additionally, we provide an ablation study on the choice of the frame in our baselines, where we compare the selection of the first frame, which is our first baseline MLLM + SAM 2.0 vs. the last frame vs. the automatically selected keyframe, which is our second baseline MLLM + SAM 2.0 ‡. Table 6 (Right) shows that the keyframe selection is persistently better across all metrics with a considerable margin. Hence, we keep the keyframe selection as our strongest baseline.

## C Impact Statement

Video multi-modal large language models are widely used in various applications, such as robotics, medical image processing and remote sensing. The pixel-level understanding within such MLLMs is necessary for such applications that require the localization and even in certain scenarios, the delineation of the boundaries for the objects of interest. It is even more important to maintain a good spatiotemporal understanding to capture motion and dynamics in the input video. In our work, we have investigated the shortcomings of video MLLMs in the video referring segmentation task, while providing a more challenging motion-centric benchmark to push these models into a better understanding of motion.

However, as with many other AI advancements, some risks could be entailed from the deployment of such models. There could be inherent biases emerging in such video MLLMs, impacting various underrepresented groups. We think that our benchmarking efforts, probing and providing a tool to understand the pitfalls in the understanding and reasoning of these models could be an initial direction for mitigating unintended biases. Nonetheless, we leave it for future work to explore this further.