CineTechBench: A Benchmark for Cinematographic Technique Understanding and Generation

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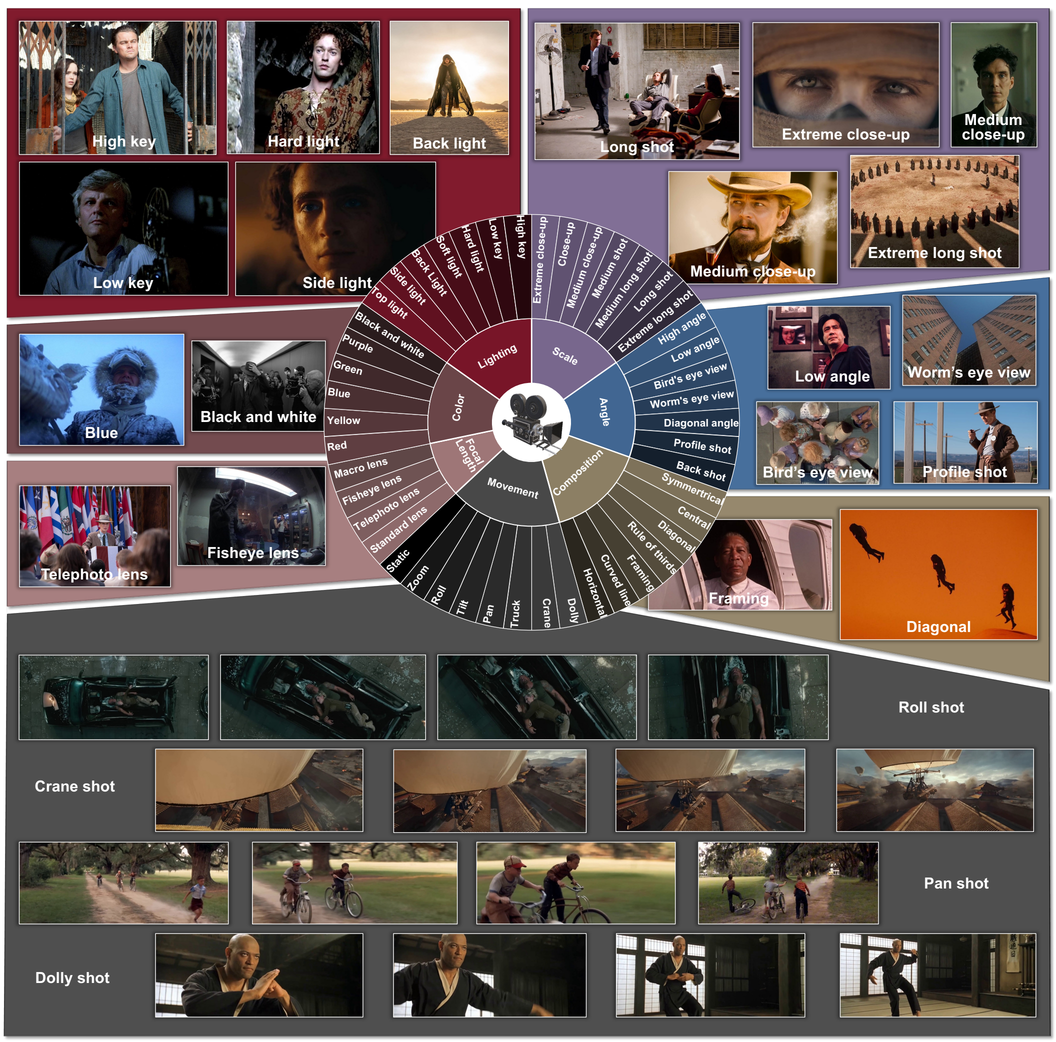

Figure 1: Cinematography taxonomy and data examples in our CineTechBench.

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Abstract

Cinematography is a cornerstone of film production and appreciation, shaping mood, emotion, and narrative through visual elements such as camera movement, shot composition, and lighting. Despite recent progress in multimodal large language models (MLLMs) and video generation models, the capacity of current models to grasp and reproduce cinematographic techniques remains largely uncharted, hindered by the scarcity of expert-annotated data. To bridge this gap, we present CineTechBench, a pioneering benchmark founded on precise, manual annotation by seasoned cinematography experts across key cinematography dimensions. Our benchmark covers seven essential aspects—shot scale, shot angle, composition, camera movement, lighting, color, and focal length—and includes over 600 annotated movie images and 120 movie clips with clear cinematographic techniques. For the understanding task, we design question–answer pairs and annotated descriptions to assess MLLMs' ability to interpret and explain cinematographic techniques. For the generation task, we assess advanced video generation models on their capacity to reconstruct cinema-quality camera movements given conditions such as textual prompts or keyframes. We conduct a large-scale evaluation on 15+ MLLMs and 5+ video generation models. Our results offer insights into the limitations of current models and future directions for cinematography understanding and generation in automatic film production and appreciation. The code and benchmark can be accessed at `https://github.com/PRIS-CV/CineTechBench`.

1 Introduction

Film production and appreciation play a vital role in both cultural expression and everyday entertainment. Whether through blockbuster movies, independent films, or short online videos, cinema shapes how people perceive stories, emotions, and experiences. Among the many elements that contribute to the impact of a film, cinematography serves as a powerful visual language. To convey mood, emotion, narrative, and other factors within a shot, cinematography is implemented by using different aspects within a film—ranging from camera movement and framing to lighting and composition [53]. With the rapid advancement of multimodal large language models (MLLMs) and video generation models, computer vision has made significant strides in analyzing and generating cinematic content. These models have demonstrated promising capabilities in recognizing scenes, describing plots, and even creating visually coherent video clips. However, there remains a critical gap: the lack of a standardized benchmark to assess whether MLLMs can truly understand the cinematographic techniques used in the film and video generation model can generate cinema-quality camera movements.

Recent efforts in computational movie understanding have predominantly centered on high-level semantics. This includes tasks focused on narrative comprehension, such as story-based question-answering [43], analyzing human-centric situations [48], and long video understanding [42]. Other work has targeted coarse-grained visual tasks like scene recognition [5]. While some large-scale datasets, notably MovieNet [19], have begun to incorporate "cinematic style" annotations, these labels are often holistic and lack a fine-grained decomposition into their constituent elements. In contrast, cinematography—the visual core of cinematic storytelling—finds its essence in a series of professional and specific visual techniques, including camera movement, shot scale, lighting and other dimensions. These techniques fundamentally shape a film's tone and the audience's emotional experience, yet they are not readily available from online movie reviews and require expert knowledge for meticulous visual analysis and labeling. This new era of powerful MLLMs and video generation models holds immense potential for both analyzing and creating cinematic content. Whether these models can truly understand the nuances of cinematography or generate content that artistically employs them is a frontier that remains largely unexplored due to the lack of targeted evaluation frameworks. To address this gap, we have developed a benchmark that specifically targets these fine-grained cinematographic dimensions.

In this paper, we introduce CineTechBench, a benchmark designed to evaluate the understanding and generation capabilities of MLLMs and video generation models in the context of cinematographic techniques. Our benchmark encompasses the most important dimensions of cinematography, including **shot scale, shot angle, composition, camera movement, lighting, color, and focal length**.

These dimensions play a pivotal role in shaping the visual and emotional language of film, making them essential for evaluating model's cinematographic understanding and generation abilities. To assess the understanding capability across these dimensions, we collect more than 120 video clips featuring clear and intentional camera movements, along with over 600 curated images covering the remaining dimensions. Each sample is carefully selected or annotated to highlight key cinematographic elements, providing a rich and diverse testbed for evaluating multimodal large language models and video generation models in the context of cinematographic techniques.

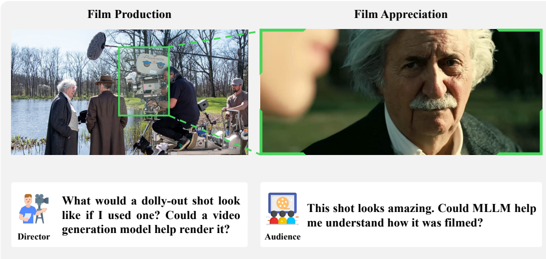
For the understanding task, we design a set of question–answer pairs and annotated cinematography-focused descriptions for both images and videos. These are used to evaluate how well multimodal large language models (MLLMs) can recognize, interpret, and describe cinematographic techniques. This task assesses the models' ability to not only identify visual elements but also articulate their narrative and emotional significance within a scene. For the generation task, we assess the ability of video generation models to recreate cinematic camera movements based on specific input conditions, e.g., textual description containing camera movement cues or the first and last frames of a clip. This setting allows us to measure how effectively video generation models can translate cinematographic intent into coherent visual outputs.

Our main contributions are as follows: (1) **We construct a taxonomy of cinematographic techniques covering 7 core dimensions**: shot scale, angle, composition, camera movement, lighting, color, and focal length. This taxonomy provides a structured foundation for the analysis and evaluation of cinematic visual understanding. (2) **We build a high-quality benchmark by collecting over 600 high-resolution film images and 120 flim clips** from critically acclaimed films, each exhibiting clear and professional cinematographic techniques. All data are manually annotated with relevant dimension labels. Based on these annotations, we further synthesize a set of cinematography-focused question–answer pairs and descriptive captions, forming a test set for evaluating both recognition and description generation. (3) **We evaluate the advanced MLLMs and video generation models on cinematographic technique understanding and camera movement generation, respectively.** Through experiments on over 15 MLLMs and 5 video generation models, we reveal that current MLLMs still struggle with fine-grained cinematograph understanding, and video generation models perform poorly on camera movement with intense rotation amplitude, highlighting the need for further research in this area.

2 Related Work

2.1 Movie Understanding Benchmarks

Previous datasets in the movie understanding domain have primarily focused on high-level semantic analysis, such as genre classification [70, 41], story comprehension [43, 42], situation recognition [48], content authenticity [13], and character detection and identification [42]. For instance, MND [30] introduced a dataset to classify scenes by their narrative function (e.g., Setup, Climax), advancing the study of macro-level story structures. To better enhance the audience's film comprehension experience, other works have focused on movie narration generation. For example, Movie101 [59] introduced a benchmark for generating role-aware narrations, which was subsequently improved and expanded into a large-scale bilingual dataset in Movie101v2 [60]. These tasks generally aim at understanding the plot or identifying key narrative elements in films, which are valuable for understanding a film's thematic content. In contrast, fewer works have explored cinematography-specific understanding, which is a crucial yet often overlooked aspect of visual storytelling [64]. Several notable efforts have explored specific cinematographic elements. For instance, MovieNet [19] provides a high-quality dataset focused on movie understanding, which includes annotations for shot scale and camera movements. MovieShots [39] offers a large-scale dataset for scale types and movement types classification. MotionSet [10] is a dataset centered around camera movement clips with movement types annotations. MovieCLIP [5, 19] utilizes CLIP [38] to automatically assign shot scale labels to shot clips, providing another perspective on annotation collection. Additionally, Camerabench [29] is focused on movement understanding, constructing a comprehensive taxonomy of camera motion primitives. However, these datasets address individual facets of cinematography, focusing on isolated aspects and lack a unified and comprehensive benchmark for evaluating fundamental cinematographic understanding across multiple core dimensions. To bridge this gap, both our work and the concurrent work ShotBench [31] have simultaneously focused on understanding the core dimensions of cinematographic techniques. While their work makes a valuable contribution to



Cinematography Benchmark Comparison

Understanding Dimensions	*Movie Shots*	*Movie Net*	*Cine Scale2*	*Camera Bench*	*Shot Bench*	*CineTech Bench*
Scale	✓	✓	×	×	✓	✓
Lighting	×	×	×	×	✓	✓
Angle	×	×	✓	×	✓	✓
Camera Movement	✓	✓	×	✓	✓	✓
Composition	×	×	×	×	✓	✓
Color	×	×	×	×	×	✓
Focal Length	×	×	×	×	✓	✓
Shot Framing	×	×	×	×	✓	×
Generation Dimensions						
Camera Movement	×	×	×	×	×	✓

Figure 2: Our benchmark focus on the **cinematographic techniques** in film production and appreciation. Compared with similar benchmarks, our benchmark include more core dimensions in cinematography.

cinematographic analysis, our work provides a broad and structured evaluation framework that is distinguished by also including an evaluation for camera movement generation.

