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MotionBench: Benchmarking and Improving Fine-grained Video Motion Understanding for Vision Language Models

Wenyi Hong[1*] Yean Cheng[2*] Zhuoyi Yang[1*] Weihan Wang[2] Lefan Wang[2]
Xiaotao Gu[2] Shiyu Huang[2] Yuxiao Dong[1†] Jie Tang[1†]
[1]Tsinghua University [2]Zhipu AI
wenyi.hong@outlook.com, cya17@tsinghua.org.cn,
zhuoyiyang2000@gmail.com, jietang@tsinghua.edu.cn

Abstract

In recent years, vision language models (VLMs) have made significant advancements in video understanding. However, a crucial capability — fine-grained motion comprehension — remains under-explored in current benchmarks. To address this gap, we propose MotionBench, a comprehensive evaluation benchmark designed to assess the fine-grained motion comprehension of video understanding models. MotionBench evaluates models' motion-level perception through six primary categories of motion-oriented question types and includes data collected from diverse sources, ensuring a broad representation of real-world video content. Experimental results reveal that existing VLMs perform poorly in understanding fine-grained motions. To enhance VLM's ability to perceive fine-grained motion within a limited sequence length of LLM, we conduct extensive experiments reviewing VLM architectures optimized for video feature compression and propose a novel and efficient Through-Encoder (TE) Fusion method. Experiments show that higher frame rate inputs and TE Fusion yield improvements in motion understanding, yet there is still substantial room for enhancement. Our benchmark aims to guide and motivate the development of more capable video understanding models, emphasizing the importance of fine-grained motion comprehension. Project page: https://motion-bench.github.io.

1. Introduction

With the rapid development of pre-training, an increasing number of studies focus on leveraging large vision language models (VLMs) for video understanding [15, 19, 27, 29, 34]. For instance, CogVLM2-Video [15], LLaVA-Video [51] and PLLaVA [44] continually train image-understanding models to achieve video-understanding models, and Qwen2-VL[37], LLaVA-OneVision [18] explore mixed training upon both images and videos. To effectively evaluate video understanding VLMs as well as guide further advancement, a series of video understanding benchmarks emerged, with focuses on general video understanding capability [8, 23, 24, 39] or specific capabilities such as long video understanding [39, 41, 54]. Video understanding questions can be categorized into three levels based on the

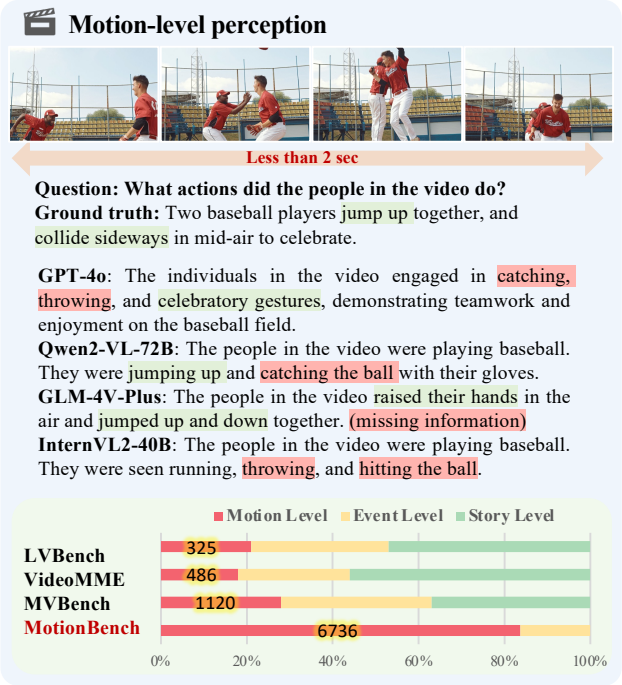


Figure 1. State-of-the-art video understanding models struggle with basic motion-level perception. Compared to existing benchmarks, our proposed MotionBench focuses on assessing the model's Motion level perception capability, which is critical in understanding videos with fast and instant interactions and motions.

*Equal contribution.
†Corresponding authors
Work was done when WH, ZY interned at Zhipu AI.

granularity of understanding: *motion-level* (capturing fine-grained motion), *event-level* (addresses distinct segments of activities [7]), and *story-level* (a holistic understanding of the storyline across the video [9]). Among them, motion-level understanding acts as a foundational ability and plays a pivotal role in applications such as anomaly detection, open-domain action analysis, detailed video captioning, *etc*. However, while some benchmarks shifted their focus toward *event-* and *story-level* understanding, most benchmarks lack a dedicated set for evaluating *motion-level* understanding. To quantitatively analyze the granularity distribution across benchmarks, we leverage GPT-4o[1] for question analysis. The results in Figure 1 indicate that the foundational motion-level comprehension is being overlooked, with the data volume and diversity for *motion-level* content being limited. Some datasets from earlier years focused on *low-level* action recognition within specific domains, but their content and categories are highly constrained.

Is this because *motion-level* understanding is too trivial to merit attention? To answer this question, we build MotionBench to thoroughly evaluate the *motion-level* capability of current video models. MotionBench comprises 8,052 questions covering six main categories of video motion, with diverse video collected from the web (Panda-70M [3], Pexels[2]), public datasets (MedVid [13], SportsSloMo [2], Ha-ViD [53]), and self-synthetic videos generated via Unity[3], capturing a broad distribution of real-world application. Surprisingly, most state-of-the-art models can only achieve accuracy lower than 60%, significantly below the threshold for practical applications, which highlights two primary technical challenges:

High Frame Rate vs. Computational Cost: The first challenge lies in the contradiction between the high frame rate required for fine-grained motion understanding and the high computational cost of long sequence lengths. Long sequence lengths substantially increase the computational and memory burden in both training and inference. Consequently, most current video understanding models can only handle a limited number of frames, falling short of the demands for fine-grained motion analysis. For example, Intern-VL2 [5], LLaVA-Next-Video [50] and CogVLM2-Video [15] can only accept 16 to 64 frames, thus can only sample frames at an extreme-low rate of 1 frame every 5 seconds (*i.e*., 0.2 fps) for a 5-minute video which is common in daily life. To address this, we **conduct the first comprehensive evaluation** over existing video feature compression architectures and identify their common shortcomings-shallow fusion. Based on these findings, **we propose a novel VLM architectural paradigm—Through-Encoder Fusion** (TE Fusion), which enhances video feature representation under a fixed decoder sequence length by applying deep fusion throughout the visual encoder. Experiments on benchmarks across various video lengths and contents demonstrate that TE Fusion achieves state-of-the-art performance, and shows particular advantages under high compression ratios.

Limited Fine-Grained Motion Understanding: The second challenge arises from the limited foundational capability to comprehend fine-grained motion in current video understanding models. While a higher frame rate brings some performance improvements (Tab. 4), models' *motion-level* understanding remains constrained, achieving accuracies of below 60% on MotionBench (Tab. 3). To address this, **we additionally release a dataset of 5,000 videos with manually annotated fine-grained motion descriptions**, which are annotated and double-checked together with the benchmark annotation process (refer to Fig. 4 for example). Each video includes dynamic information descriptions with annotation density reaching 12.63 words per second, providing researchers with resources for further development and training to enhance video models' *motion-level* comprehension capabilities.

Contribution. Our main contributions include:

- We introduce MotionBench, the largest *motion-level* video benchmark, featuring a wide range of video sources and question types, along with a carefully designed annotation pipeline that ensures diversity and accuracy.
- MotionBench reveals a critical deficiency in *motion-level* understanding among current video understanding models, which is largely overlooked by existing research.
- We propose TE Fusion, a novel compression architecture to enhance *motion-level* understanding under constrained LLM context length. Experimental results demonstrate that TE Fusion achieves state-of-the-art results on MotionBench and outperforms other compression methods across MotionBench, MVBench [23], LVBench [39], and VideoMME [8] in the ablation study, and shows a particular advantage in high compression ratio scenarios.

2. Related Work

2.1. Video Understanding Benchmarks

To effectively evaluate video understanding models and drive their advancement, a series of benchmarks are proposed. Traditional benchmarks like MSRVTT-QA [43] and ActivityNet-QA [48] primarily focus on basic action recognition and video question answering with short clips. While these benchmarks provide a foundation for assessing video understanding capabilities, they lack the granularity to evaluate subtle motion comprehension. Recently, more benchmarks emerged to assess video VLMs, as shown in Tab. 1. MVBench [23] emphasizes general video understanding, introducing 20 temporal-related tasks across

[1] gpt-4o-2024-08-06
[2] https://www.pexels.com
[3] https://unity.com/cn

Table 1. The comparison of existing video VLM benchmarks with MotionBench. MotionBench collects various video sources including web videos and synthetic videos, and provides a new evaluation perspective in motion level perception.

Benchmarks	#Videos	#QAs	Perception Level	Data source	Dataset Feature
MVBench [23]	4,000	4,000	general, motion<30%	existing datasets	general
TempCompass [28]	410	1,580	general, motion<20%	ShutterStock	temporal concept
VideoMME [8]	900	2,700	general, motion<20%	Youtube	general
AutoEval-Video [4]	327	327	event level	Youtube	open-ended QA
EgoSchema [31]	5,031	5031	event level	ego-centric video	ego-centric
LVBench [39]	103	1,549	event & story level	Youtube	long video
LongVideoBench [41]	3,763	6,678	event & story level	web channels	long videos
MovieChat-1K [35]	130	1,950	story level	movies	movie
Short Film Dataset [9]	1,078	4,885	story level	short films	story-level
MotionBench	5,385	8,052	motion level	web videos, movies, synthetic videos, datasets	motion perception