2.2 Movie & Video Generation Benchmarks

The field of video generation has recently seen burgeoning growth, with a significant number of innovative works emerging that aim to produce movie-level visuals. These include foundational video generation models [50, 18, 7, 68, 4, 40, 69, 11, 22, 62, 22, 16], controllable visual generation framework [1, 12, 57, 51, 17, 66, 63], identity-preserving video generation [17] and audio and video synchronous generation [52]. Furthermore, to construct coherent narratives, the community has proposed multi-shot generation methods [54]. Several benchmarks are established to corresponding visual generation evaluation benchmarks [58, 33, 71] to evaluate these technologies. However, evaluating the film-level generation capabilities of these models—especially regarding cinematographic aspects such as camera movement—remains a challenging task. Several recent benchmarks have addressed general video generation evaluation. VBench [20, 21] provides a comprehensive benchmark suite that dissects video generation quality into hierarchical, disentangled dimensions with tailored prompts and evaluation protocols. DEVIL [27] focuses on the dynamics dimension, offering a detailed protocol for evaluating the temporal coherence of text-to-video (T2V) generation models. Meanwhile, MovieGen Video Bench [36] evaluates video generation models from the perspectives of visual quality, realism, and aesthetics. Concurrently, SCINE [6] focuses on prompt-driven T2V evaluation, measuring generated-video quality via filmmaking taxonomies with an automatic evaluator and a question-generation pipeline. Despite these advances, there is still a lack of benchmarks tailored specifically for the reconstruction of cinematographic technique, particularly camera movement, against original videos, in generated video content. Our benchmark fills this gap by focusing on the assessment of cinema-level camera movement generation.

3 CineTechBench

CineTechBench offers high-quality, expert-annotated data across multiple dimensions of cinematography. As illustrated in Figure 2, our benchmark focuses specifically on the domain of cinematographic techniques in film production and appreciation. Different from existing movie and camera understanding benchmarks, CineTechBench establishes the first comprehensive taxonomy that covers seven core dimensions of cinematography: shot scale, angle, composition, movement, lighting, color, and focal length. These dimensions reflect the visual language used by professional filmmakers and provide a structured foundation for evaluation.

3.1 Taxonomy Building

Establishing a rigorous taxonomy is essential for evaluating model performance in any specialized domain. As shown in Figure 3, we began by collecting keywords from online sources in film review websites, YouTube tutorials, and cinematography-focused educational content, such as videomaker[3],

[3] www.videomaker.com

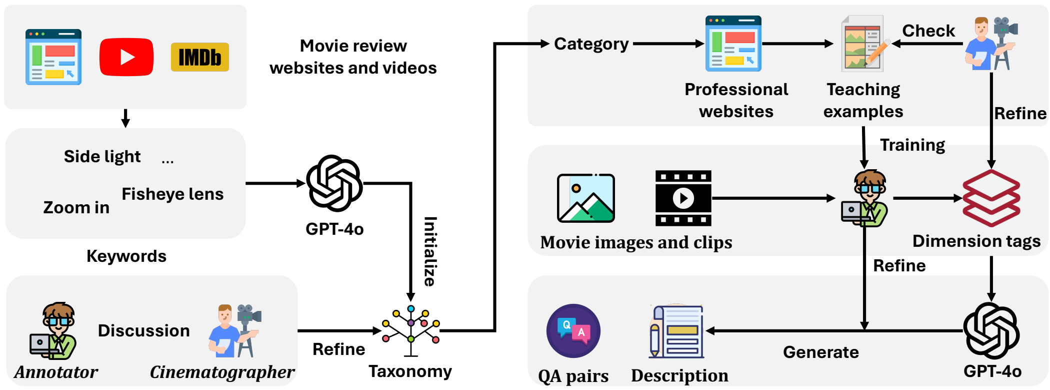


Figure 3: Overview of our benchmark building process.

studiobinder[4], and nofilmschool[5]. We then organized these keywords into a hierarchical taxonomy using GPT-4o, which was further refined through iterative feedback from professional cinematographers. Following are the seven core dimensions in our cinematographic taxonomy, a more detailed explanation of the categories within each dimension is provided in Appendix I.

Scale refers to the shot distance, which defines the spatial relationship between the subject and the frame. This dimension influences the viewer's perception of detail, context, and emotional intensity.

Angle describes the orientation of the camera relative to the subject, shaping the viewer's perspective and emotional response. Different angles can evoke varied psychological effects.

Composition concerns the arrangement of visual elements within the frame. It guides the viewer's attention, establishes visual harmony or tension, and enhances narrative expression.

Colors encompasses the hue, saturation, and tonal palette used in a shot. Colors are central to setting mood, evoking emotion, and reinforcing thematic motifs.

Lighting addresses the quality, direction, and intensity of illumination in a scene. It plays a critical role in establishing atmosphere, emphasizing form, and generating visual depth.

Focal Length pertains to the optical characteristics of the camera lens. This dimension affects spatial representation, subject emphasis, and visual aesthetics.

Camera Movement This dimension captures the dynamic motion of the camera during a shot. Following CameraBench [29], we categorize camera movements into five types: (1) **Translation**: lateral (truck), forward / backward (dolly), and vertical (pedestal) movements. (2) **Rotation**: angular movements including pan (horizontal), tilt (vertical), and roll (diagonal). (3) **Zoom**: optical zoom in and zoom out, altering framing without moving the camera. (4) **Static**: fixed shots where the camera remains completely stationary. (5) **Combined movement**: compositions involving multiple consecutive or simultaneous camera motions.

3.2 Data Collection & Annotation

Movie images and clips. Since no existing data source or website gather film clips and images showcasing clear, professional cinematographic techniques, it is very difficult for us to use automated methods to collect materials and corresponding annotations on a large scale. Therefore, we manually assembled our own benchmark. First, we gathered over 600 high-resolution stills, each illustrating a distinct static shot style (e.g., shot scale, composition, lighting) from IMDb's Top 250 films [6]and other curated movie databases. Every image was annotated across the relevant cinematographic dimensions. Second, we downloaded more than 120 short video clips from the YouTube channel Movieclips [7], specifically selecting segments that demonstrate clear camera movements (e.g., pan, tilt, dolly, zoom).

[4] `www.studiobinder.com`
[5] `www.nofilmschool.com`
[6] `https://www.imdb.com/`
[7] `https://www.youtube.com/@MOVIECLIPS`

Table 1: Accuracy of various MLLMs on static cinematographic technique question answering understanding. The best and second best results are highlighted by blue and green respectively.

MLLMs	Params	Overall	Scale	Angle	Composition	Color	Lighting	Focal Length
Commercial								
GLM-4V-Plus [15]	–	60.00	50.71	69.14	67.50	83.33	56.36	31.67
Qwen-VL-Plus	–	61.36	40.71	73.33	67.50	81.67	66.36	43.33
Gemini-2.0-Flash	–	59.34	46.43	74.17	40.83	91.67	70.91	43.33
Gemini-2.5-Pro	–	69.67	71.43	83.33	67.50	88.33	62.73	36.67
Doubao-1.5-vision-pro	–	56.07	42.86	68.33	41.67	78.33	60.00	61.67
GPT-4o [34]	–	70.16	75.00	82.50	57.50	93.33	71.82	33.33
Open-source								
Kimi-VL [45]	3B	46.39	32.14	63.33	31.67	73.33	55.54	31.67
Phi3.5 [47]	4B	40.82	20.00	49.17	41.67	61.67	56.36	21.67
Gemma3-it [44]	4B	39.18	17.86	45.00	41.67	58.33	52.73	28.33
Qwen2.5-VL [2]	7B	50.66	30.00	61.67	43.44	83.33	62.73	36.67
Qwen2.5-Omni [55]	7B	54.75	45.00	65.83	61.67	70.00	49.09	36.67
LLaVA-OneVision [25]	7B	45.90	31.43	54.17	42.50	75.00	54.55	25.00
LLaVA-NeXT [24]	8B	38.69	22.86	42.50	39.17	63.33	44.55	31.67
MinCPM-V-2.6 [56]	8B	45.90	32.86	57.50	35.00	80.00	50.91	31.67
InternVL2.5 [8]	8B	54.59	39.29	63.33	65.00	90.00	52.73	20.00
InternVL3 [72]	8B	55.25	45.00	66.67	53.33	76.67	57.27	35.00
Llama-3.2-Vision [46]	11B	47.21	33.57	48.33	50.83	78.33	45.45	41.67

These clips form our test set for video generation and motion-understanding tasks. By restricting our selection to films in IMDb's Top 250, we ensure that all materials exhibit exemplary technical craftsmanship, visual storytelling, and enduring cinematic value. More statistical information about our benchmark can be found in Appendix A.

Annotation To support high-quality annotation, we first searched for professional websites using cinematography-related category keywords (e.g., "extreme close up shot", "camera movement"). These websites typically include visual examples, images or video snippets, corresponding to each category. We curated five representative examples per category (a sample website is provided in Appendix A) and used them to train a team of annotators with a foundational understanding of cinematography. After training, the annotators labeled the collected images and video clips according to the relevant cinematographic dimensions. During annotation, any instance that was ambiguous or difficult to classify was either escalated to a professional cinematographer for review or discarded to maintain the overall quality of the dataset. Building on basic category annotations across key cinematographic dimensions, we further enriched the data set by generating question-answer pairs and descriptive annotations using GPT-4o. GPT-4o was guided by our predefined taxonomy and the existing category labels to ensure relevance and consistency. All generated content was manually reviewed and refined by trained annotators to ensure accuracy, clarity, and alignment with professional cinematography standards. More annotation details are shown in Appendix B. This process result in 610 image QA pairs, 128 video QA pairs, 100 detailed image descriptions (average length $\approx$176 words) and 128 detailed video descriptions (average length $\approx$168 words).

4 Evaluation

In this section, we evaluate both understanding and generation tasks using our proposed CineTech-Bench. For the understanding task, we assess over 15 advanced MLLMs on both dynamic aspects (e.g., camera movement) and static aspects (e.g., shot angle, shot style) of visual content, through both question-answering and description generation tasks (see Section 4.1). These evaluations leverage movie images and clips to comprehensively examine MLLMs' ability to interpret various cinematographic dimensions. For the generation task, we benchmark over five advanced video generation models on the camera movement generation task (see Section 4.2) to assess their ability to generate coherent camera movements. The detailed experiment settings are shown in Appendix D.

4.1 Cinematographic Technique Understanding

Metrics For question-answering tasks, we report overall accuracy as well as accuracy broken down by each cinematography dimension. For description generation tasks, we use four reference-based metrics. Three of these—BLEU [35], METEOR [3], and ROUGE [28]—are based on n-gram overlap. However, such metrics are limited in evaluating fine-grained, detailed descriptions [14]. To address

Table 2: Accuracy of various MLLMs on camera movement question answering understanding. The best and second best results are highlighted by blue and green respectively.

MLLMs	Params	Frames	Overall	Static	Translation	Rotation	Zoom	Combined
Commercial								
GLM-4V-Plus [15]	–	1fps	52.34	100.00	40.74	41.94	57.14	68.00
Qwen-VL-Plus	–	8fps	52.40	100.00	56.60	33.33	57.14	43.48
Doubao-v1.5-vision-pro	–	2fps(>=8)	40.00	100.00	40.74	16.13	14.29	48.00
GPT-4o	–	2fps(>=8)	50.00	90.91	61.11	25.81	28.57	44.00
Gemini-2.0-Flash	–	1fps	49.22	27.27	61.11	32.26	28.57	60.00
Gemini-2.5-Pro	–	1fps	56.69	81.82	66.04	45.16	14.29	52.00
Open-source								
Phi3.5 [47]	4B	1fps(>=4)	27.19	10.00	33.33	31.03	40.00	26.32
gemma3-it [44]	4B	1fps(>=4)	33.33	60.00	36.54	16.67	14.29	45.83
Qwen2.5-VL [2]	7B	1fps	50.78	100.00	55.56	19.35	71.43	52.00
Qwen2.5-Omni [55]	7B	–	46.09	72.73	46.30	19.35	42.86	68.00
LLaVA-NeXT-Video [24]	7B	64	28.00	45.45	29.63	19.35	14.29	32.00
LLaVA-OneVision [25]	7B	32	36.00	90.91	35.19	16.13	42.86	36.00
LLaVA-NeXT [24]	8B	4	29.13	63.64	31.48	13.33	28.57	28.00
MinCPM-V-2.6 [56]	8B	1fps	35.94	27.27	42.59	25.81	0.00	48.00
InternVL2.5 [8]	8B	all	34.38	72.73	40.74	16.13	57.14	20.00
InternVL3 [72]	8B	all	41.41	81.82	35.19	29.03	42.86	52.00
Llama-3.2 [46]	11B	4	31.25	18.18	27.78	35.48	14.29	44.00

Table 3: Performance of various MLLMs on cinematographic technique description. The best and second best results are highlighted by blue and green respectively.

MLLMs	Params	BLEU@4	METEOR	ROUGE-L	CAPability			
					HR	AP	AR	F1
Commercial								
GLM-4V-Plus [15]	–	4.33	18.63	25.41	84.43	50.15	40.45	43.18
Qwen-VL-Plus	–	0.72	15.24	12.97	81.29	48.25	36.24	40.38
Doubao-v1.5-vision-pro	–	4.02	19.44	24.93	82.91	53.01	39.27	42.67
GPT-4o	–	6.08	19.76	27.13	86.18	56.86	45.66	49.08
Gemini-2.0-Flash	–	4.17	19.07	25.14	85.42	51.28	40.75	44.43
Gemini-2.5-Pro	–	6.12	21.64	25.35	88.81	57.82	48.67	52.27
Open-source								
Phi3.5 [47]	4B	2.24	15.76	21.97	11.72	73.33	8.59	15.38
gemma3-it [44]	4B	2.11	17.53	21.15	89.14	44.75	36.70	39.07
Qwen2.5-VL [2]	7B	3.14	17.73	23.28	86.71	52.30	42.05	44.39
Qwen2.5-Omni [55]	7B	3.67	17.89	24.80	85.92	45.81	37.13	39.92
LLaVA-OneVision [25]	7B	2.58	17.42	22.16	81.31	46.69	34.68	37.32
LLaVA-NeXT [24]	8B	1.89	17.11	21.64	81.39	45.38	32.93	35.62
MinCPM-V-2.6 [56]	8B	3.06	16.15	23.05	77.07	45.73	30.89	34.48
InternVL2.5 [8]	8B	3.44	17.56	24.08	85.72	51.21	39.83	42.16
InternVL3 [72]	8B	4.10	19.12	25.38	86.91	55.64	45.91	47.86
Llama-3.2 [46]	11B	2.66	17.41	23.65	85.60	45.51	37.57	39.58

this, we additionally incorporate evaluation metrics from the CAPability benchmark [32] based on our taxonomy, which reliably assess both the correctness and thoroughness of MLLM-generated descriptions using hit rate (HR), average precision (AP), average recall (AR) and F1-score.

Results We first evaluate MLLMs' understanding of static cinematographic techniques—scale, angle, composition, color, lighting, and focal length using annotated image question-answer pairs. Results are shown in Table 1. Among commercial models, GPT-4o and Gemini-2.5-Pro achieve the highest and second-highest overall scores (70.16% and 69.67%, respectively), primarily due to their strong performance on scale (75.00%, 71.43%) and angle (82.50%, 83.33%). Gemini-2.0-Flash, while slightly lower in overall accuracy (59.34%), exhibits the leading color understanding performance (91.67%) and strong lighting perception (70.91%). Doubao-1.5-Vision-Pro, although underperforming across most dimensions, achieves the highest focal length accuracy (61.67%) among all MLLMs. Open-source MLLMs lag significantly behind, averaging about 15 percentage points lower in overall accuracy. Among them, InternVL3 leads with 55.25%, showing relative strength in angle (66.67%), scale (45.00%), and lighting (57.27%). Notably, Qwen2.5-VL-7B achieves the best lighting perception (62.73%) among open-source models, outperforming even some commercial counterparts. We next assess models' understanding of camera movement using video question answering pairs. As shown in Table 2, Gemini-2.5-Pro achieves the best overall performance (56.69%). Among open-source models, Qwen2.5-VL and Qwen2.5-Omni rank first and second, respectively. Surprisingly, several open-source MLLMs struggle to recognize fixed shots, resulting in poor performance on the "static" category—e.g., LLaVA-NeXT-Video. Across all models, camera rotation remains a particularly challenging dimension, with consistently low accuracy. To evaluate overall comprehension, we test each MLLM's ability to generate comprehensive descriptions. As shown in Table 3, Gemini-2.5-Pro achieves the highest average precision (AP), average recall (AR), and F1 score, indicating its outputs are both accurate and complete. Among open-source models, InternVL3 performs best—surpassing even some commercial MLLMs such as Gemini-2.0-Flash. More understanding results are shown in Appendix E.

Qualitative Analysis We further illustrate these findings with qualitative examples in Figure 4. In example (b), which tests shot angle recognition, both Llama-3.2 and GLM-4V-Plus misclassify the scene as Diagonal instead of the correct Profile. Example (d), evaluating color palette understanding, shows Gemma3 and LLaVA-OneVision incorrectly focusing on a local object (a desk lamp) rather than assessing the overall scene color. In example (e), where the ground truth is Side Light, all MLLMs fail, with Gemini-2.0-Flash misclassifying it as Back Light. Example (f) further reveals widespread difficulty across models in recognizing lighting and focal length. Examples (g) and (h) illustrate challenges in camera movement understanding, even GPT-4o misinterprets camera rotation direction. In example (i), generated descriptions from all MLLMs fail to accurately reflect the ground truth, highlighting limitations in comprehensive and correct description generation.

Table 4: Cinematic camera motion control performance of different image-to-video models. F, L and T means the first frame, the last frame and textual description of the movie clip, respectively. The best results are highlighted in blue.

I2V models	Condition	RotError ↓	TransError ↓		CamMC ↓		CLIP-IS ↑
			Rel.	Abs.	Rel.	Abs.	
Commercial							
Klingv1.6	FLT	21.68	48.49	196.14	62.57	207.65	90.15
Gen4turbo	FT	23.61	49.84	102.32	64.47	117.07	86.96
Open-source							
Wan2.1-FLF-14B-720P [50]	FLT	27.80	48.31	99.61	67.82	115.76	89.65
FramePack-FLF2V [62]	FLT	23.88	58.10	82.00	71.98	95.62	89.30
FramePack-I2V [62]	FT	26.93	61.94	192.08	78.17	208.78	82.70
Hunyuan-Video-I2V [22]	FT	33.42	71.65	268.62	91.87	289.36	83.98
SkyReels-V2-I2V-1.3B-540P [7]	FT	40.05	74.86	423.52	100.96	442.34	78.42

4.2 Camera Movement Generation

Metrics In this section, we use video generation models to reconstruct the camera movement in the original film clip by inputting the first frame, the last frame (if applicable), and textual description. Following [49, 26, 66], we quantify trajectory similarity between the generated and the original video clips via three metrics: rotation error (RotErr), translation error (TransErr), CamMC. The TransErr and CamMC metrics are reported in two forms: relative (Rel) and absolute (Abs). The relative error normalizes each video by its own scene scale, focusing purely on the correctness of the camera path. It provides a more stable and reasonable evaluation than the absolute error, which also penalizes inaccuracies in the overall scene scale. Consequently, our subsequent analysis focuses primarily on the relative metrics. We use MonST3R [61] to estimate the camera trajectory of the generated and original movie clip. Finally, we also report a CLIP-based frame similarity score (CLIP-IS) to capture visual consistency. The detailed introduction of these metrics are in Appendix C.

Results The overall results are shown in Table 4. Among the commercial video generation models, Klingv1.6 with first and last frame control achieves the best performance on both RotError and TransError. Among open-source models, Wan2.1 and FramePack support first frame and last frame control, obtain relatively good performance compared to the models conditioned purely on the first frame, such as HunyuanI2V and FramePack-I2V. We further divide the test examples by their camera movement translation speed and camera rotation angular velocity, and average their translation error and

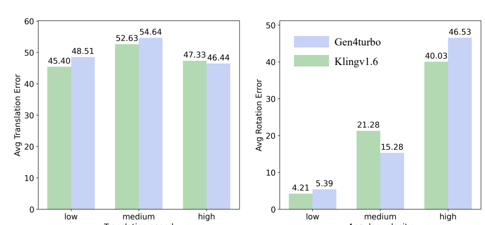


Figure 6: Average TransError and RotError on different translation speed and angular velocity.