six domains. Video-MME [8] offers an evaluation framework featuring videos of varying durations—from 11 seconds to over an hour—while incorporating multimodal elements such as subtitles and audio. Some benchmarks focus on specific, challenging capabilities. For example, LVBench [39], LongVideoBench [41], and MLVU [54] target event- or story-level understanding across long temporal horizons. However, these benchmarks primarily focus on general video understanding, lacking a dedicated dataset or subset specifically designed for motion-level assessment. This limitation results in reduced volume and diversity in evaluating motion dynamics. Furthermore, most benchmarks rely on data from a single source, falling short of representing a comprehensive distribution of downstream applications.

To address these gaps, we propose MotionBench, a benchmark dedicated to fine-grained motion understanding. By leveraging data from seven distinct sources and encompassing six motion-oriented task categories, MotionBench offers a diverse range of video content and a specialized focus on motion-level perception, advancing the evaluation of video understanding models in this crucial area.

2.2. VLMs for video understanding

Recent advancements in Visual Language Models (VLMs) have demonstrated significant potential in video understanding, mostly extending pre-trained VLMs [25, 38] to handle video modality. Video VLMs typically comprise three core components: a visual encoder for visual feature extraction, a modality alignment module to integrate visual features into the language model's embedding space, and an LLM backbone for decoding multi-modal context. A straightforward architecture is LLaVA-Next-Video [50], CogVLM2-Video [15] and Intern-VL2 [6], where videos are treated as sequences of images, extending VLM's strong image understanding capabilities to videos. Qwen2-VL [36] further introduces 3D-RoPE to enable understanding of arbitrary-length videos. However, the high computational and memory demands of handling high-frame-rate, long-duration videos have prompted initial explorations into video compression in both pixel and feature spaces. For instance, InternVideo2 [40] and Video-LLaMA [49] adopt QFormer [20] for video feature extraction, PLLaVA [44] utilizes adaptive pooling, Kangaroo [26] employs a unified spatial-temporal patchification, and Qwen2-VL [36] fuses neighboring frames before visual encoder.

Despite these advancements, to our knowledge, no comprehensive and fair comparison exists among these compression methods and evaluating their performance as compression ratios increase. Moreover, current approaches are generally limited to shallow fusion that is confined to the compression operator itself, which restricts their performance, especially in high compression rate scenarios

3. MotionBench: Motion-Level Benchmarking

We introduce MotionBench, an evaluation benchmark designed to assess the motion-level perception capability of video VLMs. Fine-grained motion understanding is of paramount importance across a variety of daily scenarios, including human interaction, expression recognition, medical instruction, ambient object motion, sports replay, virtual reality, *etc*. Our approach begins with the collection of video clips from these diverse cases, which are then filtered and processed into the desired formats. We devise six primary categories of question types to evaluate the candidates' motion-level understanding, and we manually annotate the questions and answers within these categories, yielding the proposed MotionBench. Table 2 provides an overview of our data construction pipeline.

3.1. Data Curation

In this section, we elaborate on the video curation, filtering, and annotation process.

Video Collection. We obtain raw videos from publicly

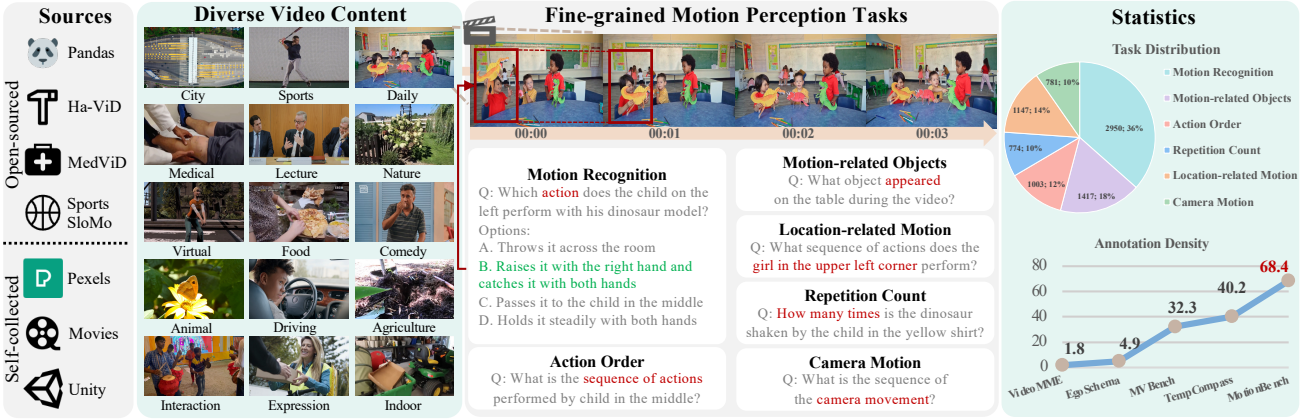


Figure 2. We propose MotionBench, a collection of manually curated multi-choice queries with video clips featuring dynamic changes from various scenes such as daily life and medical instructions. We devise six primary tasks to evaluate the capability of motion-level perception. Unlike previous story-level and event-level benchmarks, MotionBench is characterized by a significantly higher annotation density, allowing for the assessment of fine-grained motions.

Table 2. The MotionBench curation process. Categories [1-3] refer to "videos with intricate interactions", "videos from specific fields" and "virtual videos", detailed in Sec. 3.1. N. Vid/QA refers to the number of videos and queries in a category. min(H, W) is the minimum of the height and width of the video frames. *len* refers to the processed video duration. We automatically construct the queries in Virtual scenes, and manually annotate the other QA pairs in MotinBench.

Category	# Videos/QAs	Source	Collection	Post-process	Annotation
1	2,355/4,922	Pexels	Self-collected	Directly adopt	Caption & QA
		Pandas-70M [3]	Open-sourced	Segment with scene detection	Caption & QA
		Movie clips	Self-collected	Segment with scene detection	Caption & QA
2	2,430/2,530	MedVid [14]	Open-sourced	$\min(H, W) > 448$ & len$\in [3, 60]$sec	QA
		SportsSloMo [2]	Open-sourced	$\min(H, W) > 448$ & len$\in [3, 60]$sec	QA
		HA-ViD [52]	Open-sourced	$\min(H, W) > 448$ & len$\in [3, 60]$sec	QA
3	600/600	Virtual scenes	Self-collected	Remove renderings with occlusion	Automatic QA

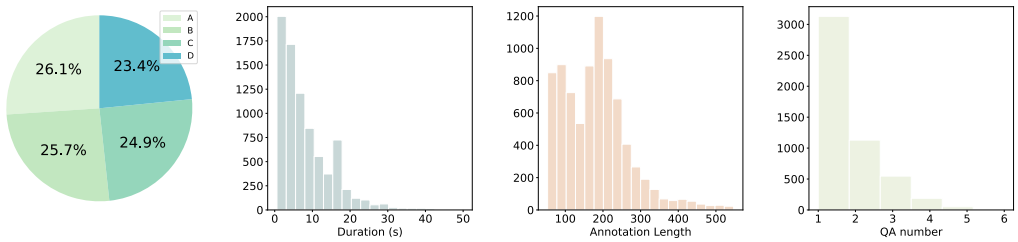
available datasets as well as from our self-collected corpus. Based on the video sources, the vividness of the scenes, and the complexity of the scenarios, we split the videos into three distinct categories. Each category is processed and annotated using tailored pipelines accordingly:

- **Videos with intricate interactions**: We acquire publicly-available videos from Panda-70M [3] and Pexels[4] and collect high-quality movie clips featuring various actions and motions, attributing to a total of 2355 videos. To ensure uniformity in clip duration, we follow the methodology in Panda-70M [3] to utilize a scene detection tool[5] to segment these videos into event-level clips.
- **Videos from specific fields**: We collect videos from MedVid [14], SportsSloMo [2] and Ha-ViD [52], representing specific use cases in medical, sports and industrial applications. These videos usually consist of one or two simple motions and demonstrate less complicated interactions. For this category, we filter out videos longer than 60 seconds or resolutions less than 448×448 pixels. An amount of 2430 videos are retrieved in this category.
- **Synthetic videos**: The above-mentioned videos are mostly from real-world scenes. For further evaluation in virtual reality applications, we render avatars with simple motions using the Unity rendering engine. Furthermore, graphic engines generate renderings that exclusively focus on motion changes, making them highly suitable for the assessment of motion perception. We randomly sample 20 motions from a publicly available website[6], and select 6 avatars and 5 scenes to render virtual avatars from a pool of 15 different viewpoints. Renderings with occlusion are manually filtered. Please refer to the supplementary for details in rendering.

Task Definition. To assess the capability in motion-level perception, we propose six categories of questions. Examples and the distribution of each category are illustrated in Fig. 2. A detailed description of each category is listed:

- **Motion Recognition (MR)**: Questions focus on what kind of motion emerged in the given video clips.

[4]https://www.pexels.com
[5]https://github.com/Breakthrough/PySceneDetect
[6]https://www.mixamo.com



(a) Option distribution (b) Video duration (c) Annotation length (d) QA per video

Figure 3. Basic statistics of MotionBench.