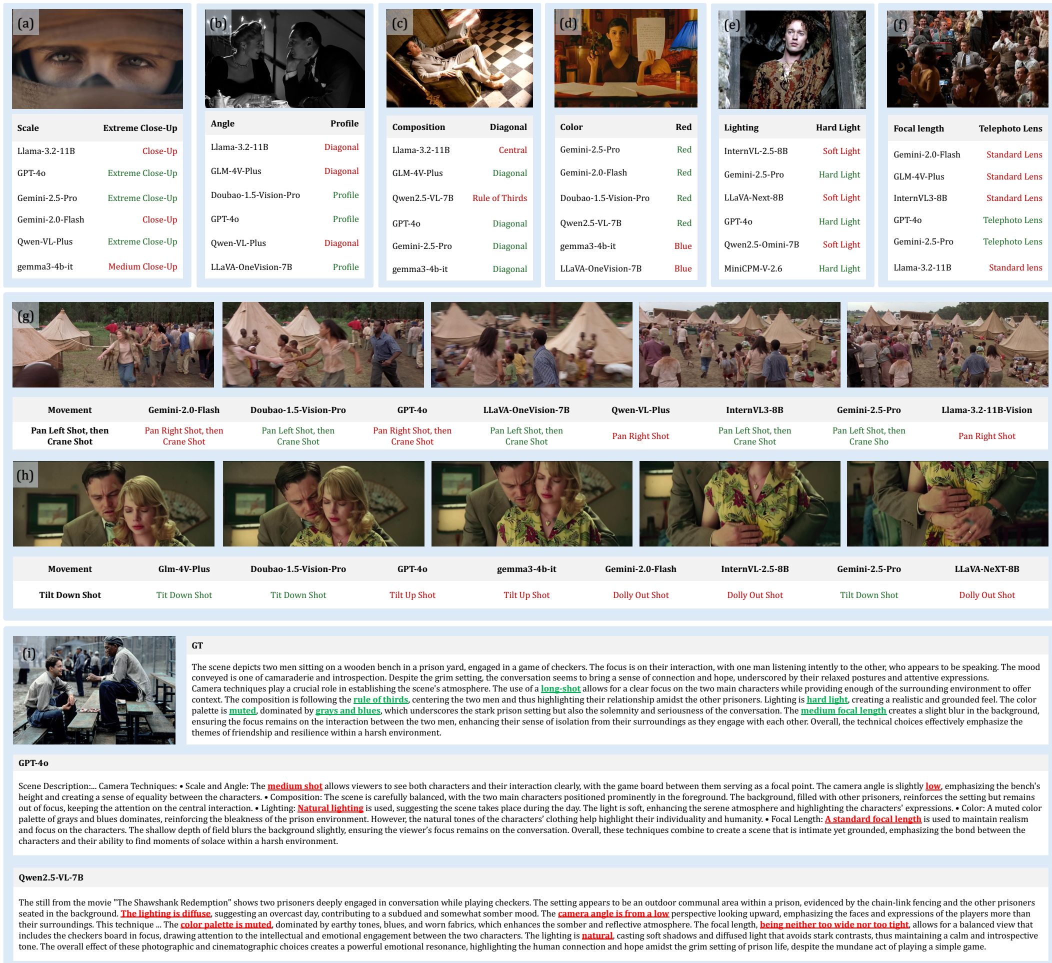


Figure 4: Visualization of MLLMs' answers on cinematographic technique question answering task. The red text highlights the wrong answers and the green text highlights the correct answers. More visualization examples can be seen in Appendix G.

Figure 5: Generated movie clips by different video generation models and the corresponding camera trajectory estimated by Monst3r [61]. More examples are shown in Appendix G.

rotation error respectively, the results are shown in Figure 6. The video generation models usually have a higher error on examples with high camera rotation angular velocity, which is mainly used in shots with intense fighting scenes. We show generation results of different video generation models in the Figure 5. The original clip applies a counter-clockwise roll camera movement. Among the three models, Wan2.1 doesn't generate a roll camera movement at all. Although the video generated by Kling has a sense of rotation, its roll direction is clockwise, which is the opposite of the intended motion. Only Gen4turbo generates the correct camera movement with correct direction. We further analyze more generation examples in Appendix G.

5 Future Direction

Future extensions of this work could deepen the evaluation of cinematographic understanding by establishing explicit connections between camera techniques and narrative structure. For example, models could be assessed on their ability to recognize how specific shot types—such as over-the-shoulder angles, tracking shots, or extreme close-ups—contribute to character development, emotional tone, or plot progression. A richer understanding of film language would also benefit from expanding the diversity and scale of the underlying video corpus, incorporating a broader range of genres, cultures, and directorial styles to reduce bias and improve generalization. On the generation side, current evaluation tasks focus on reconstruction—that is, whether models can reproduce specific cinematographic techniques in a visually coherent manner. While this serves as a useful starting point, it represents only a constrained form of generation. Future work could explore more advanced tasks such as cinematographic re-composition, where models are required to modify or re-edit videos based on high-level stylistic and narrative instructions (e.g., changing shot scale, adjusting lighting, or reconfiguring spatial composition). With the emergence of more capable video models, such as Runway's Aleph, this line of evaluation is becoming increasingly feasible. These directions would help move the field closer to assessing and developing models with not only visual fluency but also narrative and stylistic awareness—key components of true cinematic intelligence.

6 Conclusion

In this work, we introduce CineTechBench, the first benchmark that evaluates MLLM understanding across seven core dimensions (shot scale, angle, composition, camera movement, lighting, color, focal length) and video generation models on camera movement generation. We curated and annotated over 600 still images and 120 video clips from acclaimed films, each paired with targeted QA pairs and descriptions. Our evaluation of over 15 state-of-the-art models, reveals key limitations in current models on understanding and generation of cinematographic techniques. Specifically, for understanding, we found that multimodal large language models profoundly struggle with complex, relational concepts like lighting direction and camera movement. This is demonstrated by a significant score gap between high hit rates and low F1 scores, as shown in Figure 12, suggesting that models often resort to heuristic guessing over robust interpretation. We trace this failure to the scarcity of technical terms in pre-training corpora (e.g., "focal length" in 0.05% of LLaVA-Video-178k captions [65]). Fundamentally, this weak performance highlights the limited capacity of current models for spatial reasoning and coherent dynamic change perception in visual media. For generation, we found that video generation models struggle to synthesize dynamic camera motions. While conditioning on first and last frames improves control for simple movements, models largely fail to render intense camera rotations, such as those common in action sequences. By providing this benchmark, we aim to drive multimodal large language models and video generation models with more nuanced cinematic analyzing and robust motion synthesis capabilities. Future work might focus on scaling these annotations in a more efficient way to further elevate model performance.

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Appendix

A Benchmark Statistical Information

As shown in Figure 7, our benchmark spans 93 years of cinematic history (1931–2024) and includes 48 distinct film genres, from classic Hollywood dramas to contemporary global art house cinema. This cross-decade temporal coverage and genre diversity capture the evolution of cinematographic styles and technical innovations, from the early days of monochrome filmmaking to modern high-definition digital cinematography. By encompassing films across eras and genres, the dataset avoids bias toward specific stylistic trends, providing a robust foundation for evaluating MLLMs' ability to generalize across diverse visual and narrative contexts.

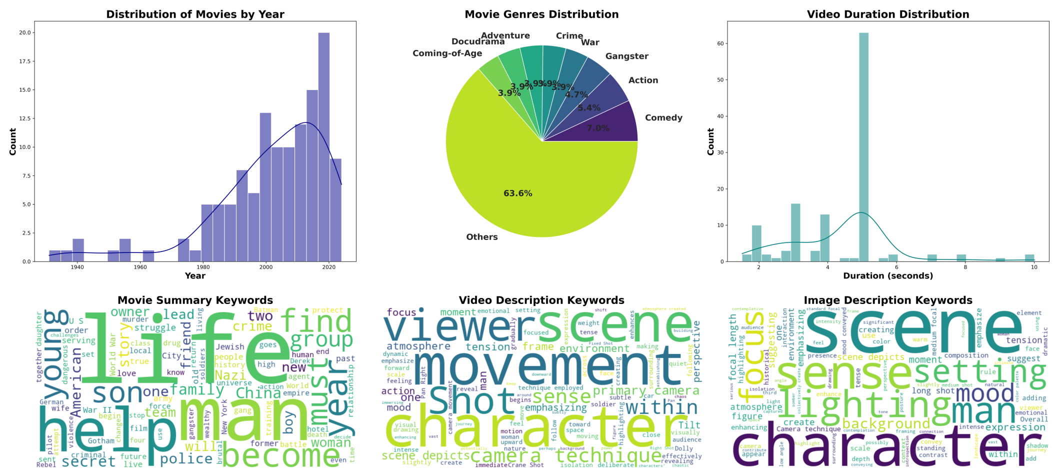

Figure 7: Statistical and semantic overview of the CineTechBench.

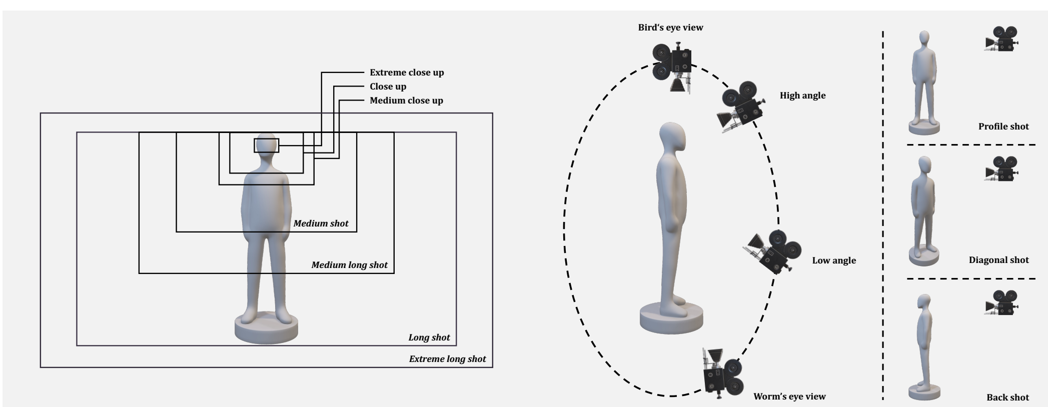

Figure 8: Illustration of categories in the angle and scale dimension.

B Annotation Process Detail

B.1 Annotation Instruction for Description Refinement

Overall Workflow In this refine task, annotators are required to refine the descriptions generated by a large model for images or videos. The descriptions are initially generated based on specific keywords representing various cinematographic techniques. The purpose of this instruction is to ensure consistency, accuracy, and clarity in the annotation process.

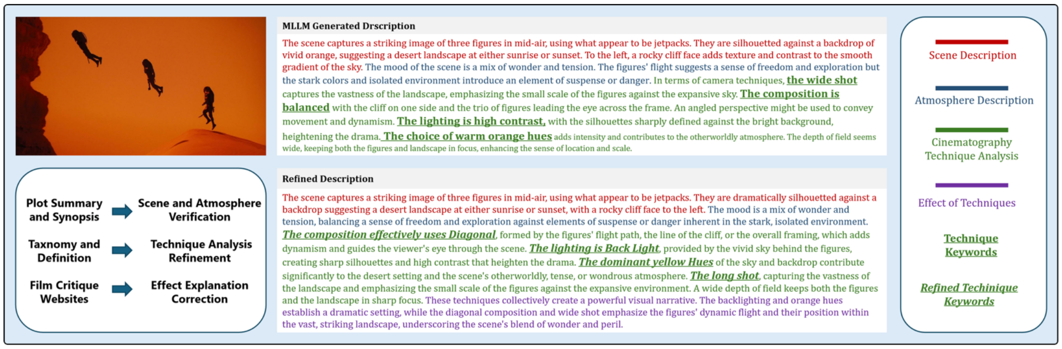

Figure 9: An annotation refine example for MLLM generated description.

1. **Description Structure:** These generated descriptions generally follow a standard structure:
    - **Scene Description:** A general depiction of the visual scene.
    - **Atmosphere Description:** A brief description of the mood or feeling conveyed.
    - **Cinematographic Technique Analysis:** An analysis of the specific cinematographic techniques identified in the scene.
    - **Effect of Techniques:** An explanation of the impact of these techniques on the visual experience. Depending on the context, the effect may be integrated within the technique analysis or provided as a separate section at the end.
2. **Scene and Atmosphere Verification:**
    - Review the scene and atmosphere descriptions.
    - Cross-reference with the context or plot summary of the film to ensure accuracy.
    - Make necessary corrections for clarity, factual accuracy, and alignment with the scene.
3. **Technique Analysis Refinement:**
    - Verify that the description covers all relevant cinematographic techniques.
    - Remove any unnecessary or inaccurate techniques.
    - Ensure that all technical terms align with the predefined standardized taxonomy.
4. **Effect Explanation Correction:**
    - Refine the explanation of the effects generated by the identified techniques.
    - Cross-check with film critique websites to ensure the effects are consistent with expert interpretations.
5. **Final Review:**
    - Ensure the description is coherent, grammatically correct, and accurately represents the visual content.
    - Submit the refined description.

Quality Control

- Each refined description will be reviewed by a senior annotator for quality assurance.
- Descriptions failing to meet the specified standards will be sent back for correction.

An example refine process for MLLM generated description is shown in Figure 9.

B.2 Annotation Interface

Figure 10 illustrates an example of our labeling interface, The tags displayed beneath the image represent accurate dimension labels refined by experts. Annotators can reference these tags to quickly identify the cinematographic technique keywords and refine the corresponding descriptions.

B.3 Crowdsourcing Compensation

Our annotation process was conducted by a team of project authors, skilled students, and professional experts, with all external contributors receiving fair compensation. Three students handled the primary annotation tasks at competitive per-item rates (ranging from 5 to 20 CNY) scaled by task difficulty and set above typical student wages. Additionally, two professional cinematographers provided expert oversight, refined our taxonomy, and served as final arbiters, each receiving a 2,000 CNY consultancy fee for their significant contribution.

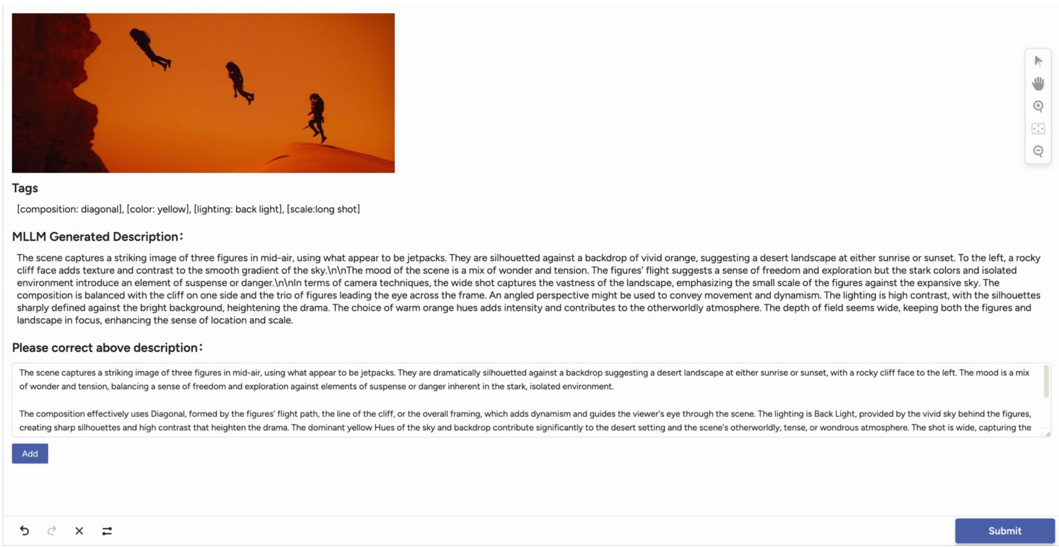

Figure 10: An example label interface.

C Evaluation Metrics

C.1 Description Evaluation Metrics

Inspired by the CAPability benchmark [32], which proposes a comprehensive framework to evaluate the correctness and thoroughness of visual captions, we adopt a similar metric design to assess the descriptive quality of cinematographic techniques in our dataset.

To determine whether a caption correctly addresses a specific dimension, we follow the classification scheme proposed by CAPability [32]. Each caption is categorized into one of the following three cases:

- **Miss**: The caption does not mention any information relevant to the dimension;
- **Positive**: The caption includes information related to the dimension, and the content is consistent with the human annotation;
- **Negative**: The caption mentions the dimension, but the content is incorrect compared to the annotation.

Based on this categorization, we compute four quantitative metrics to evaluate model performance:

- **Hit Rate (HR)**: Measures whether a caption mentions a particular dimension, regardless of correctness. It reflects the referential completeness:
$$\mathrm{HR} = \frac{|\mathcal{S}_{\mathrm{All}} - \mathcal{S}_{\mathrm{Miss}}|}{|\mathcal{S}_{\mathrm{All}}|}$$
- **Precision (AP)**: The proportion of correctly described dimensions among all mentioned:
$$\mathrm{Precision} = \frac{|\mathcal{S}_{\mathrm{Pos}}|}{|\mathcal{S}_{\mathrm{All}} - \mathcal{S}_{\mathrm{Miss}}|}$$

```
You are a cinematography technique analysis expert specializing in evaluating the accuracy of image captions. Please carefully analyze the user-provided caption and complete the task according to the metric specified.

Given an image caption, your task is to determine which kind of {task} is included in the caption.
Image Caption:
"{caption}"
Please analyze the image caption and classify the descriptions of {task} into the following categories: {category1, category2, ...}
Here are the explanations of each category: {definition}

If the caption explicitly mentions one or some of the above {task} categories, write the result of the categories with a python list format into the 'pred' value of the json string. You should only search the descriptions about the {task}. If there is no description of the {task} in the image caption or the description does not belong to any of the above categories, write 'N/A' into the 'pred' value of the json string.

Output a JSON formed as:
{"pred": "put your predicted category as a python list here", "reason": "give your reason here"}
DO NOT PROVIDE ANY OTHER OUTPUT TEXT OR EXPLANATION. Only output the JSON. Do not add Markdown syntax. Output:
```

```
You are a video analysis expert specializing in evaluating movement in video captions.

Given a video description and a specified camera movement, your task is to evaluate whether the movement is accurately reflected in the description, and explain why.
Video description:
"{caption}"
Proper camera movement: "{annotation}"

Here are the explanations of each category: {definition}

Please provide a justification for your judgment, with particular attention to the sequence and types of camera movements involved.
Give score of 0 if there is no mention of the movement in the caption.
Give score of 1 if the description describes the movement correctly.
Give score of -1 if the caption describes the movement incorrectly.

Output a JSON formed as:
{"score": put your score here, "reason": "give your reason here"}
DO NOT PROVIDE ANY OTHER OUTPUT TEXT OR EXPLANATION. Only output the JSON. Do not add Markdown syntax. Output:
```

Figure 11: Prompt template used for static dimension evaluation (e.g., *Scale*, *Angle*, etc.) and dynamic dimension evaluation (*Camera Movement*).

- **Recall (AR)**: The proportion of correctly described dimensions among all ground-truth annotations:

$$\text{Recall} = \frac{|\mathcal{S}_{\text{Pos}}|}{|\mathcal{S}_{\text{All}}|}$$

- **F1-score (F1)**: The harmonic mean of precision and recall, used as the main metric for overall capability:

$$\text{F1} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Note: When the hit rate (HR) reaches 100%, i.e., every caption mentions the target dimension, the average precision (AP), average recall (AR), and F1-score become mathematically identical.

While CAPability originally defines 12 static and dynamic visual dimensions, we adapt this metric suite to assess the understanding and generation of **cinematographic technique descriptions**. Specifically, we evaluate performance across 7 tailored dimensions: six static dimensions—*Scale, Angle, Composition, Colors, Lighting, Focal Lengths*—and one dynamic dimension—*Camera Movement*. The generated descriptions are compared to human-annotated references to compute the metrics, thereby providing an objective measurement of a model's expressive capacity in film-oriented tasks.

To automate this evaluation process, we use `GPT-4.1-nano` to assess each generated caption with respect to the ground-truth annotations. Specifically, we design one prompt template for evaluating static dimensions (*Scale*, *Angle*, *Composition*, *Colors*, *Lighting*, *Focal Lengths*), and another distinct template for the dynamic dimension (*Camera Movement*). These prompt templates guide the `GPT-4.1-nano` to determine whether the relevant dimension in the caption should be categorized as **Positive**, **Negative**, or **Miss**. Detailed prompt formats are provided in Figure 11.

C.2 Camera Movement Evaluation Metrics

Formally, we denote the i^{th} frame relative camera-to-world matrix of ground truth as $\left\{R_i^{3\times3}, T_i^{3\times1}\right\}$, and that of generated video as $\left\{\tilde{R}_i^{3\times3}, \tilde{T}_i^{3\times1}\right\}$. We calculate camera rotation errors by the relative angle between generated videos and ground truths in radians for rotation accuracy and we calculated translation error (TransErr) measures the cumulative difference between the predicted and ground truth camera translations across a trajectory:

$$\text{RotErr} = \sum_{i=1}^{n} \arccos \frac{\operatorname{tr}\left(\tilde{R}_i R_i^{\text{T}}\right) - 1}{2}, \quad \text{TransErr} = \sum_{i=1}^{n} \left\| \frac{\tilde{T}_i}{\tilde{s}_i} - \frac{T_i}{s_i} \right\|_2 \tag{1}$$

where $\tilde{T}_i$ and T_i are the predicted and ground truth translations at timestep i, and $\tilde{s}_i$ and s_i are their respective scale factors. For relative TransErr, we perform scene scale normalization on the camera positions of each video clip. The scene scale of generated video $\tilde{s}_i$ and ground truth s_i are individually calculated as the $\mathcal{L}_2$ distance from the first camera to the farthest one for each video clip. For absolute TransErr, we normalize both the video clip to the scene scale of ground truth video, i.e. $\tilde{s}_i = s_i$. CamMC consider camera translation and rotation error at the same time by directly calculating $\mathcal{L}_2$ distance on camera-to-world matrices:

$$\text{CamMC} = \sum_{i=1}^{n} \left\| \left[\tilde{R}_i \,\middle|\, \frac{\tilde{T}_i}{\tilde{s}_i} \right]^{3\times4} - \left[R_i \,\middle|\, \frac{T_i}{s_i} \right]^{3\times4} \right\|_2 . \tag{2}$$

We further use CLIP frame similarity [37] to evaluate the semantic reconstruction performance:

$$\text{CLIP-IS} = \sum_{i=1}^{N} \frac{f_{\text{image}}\left(x_i\right) \cdot f_{\text{image}}\left(\tilde{x_i}\right)}{\|f_{\text{image}}(x_i)\| \cdot \|f_{\text{image}}(\tilde{x_i})\|}, \tag{3}$$

where $\tilde{x_i}$ and x_i are the i^{th} frame of generated video clip and original video clip. Since some commercial video generation models do not allow setting the number of generated frames, we downsample longer videos to match the same frame count before calculating the above metrics.