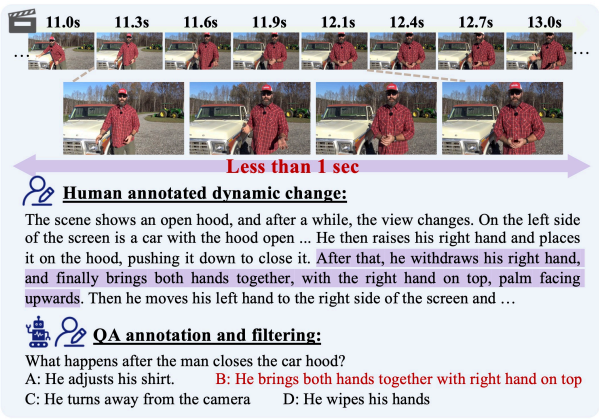


Figure 4. Example of dynamic information annotation

- **Location-related Motion (LM)**: Questions assessing the relative location changes before and after the motion takes place, and queries regarding a specific location.
- **Action Order (AO)**: Complex actions are composed of a sequence of motions. Questions in this category focus on the order of these motions.
- **Repetition Count (RC)**: Certain subtle motions occur rapidly but are repeated multiple times, such as nodding or jumping. This category of questions evaluates the model's ability to recognize and interpret such motions.
- **Motion-related Objects (MO)**: Queries designed to evaluate the model's ability to identify small objects involved in motion interactions.
- **Camera Motion (CM)**: Questions focus on the camera motion changes and trajectory, including the order and combinations of different motion types.

Question Answer Annotation. We employ different annotation pipelines for the above-mentioned video categories. For videos with intricate interactions, it is impractical to directly annotate the whole video clip, since the total complexity and quantity of the motions are too large. Therefore, we first manually annotate these videos with captions that focus on the dynamic changes within the video. Subsequently, we prompt GPT-4o [33] to generate 6 question-answer pairs for each video clip. For the prompt template and more details, please refer to the supplementary material. We find that the generated QA pairs are not only diverse in type but also presented in various sentence structures. We show an example of the dynamic information annotation pipeline in Fig. 4.

In addition, we also drop all the questions that can be answered solely based on common knowledge and a single frame. We use various **image** VLMs to predict answers using the first frame as input and discard questions that are answered correctly by all VLMs. Then, we manually filter out any questions with incorrect phrasing or ambiguous answers and categorize them. Finally, 4922 queries and answers are retained.

For videos from specific fields, we directly annotate the questions within the designed task types. A total of 2530 QA pairs are selected. For virtual videos, where we already possess the ground truth annotations for each query, we automatically construct the questions and corresponding options. Finally, 600 QA pairs are generated.

Evaluation protocal. we use regular expression matching to identify the first uppercase letter in the response as the prediction. We append "Only reply with the best option." to the end of each question for instruction following.

3.2. Dataset Statistics

MotionBench consists of 5385 videos and 8052 QAs, and each QA pair consists of a question, four options, an answer, and a category. The task distribution is displayed in Fig. 2.

Annotation Density. MotionBench is designed especially for evaluating the video VLM's motion-level perception capability. Such evaluation requires a larger annotation density per second. We define "Annotation Density" to represent such attribute, defined as follows:

$$\text{Annotation Density} = \frac{\text{Total length of questions}}{\text{Video duration}} \quad (1)$$

The results are demonstrated in Fig. 2. MotionBench features an Annotation Density of 68.4, which is two times more than existing benchmarks.

Basic Statistics. In Fig. 3, we illustrate the distribution of options, number of QAs per video, duration, and annotation

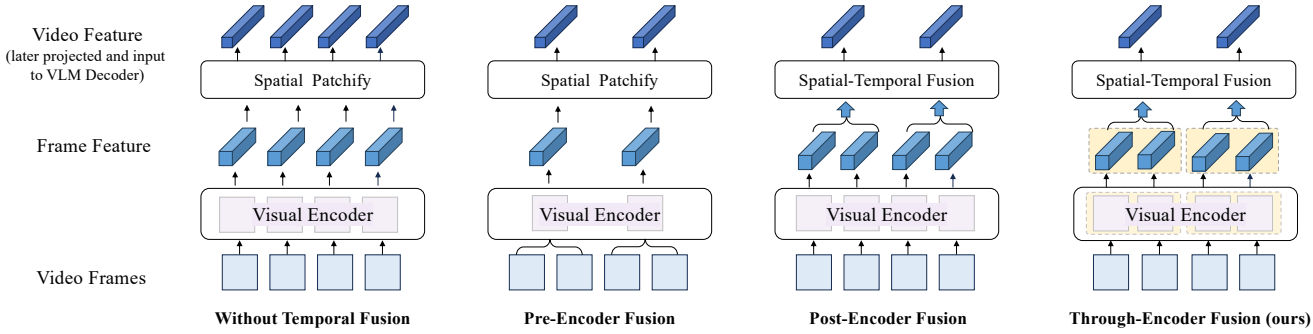


Figure 5. Summarization of prevalent paradigms for video compression and our proposed Through-Encoder Fusion (TE Fusion). Here we only illustrate the part before the VLM decoder where temporal compression performs.

length in the MotionBench. Regarding the distribution of answer options in MotionBench, it can be observed that the various options generally adhere to a random distribution. Due to our manual removal of erroneous and overly simplistic questions, it can be seen that the QA pairs in "Videos with intricate interactions" have been thoroughly filtered, resulting in the elimination of nearly half of the QA data. The video lengths in MotionBench are primarily concentrated around under 10 seconds, as motion events usually occur in very brief segments of the videos.