D Experiment Settings

For commercial MLLMs, we access them via their official APIs. For open-source MLLMs, we deploy them for online inference using SGLang [67], vLLM [23] and LMDeploy [9] frameworks. To evaluate camera movement understanding, we adopt a multi-image input approach for MLLMs that do not support video input. All experiments are conducted on 2 $\times$ Tesla A800 80G GPUs. For all commercial video generation models, we set the generation duration as 5 seconds. For all open-source video generation models, we set the generation frame counts same as the original movie clips.

E Extra Results

Table 1 presents the sub-category accuracy results for question-answering understanding in the angle and lighting dimensions. Unlike other static cinematogrphic technique dimensions, the angle and lighting dimensions are inherently more complex due to their multi-dimensional nature, each encompassing multiple subcategories that introduce significant visual variability. The angle dimension is divided into two main perspectives: vertical and horizontal. The vertical perspective includes four subcategories: high angle, low angle, bird's eye view, and worm's eye view. The horizontal perspective comprises three subcategories: diagonal shot, profile shot, and back shot. The lighting dimension is categorized into three aspects: intensity, quality, and direction. Intensity is divided into high key and low key lighting. Quality is represented by hard light and soft light, while direction is further classified into side lighting, back lighting, and top lighting.

Angle Dimension Among all commercial MLLMs, GPT-4o demonstrates a superior performance (83. 15%) in the vertical perspectives, while achieving the second-highest (80. 65%) in the horizontal perspectives. In contrast, Gemini-2.5-Pro outperforms others in the horizontal perspective (87.10%), while maintaining a strong second position in the vertical perspective (82.03%). Regarding open-source MLLMs, Qwen2.5-Omini and InternVL3 demonstrate the highest accuracy (64.04%) in the vertical perspective, with Kimi-VL securing the second-highest (60.67%). Kimi-VL leads in the horizontal perspective (79.97%), while Qwen2.5-VL, InternVL2.5, and InternVL3 share the second-highest performance (74.19%). These results indicate that, among commercial MLLMs, both vertical and horizontal perspectives are recognized with comparable accuracy. In contrast, for open-source MLLMs, vertical perspectives are generally more challenging for the models to accurately identify, indicating a potential area for further optimization in recognizing fine-grained angle differences.

Lighting Dimension Among commercial MLLMs, Gemini-2.0-Flash achieves the highest accuracy (93.75%) in the intensity category, followed closely by GPT-4o (90.62%). In the quality category, Qwen-VL-Plus stands out with the best performance (78.26%), with Gemini-2.0-Flash ranking second (71.74%). However, in the direction category, all models exhibit a significant drop in accuracy, with GPT-4o outperforms others (53.12%), while Qwen-VL-Plus and Gemini-2.5-Pro share the second-best performance (50.00%). In open-source MLLMs, LLaVA-OneVision demonstrates strong performance in the intensity category (81.25%), with InternVL2.5 securing the second position (78.12%). For quality, Qwen2.5-VL achieves the highest accuracy (76.09%), followed by Phi3.5 (65.22%). The direction category again shows a clear performance drop. InternVL3 attains the best performance (46.88%), with Kimi-VL following closely (43.75%). These findings confirm that the direction category in the lighting dimension is consistently the most challenging for both commercial and open-source models. This can be attributed to the complex nature of light direction recognition, where even subtle changes in lighting angles can dramatically alter the visual appearance of a scene.

Table 6 shows the CAPability performance on seven dimensions of cinematographic technique description generation. In the description generation task among commercial models, Gemini-2.5-Pro and GPT-4o stand out significantly, achieving a clear lead over other models. Specifically, Gemini-2.5-Pro secures 14 first-place rankings and 2 second-place rankings, while GPT-4o achieves 10 first-place rankings and 8 second-place rankings, demonstrating their superior descriptive capabilities. Remarkably, InternVL3 emerges as the best-performing model among open-source models, with 12 first-place rankings and 6 second-place rankings, making it the strongest contender in this category. Notably, several of its results are comparable to those of the top commercial models, Gemini-2.5-Pro and GPT-4o. This performance highlights InternVL3's exceptional capability in description generation.

Figure 12 presents the average performance of hit rate (HR) and F1 score on seven dimensions of cinematographic technique description generation. In the hit rate (HR) chart (left), the models exhibit consistently high accuracy across six dimensions, all exceeding 80%. However, a notable decline is observed in the Movement dimension (29.83%), indicating that recognizing and describing dynamic actions remains a significant challenge for these models. In contrast, the F1 Score chart (right) reveals a starkly different trend. While HR values remain high across most dimensions, the F1 scores are significantly lower, ranging about from 30% to 50% across all dimensions. This substantial disparity between HR and F1 score suggests that although models are capable of recognizing certain cinematographic features (as indicated by high HR), they struggle to generate precise and consistent descriptions of these features. Such a gap highlights a critical issue in the models' ability to translate visual recognition into accurate textual descriptions, reflecting limitations in their descriptive generation capabilities.

Error Bars We conducted an error bar test on six models (GLM-4V, Gemini-2.0-Flash, Qwen2.5-VL-7B, InternVL3-8B, LLaVA-OneVision-7B, Wan2.1-FLF2V-14B), testing each model three times on the corresponding tasks to calculate the standard deviation of three trials. The observed average standard deviations were 2.67% (Acc) for video QA, 1.59% (Acc) for image QA, 1.21% (F1) for description, 2.21% (CamMC) for camera movement reconstruction, which reflect the stability and reliability of our evaluation pipeline.

F Limitation

Camera Trajectory Estimation Tools One limitation of our benchmark is the lack of ground-truth camera trajectories for the collected movie clips. Acquiring such data is extremely challenging, as professional camera motion metadata is rarely publicly available. To approximate the motion, we employ open-source camera pose estimation tools to reconstruct trajectories from the video clips. However, these methods often introduce inaccuracies due to complex cinematographic factors such as dynamic scenes, motion blur, and non-rigid object motion. This limits the precision of motion-related evaluations, and highlights the need for more accurate and robust trajectory estimation techniques to support fine-grained analysis in future work.

Annotation Process Our annotations rely on trained human experts manually labeling each still image and video clip across seven cinematographic dimensions. While this ensures high semantic fidelity, it also introduces subjectivity and potential inconsistency across annotators. Even with detailed guidelines and cross-checking protocols, subtle distinctions—such as grading "medium" versus "close" shot scales or identifying nuanced lighting contrasts—can vary between annotators.

Table 5: Sub-category accuracy of various MLLMs on angle and lighting question answering understanding. The best and second best results are highlighted by blue and green respectively.

MLLMs	Params	Angle		Lighting		
		Vertical	Horizontal	Intensity	Quality	Direction
Commercial						
GLM-4V-Plus [15]	–	67.42	74.19	71.88	58.70	37.50
Qwen-VL-Plus	–	74.16	70.97	65.62	78.26	50.00
Gemini-2.0-Flash	–	76.40	67.74	93.75	71.74	46.88
Gemini-2.5-Pro	–	82.03	87.10	71.88	65.22	50.00
Doubao-1.5-vision-pro	–	67.42	70.97	84.38	58.70	37.50
GPT-4o [34]	–	83.15	80.65	90.62	69.57	53.12
Open-source						
Kimi-VL [45]	3B	60.67	79.97	62.50	58.70	43.75
Phi3.5 [47]	4B	51.69	41.94	62.50	65.22	37.50
Gemma3-it [44]	4B	41.57	54.84	53.12	63.04	37.50
Qwen2.5-VL [2]	7B	57.30	74.19	65.62	76.09	40.62
Qwen2.5-Omni [55]	7B	64.04	70.97	59.38	52.17	34.38
LLaVA-OneVision [25]	7B	53.93	54.84	81.25	52.17	31.25
LLaVA-NeXT [24]	8B	37.08	58.06	65.62	50.00	15.62
MinCPM-V-2.6 [56]	8B	58.43	54.84	75.00	50.00	28.12
InternVL2.5 [8]	8B	59.55	74.19	78.12	47.83	34.38
InternVL3 [72]	8B	64.04	74.19	68.75	56.52	46.88
Llama-3.2-Vision [46]	11B	43.82	61.29	53.12	47.83	34.38

Table 6: CAPability performance of different MLLMs' on seven dimensions of cinematographic technique description generation.

	Metrics	GLM-4V-Plus	Qwen-VL-Plus	Doubao-v1.5-vision-pro	GPT-4o	Gemini-2.0-Flash	Gemini-2.5-Pro	Kimi-VL	Phi3.5	gemma3-it	Qwen2.5-VL	Qwen2.5-Omni	LLaVA-OneVision	LLaVA-NeXT	LLaVA-NeXT-Video	MinCPM-V-2.6	InternVL2.5	InternVL3	Llama-3.2
AG	HR	85.37	73.17	67.44	82.05	55.81	59.52	97.62	67.50	100.00	90.48	92.68	85.71	90.00	N/A	83.33	95.24	93.02	87.50
	AP	60.00	60.00	62.07	71.88	70.83	88.00	56.10	66.67	60.47	47.37	52.63	52.78	47.22	N/A	51.43	47.50	65.00	54.29
	AR	51.22	43.90	41.86	58.97	39.53	52.38	54.76	45.00	60.47	42.86	48.78	45.24	42.50	N/A	42.86	45.24	60.47	47.50
	F1	55.26	50.70	50.00	64.79	50.75	65.67	55.42	53.73	60.47	45.00	50.63	48.72	44.74	N/A	46.75	46.34	62.65	50.67
SC	HR	94.95	90.91	100.00	90.91	100.00	100.00	90.91	78.79	96.97	98.99	96.97	86.87	85.57	N/A	62.63	96.97	98.99	93.94
	AP	45.74	41.11	44.44	45.56	42.42	38.38	53.33	34.62	34.38	42.86	42.71	40.70	45.78	N/A	41.94	43.75	45.92	39.78
	AR	43.43	37.37	44.44	41.41	42.42	38.38	48.48	27.27	33.33	42.42	41.41	35.35	39.17	N/A	26.26	42.42	45.45	37.37
	F1	44.56	39.15	44.44	43.39	42.42	38.38	50.79	30.51	33.85	42.64	42.05	37.84	42.22	N/A	32.30	43.08	45.69	38.54
CL	HR	97.83	100.00	100.00	100.00	100.00	97.87	100.00	97.83	97.96	100.00	95.35	100.00	93.88	N/A	97.96	100.00	100.00	100.00
	AP	55.56	47.83	43.18	72.00	52.17	50.00	55.32	42.22	39.58	60.00	51.22	50.00	52.17	N/A	39.58	53.19	63.04	47.73
	AR	54.35	47.83	43.18	72.00	52.17	48.94	55.32	41.30	38.78	60.00	48.84	50.00	48.98	N/A	38.78	53.19	63.04	47.73
	F1	54.95	47.83	43.18	72.00	52.17	49.46	55.32	41.76	39.17	60.00	50.00	50.00	50.53	N/A	39.17	53.19	63.04	47.73
CP	HR	100.00	100.00	100.00	100.00	100.00	100.00	100.00	97.67	100.00	100.00	97.75	100.00	98.86	N/A	100.00	100.00	100.00	100.00
	AP	32.58	31.46	32.58	33.71	30.34	46.07	32.58	32.14	23.60	29.21	22.99	32.95	32.18	N/A	32.18	35.95	40.45	15.91
	AR	32.58	31.46	32.58	33.71	30.34	46.07	32.58	31.39	23.60	29.21	22.47	32.95	31.82	N/A	32.18	35.95	40.45	15.91
	F1	32.58	31.46	32.58	33.71	30.34	46.07	32.58	31.77	23.60	29.21	22.73	32.95	32.00	N/A	32.18	35.95	40.45	15.91
LT	HR	85.53	92.11	89.47	98.68	92.11	94.74	96.05	90.67	90.79	94.67	89.33	93.42	94.74	N/A	94.74	94.74	96.05	97.33
	AP	40.00	34.29	42.65	44.00	32.86	38.89	42.47	32.35	30.43	46.48	34.33	35.21	25.00	N/A	34.72	45.83	45.20	41.10
	AR	34.21	31.58	38.16	43.42	30.26	36.84	40.79	29.33	27.63	44.00	30.67	32.90	23.68	N/A	32.90	43.42	43.42	40.00
	F1	36.88	32.88	40.28	43.71	31.51	37.84	41.61	30.77	28.97	45.20	32.39	34.01	24.32	N/A	33.78	44.59	44.30	40.54
FL	HR	100.00	72.22	100.00	97.22	100.00	100.00	94.12	84.93	100.00	98.61	92.65	86.77	90.14	N/A	82.09	92.75	100.00	97.02
	AP	48.57	36.54	52.78	40.00	50.69	60.27	42.19	38.71	41.10	56.34	44.44	38.98	34.38	N/A	32.73	43.75	52.94	63.08
	AR	48.57	26.39	52.78	38.89	50.69	60.27	39.71	32.88	41.10	55.56	41.18	33.82	30.99	N/A	26.87	40.58	52.94	61.19
	F1	48.57	30.64	52.78	39.44	50.69	60.27	40.91	35.56	41.10	55.94	42.75	36.22	32.59	N/A	29.51	42.10	52.94	62.12
CM	HR	27.34	40.62	23.44	34.38	50.00	69.53	N/A	11.72	38.28	24.22	36.72	16.41	16.54	35.16	18.75	20.31	20.31	23.44
	AP	68.57	86.54	93.33	90.91	79.69	83.15	N/A	73.33	83.67	83.87	72.34	76.19	80.95	77.78	87.50	88.46	76.92	56.67
	AR	18.75	35.16	21.88	31.25	39.84	57.81	N/A	8.59	32.03	20.31	26.56	12.50	13.39	27.34	16.41	17.97	15.62	13.28
	F1	29.45	50.00	35.44	46.51	53.12	68.20	N/A	15.38	46.33	32.70	38.86	21.48	22.97	40.46	27.63	29.87	25.97	21.52

Moreover, the intensive manual effort limits the overall scale of our dataset, constraining diversity in film styles, genres and time periods. Future work should explore semi-automated annotation pipelines, active learning, or consensus-driven schemes to improve diversity and scalability.

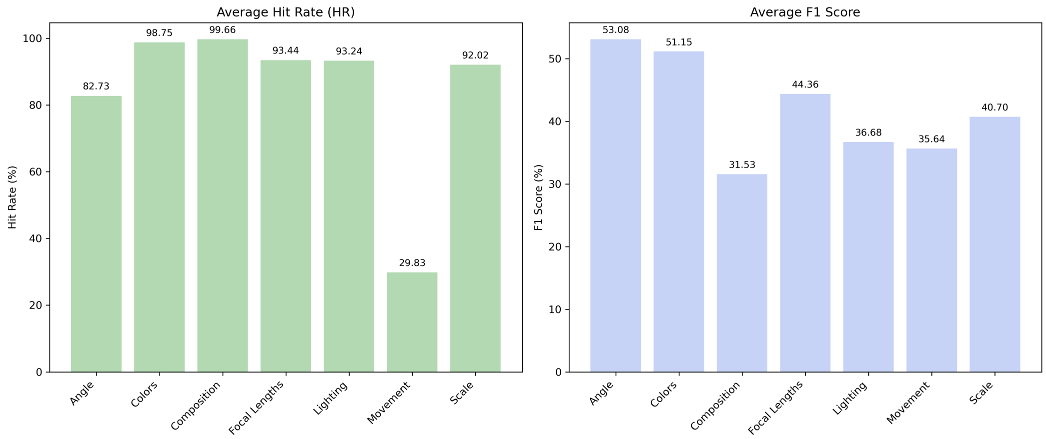

Figure 12: Average hit rate (HR) and F1 score of all MLLMs on seven dimensions of cinematographic technique description generation task.

Connection with Plots While our ultimate motivation is to enable the understanding of visual storytelling, the core contribution of CineTechBench is to provide models with the foundational capability to identify cinematic techniques and analyze their general atmospheric impact. We recognize that our current annotations do not forge the deeper connection between a technique and its specific plot or symbolic meaning, which we frame as an important area for future research.

G Visualization

G.1 Visualization of Cinematographic Technique Understanding

Figure 13 shows more visualization of the answers for the image question-answering task across all dimensions. Through these visualized cases, it is evident that color is the easiest dimension for models to recognize, achieving consistently high accuracy across all models. This result suggests that color information, being a highly distinctive and easily discernible visual feature, is effectively captured and processed by both commercial and open-source MLLMs. In contrast, focal length emerges as the most challenging dimension, where models struggle to achieve high accuracy. This difficulty likely arises from the subtle and complex visual cues associated with focal length, such as depth of field and background blur, which are less visually obvious than color differences. Among all evaluated models, GPT-4o and Gemini-2.5-Pro consistently outperform all other commercial and open-source models across most dimensions, maintaining a significant lead in accuracy. Despite a noticeable performance gap between commercial and open-source models, several open-source models, such as InternVL3 and Qwen2.5-Omini demonstrate impressive results. These models highlighting the potential of open-source MLLMs to close the performance gap with their commercial counterparts.

Also, more visualization of MLLM's answers on video question answering task and descriptions on image and video description generation task are shown in Figure 14. Through these visualized cases, it is evident that the video-based question-answering (QA) task is inherently more complex and challenging compared to the image-based QA task. This increased difficulty can be attributed to the dynamic nature of video content, where temporal information, motion, and scene transitions introduce additional layers of complexity that models must effectively process. Moreover, when comparing QA tasks to description generation tasks, the latter proves to be even more challenging. Generating accurate and comprehensive descriptions of cinematographic techniques in images or videos requires not only recognizing visual elements but also understanding their spatial and temporal relationships. Even models that perform well in perceptual tasks often struggle to generate precise and complete descriptions of cinematographic techniques. This difficulty is particularly pronounced in the context of cinematography, where subtle differences in angle, lighting, and composition can drastically alter the interpretation of a scene. As a result, achieving accurate and contextually appropriate description generation remains a significant challenge, even for models that demonstrate strong performance in other perception-based tasks.

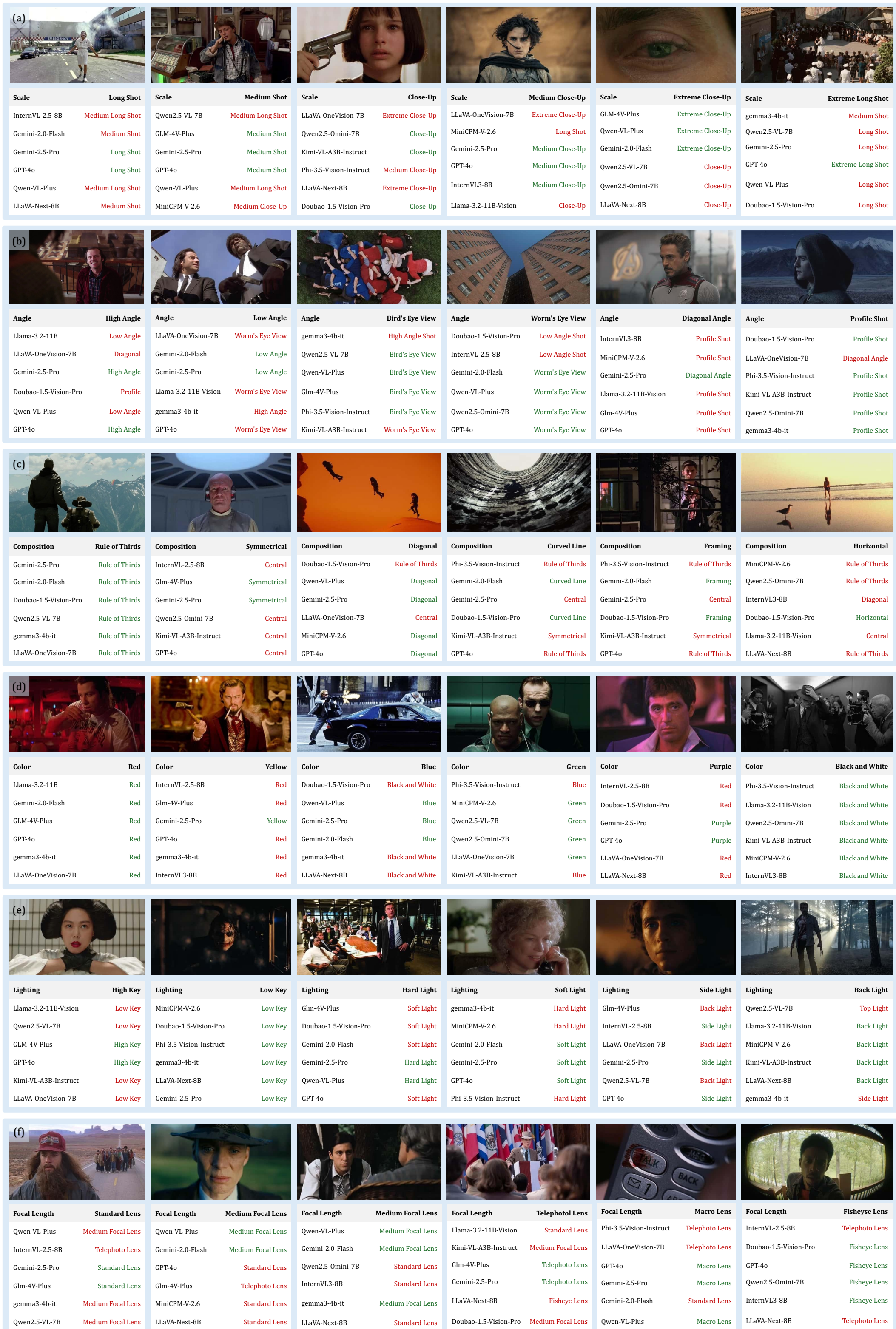

Figure 13: Visualization of MLLMs' answers on image cinematographic technique question answering task. The red text highlights the wrong answers and the green text highlights the correct answers.