4. Model Design: Motion-Level Perception

Motion-level video perception demands high-frame-rate input, while the maximum input frame rate is significantly constrained by the sequence length limitations of VLMs, which are bounded by both infrastructure and computational budgets during training and inference. Therefore, it's necessary to design an efficient video understanding model structure with dense video representation. Recent studies, particularly in the domain of long video understanding, introduce various types of video feature compression methods [26, 37, 40, 44], but lack comprehensive and fair comparisons across all methods. Therefore, We comprehensively investigate commonly used architectures for video compression and categorize prevalent paradigms in Fig. 5.

- **Without Temporal Fusion**: A baseline widely used in [15, 50]. Each frame is independently processed by the visual encoder and projected into the decoder space.
- **Pre-Encoder Fusion**: This architecture conducts temporal fusion among neighboring k frames before the visual encoder, usually in pixel space. The temporal fusion operator varies across implementations. Typical examples include Qwen2-VL [37] where two adjacent frames are concatenated along the channel dimension for joint processing, and Kim et al. [17] which merges several nearby frames into a single image.
- **Post-Encoder Fusion**: In this architecture, each frame first *independently* goes through the visual encoder to generate frame-specific features, then performs feature fusion among neighboring frames with spatial-temporal fusion modules. Note that no temporal relationships are captured during visual encoding. This paradigm is the most widely adopted in video architecture with compression, with multiple variations in temporal fusion operators such as adaptive pooling [44], QFormer [20] [40], and unified spatial-temporal patchification [26].

All compression architectures rely on the assumption that redundancy exists between frames which contributes little to the video's comprehension and can therefore be removed. Achieving a higher compression ratio requires a more precise and thorough capture of this redundant information. However, current video temporal compression methods have a common limitation: the inter-frame relationships are considered only within the small compression operator, and each frame is treated independently before the operator. Consequently, it is difficult for this kind of shallow fusion to effectively capture higher-level redundancies. For instance, in a video of a running person, the individual's position, posture, and even the camera angle vary continuously. Only by applying sophisticated inter-frame fusion techniques can the model unify their representation throughout the video and capture this higher-level redundancy. Based on this observation, we propose a novel Through-Encoder Fusion paradigm that introduces deeper fusion across neighboring frames:

- **Through-Encoder Fusion (TE Fusion)**: During the visual encoding stage, adjacent frames are grouped in sets of k and apply group-level self-attention. This design gives the capacity to compute temporal dependencies through the whole visual encoder and conduct deep fusion. Following this, spatial-temporal compression is performed on each group of k frames.

Note that Through-Encoder Fusion represents a class of temporal compression methods that perform deep frame fusion before applying the compression operator. In this work, we experiment with the straightforward approach, leaving other variations for future exploration.

Table 3. Evaluation results of the existing video VLMs. Abbreviations: MR (Motion Recognition), LM (Location-related Motion), CM (Camera Motion), MO (Motion-related Objects), AO (Action Order), RC (Repetition Count). We randomly split MotionBench into "dev" and "test". We will release the ground truth answers in the "dev" set and set up an online platform for results submission in the "test" set.

Model	LLM	# Frames	Dev AVG (4020)	Test AVG (4034)	MR	LM	CM	MO	AO	RC
Random	-	-	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
*LLM: **Text** as Input*										
GPT-4o [33]	-	-	0.33	0.33	0.31	0.34	0.36	0.37	0.42	0.23
*Video VLMs : **Text + Multiple Frames** as Input*										
Gemini 1.5 Pro [34]	-	1fps	0.51	0.50	0.51	0.52	0.54	0.67	0.40	0.22
Qwen2VL-2B [36]	Qwen2 [37]	1fps	0.48	0.47	0.49	0.49	0.42	0.62	0.32	0.28
Qwen2VL-7B [36]	Qwen2 [37]	1fps	0.52	0.52	0.52	0.55	0.49	0.68	0.39	0.32
Qwen2VL-72B [36]	Qwen2 [37]	1fps	0.57	**0.58**	0.58	**0.61**	**0.63**	0.72	**0.47**	0.31
InternVL-40B [6]	NH-2-Yi-34B [32]	8	0.55	0.54	0.54	0.58	0.49	**0.76**	0.41	0.30
PLLaVA-34B [44]	Yi-34B [32]	16	0.52	0.51	0.55	0.51	0.47	0.66	0.38	0.31
CogVLM2-Video [15]	LLaMA3-8B [1]	24	0.41	0.44	0.43	0.39	0.38	0.64	0.37	0.33
GLM-4V-plus [15]	GLM4 [10]	30	0.54	0.55	0.57	0.57	0.54	0.69	0.40	0.37
LLaVA-NeXT [50]	Yi-34B [32]	32	0.48	0.40	0.53	0.45	0.36	0.66	0.39	0.23
MiniCPM-V2.6 [46]	Qwen2 [37]	64	0.52	0.53	0.56	0.49	0.45	0.72	0.39	0.33
Oryx-34B [29]	Yi-34B [32]	64	0.49	0.49	0.48	0.52	0.44	0.65	0.42	0.32
TE Fusion (ours)	GLM4-9B [10]	16	**0.58**	**0.58**	**0.64**	0.59	0.51	0.69	0.41	**0.39**

5. Experiments

5.1. Evaluation on MotionBench

We comprehensively evaluate the performance of existing video VLMs' capability in motion-level perception on MotionBench. We include multiple models with various model sizes and VLMs. The results are listed in Table 3. TE Fusion represents our proposed model, which uses TE Fusion on GLM-4V-9B backbone, with 16 input frames and a compress ratio of 4. Among existing VLMs, Qwen2VL-72B achieves the best overall performance on the dev and test set and scores highest in 3 out of 6 categories. Surprisingly, TE Fusion achieves state-of-the-art results with a 9B LLM backbone, verifying the effectiveness of our method.

Analysis. With text input alone, GPT-4 achieves an accuracy rate of 0.3 to 0.4, surpassing the random baseline of 0.25. This result indicates that LLMs possess a prior probability for certain actions, even when based only on text (note that questions answerable purely by common knowledge are filtered out during data curation). Building on LLMs, video VLMs improve accuracy by just 0.05 to 0.2, highlighting that current video VLMs still face challenges in reliably recognizing even short, simple motions. For the Repetition Count category, all models, except GLM-4V-9B with TE Fusion and GLM-4V-plus, scored near random. This is likely because fast motions are challenging to count at low frame rates or are easily overlooked by the models. Conversely, models generally achieved high scores in the Motion-related Objects category. This could be attributed to the pretraining video data, which is often constructed from image descriptions and emphasizes the objects in the video.

We further analyze the questions that all models fail to answer. The largest proportion involves fine-grained motion, suggesting that certain actions and their associated captions may be underrepresented in the training data. When examining questions by video duration, we find that even for short videos (0-4 sec), the proportion of all-model-failed questions remains 11% to 14%, highlighting models' difficulty in distinguishing certain motions even with limited content. As video duration increases, the failure rate rises significantly, reaching 18% for videos longer than 18 seconds. Further analysis from more perspectives and case studies are provided in the appendix.

5.2. Experiments on Video Feature Compression

To comprehensively and fairly evaluate all paradigms of video compression architecture, we implement representative methods from each paradigm based on the same image foundation model, GLM-4V-9B [15]: (1) Pre-encoder fusion: Qwen2-VL [37]; (2) Post-encoder fusion: QFormer [20], PLLaVA [44], Kangaroo [26]; (3) Through-encoder fusion: our proposed implementation; (4) Baseline without temporal fusion. All models take 224×224-pixel input and are trained for 10,000 iterations with a global batch size of 768 on the same collection of open-source datasets. Note that the training data is a subset of the data used in Sec. 5.1. The details of training and architecture are further provided in the Appendix. Besides MotionBench (dev), our motion-level video benchmark, we further evaluate all models on MVBench [23], LVBench [39], and Video-MME [8] as the representation of video benchmarks of varying duration and content.

Let N_{input} represent the number of frames fed into the visual encoder, and let each frame's uncompressed length at the VLM decoder be l tokens. With a given compression ratio k, the total compressed input length for the VLM

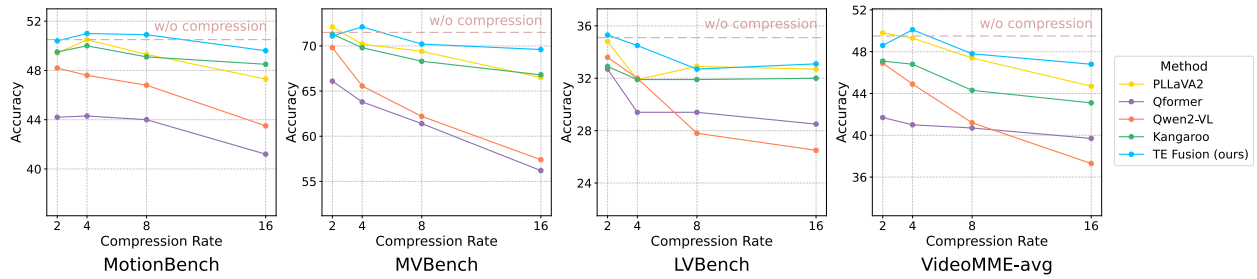


Figure 6. Model performance variation with respect to different compression ratios $k = 2, 4, 8, 16$, given a fixed VLM input frame count of $N_{\text{input}} = 16$. The pink dotted line represents the performance of the baseline model, which processes 16 frames without temporal compression. Note that each compression method is re-implemented on the GLM-4V-9B backbone to ensure a fair comparison.

Table 4. Benchmark results for different compression methods at various compression rates, all using the same sequence length in the VLM decoder. We set $\frac{N_{\text{input}}}{k} = 4$, with the baseline representing video models that process 4 frames without compression. Note that each compression method is re-implemented on the GLM-4V-9B backbone to ensure a fair comparison.

k	Method	MotionBench	MVBench	VideoMME		
				short	medium	long
1	baseline	47.6	64.5	51.4	41.0	38.3
2	QFormer	43.5	62.1	42.8	39.6	36.3
	Qwen2-VL	48.0	66.5	54.1	43.1	37.8
	PLLaVA	48.5	68.8	54.9	44.9	39.6
	Kangaroo	48.4	**69.2**	55.4	43.0	38.8
	TE Fusion (ours)	**49.1**	69.0	**55.2**	**46.3**	**40.0**
4	QFormer	44.3	63.8	45.2	41.0	36.8
	Qwen2-VL	47.6	65.6	51.8	43.4	39.4
	PLLaVA	50.5	70.2	58.9	46.4	41.3
	Kangaroo	50.0	69.8	55.3	45.6	39.5
	TE Fusion (ours)	**51.0**	**72.1**	**61.0**	**47.3**	**42.1**

decoder is $L_{\text{decoder}} = \frac{N_{\text{input}} \times l}{k}$. Our experiment centers on addressing two primary questions:

1. For a fixed sequence length at the VLM decoder (L_{decoder}), how does performance vary as the compression ratio increases?
2. For a fixed number of input frames (N_{input}), how does performance respond to changes in the compression ratio, and is there an optimal compression ratio?

For the first question, we conduct experiments with $\frac{N_{\text{input}}}{k} = 4$ and 8, varying the compression rate k at $2, 4, 6$, and 8. Results for $\frac{N_{\text{input}}}{k} = 4$ are shown in Tab. 4, with complete results included in the Appendix due to space constraints. Given the same L_{decoder}, most temporal compression methods demonstrate performance improvements across all benchmarks, with higher compression rates generally yielding better scores. Notably, PLLaVA, Kangaroo, and TE Fusion show relatively strong results, with our TE Fusion achieving the highest scores in 9 out of 10 metrics, improving upon the baseline by 11.8% on MVBench and 18.7% on VideoMME-short with $k = 4$. Qwen2-VL performs well with $k = 2$ but shows minimal improvement (or even a decline) with $k = 4$, likely due to the limited high-level compression capabilities of post-encoder fusion. QFormer, on the other hand, occasionally underperforms compared to the baseline, potentially due to the complexity of the additional module, which is challenging to optimize during the video compression training stage.

For the second question, we set the input frame count to $N_{\text{input}} = 16$ and test compression rates of $k = 2, 4, 6$, and 8 across all methods. The results, shown in Fig. 6 (with full numerical data in the appendix), reveal that while all methods experience some performance decline as the compression rate increases, our TE Fusion method exhibits almost no performance drop for $k \leq 4$. Even with a larger $k = 16$, the average performance reduction remains under 4% compared to the high-consumption baseline without compression. Additionally, the performance decline caused by temporal compression is less significant in shorter-duration videos (MotionBench, MVBench) compared to longer-duration videos (LVBench), suggesting that high-frame-rate input offers greater potential for effective, high-ratio temporal compression. Interestingly, We find that TE fusion achieves the highest score with compression-4 instead of compression-2 in 3 of 4 datasets. An explanation is that a higher compression rate increases attention length within the ViT component while decreasing it in the LLM component. This finding suggests that the computational allocation in previous video VLMs may be suboptimal and enlightens a new direction to improve model performance.

6. Conclusion

We present MotionBench, a new benchmark for assessing fine-grained motion understanding in video models. Our experiments show that current state-of-the-art models struggle with motion-level comprehension, emphasizing the need for specialized benchmarks. To tackle this, we propose the Through-Encoder (TE) Fusion method, which improves video feature representation by deeply integrating fusion within the visual encoder. TE Fusion achieves state-of-the-art results, especially under high compression, paving the way for advances in motion perception.

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