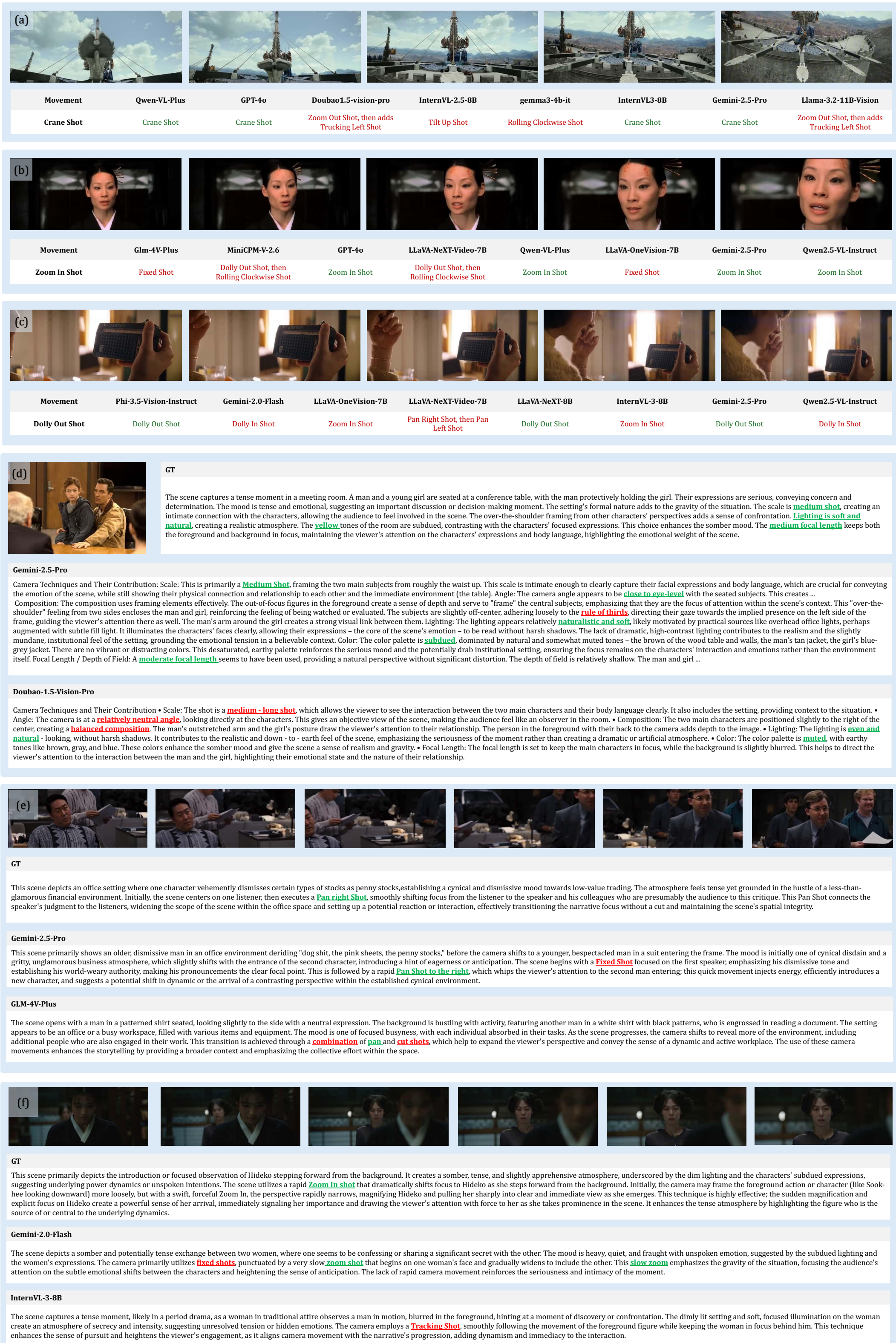

Figure 14: Visualization of MLLMs' answers on video question-answering task and generated descriptions on image and video description task. The red text highlights the wrong answers and the green text highlights the correct answers.

G.2 Visualization of Camera Movement Generation

As shown in Figure 15. The video generation models have a relatively good performance on simple camera movement, e.g., example (a) and a relatively bad performance on camera rotation, e.g., example (c), Gen4turbo and Wan2.1 didn't show qualified rotation sense.

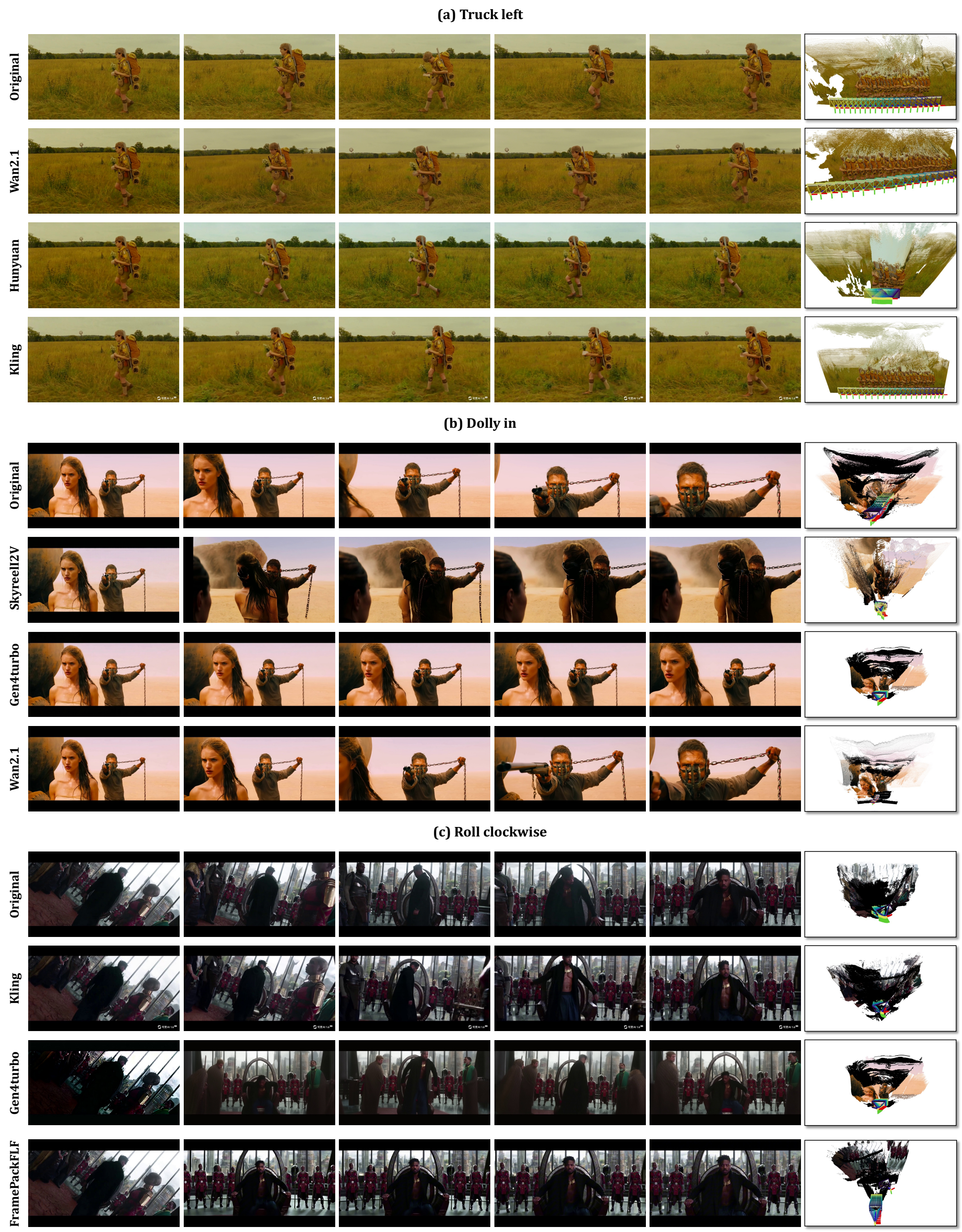

Figure 15: Generated movie clips by different video generation models and the corresponding camera trajectory estimated by Monst3r [61].

H Copyright

We fully respect the copyright of all films and do not use any clips for commercial purposes. Instead of distributing or hosting video content, we only provide links to publicly available, authorized sources (e.g., official studio or distributor channels). This approach ensures that we neither infringe on copyright nor redistribute protected materials. All assets are credited to their original rights holders, and our use of these links falls under fair-use provisions for non-commercial, academic research. Accordingly, all textual assets created for this benchmark, including our annotations, are distributed under the Creative Commons Attribution Non Commercial No Derivatives 4.0 International (CC-BY-NC-ND-4.0 `https://spdx.org/licenses/CC-BY-NC-ND-4.0`) license.

I Taxonomy Definition

In this section, we show each category definition of each dimension in our taxonomy. In detail, we show definition of categories in each dimension in Table 7, and there is an illustration for categories in shot scale and angle in Figure 8.

Table 7: Definition of categories in seven dimensions.

Scale Category	**Definition**
Extreme Close-Up	An extreme close-up (ECU) is a shot that captures a subject in an extremely tight frame, focusing on a specific detail of the subject, such as an eye, a mouth, a ring, or a handwritten letter. This shot excludes most of the surrounding context, drawing the viewer's attention exclusively to the minute details of the subject.
Close-Up	A close-up (CU) is a shot that frames the subject's face, head, or a significant object, filling the screen with detailed visual information. For human subjects, a Close-Up typically shows the head and shoulders, allowing the audience to focus on facial expressions and emotions.
Medium Close-Up	A medium close-up (MCU) is a shot that frames a subject from the chest up, providing a balance between the subject's facial details and body language. This shot maintains the emotional focus of the Close-Up while also including some contextual information.
Medium Shot	A medium shot (MS) frames the subject from the waist up, providing a clear view of both facial expressions and body language. It is a versatile shot that strikes a balance between subject focus and contextual surroundings.
Medium Long Shot	A medium long shot (MLS), also known as a "three-quarters shot", frames the subject from the knees up, providing a broader view of the subject within the setting. It is often used to maintain a sense of the subject's body language while still focusing on the individual.
Long Shot	A long shot (LS) is a wide framing that captures the entire subject from head to toe, along with a significant portion of the surrounding environment. The subject is visible but occupies a relatively smaller portion of the frame.
Extreme Long Shot	An extreme long shot (ELS), also known as a wide shot (WS) or establishing shot, captures a vast expanse of the setting, with the subject appearing very small or even insignificant within the environment. This shot may cover vast landscapes, cityscapes, or wide action scenes.
Angle Category	**Definition**
High Angle	A high angle shot is captured with the camera positioned above the subject, angled downward. This perspective often makes the subject appear smaller, weaker, or vulnerable, depending on the narrative context.
Low Angle Shot	A low angle shot is captured with the camera positioned below the subject, angled upward. This perspective makes the subject appear larger, more dominant, or intimidating.
Bird's Eye View	A bird's eye view (or overhead shot) is an extremely high angle shot taken directly above the subject, providing a top-down perspective. This view emphasizes spatial layout and geometric patterns within the scene.
Worm's Eye View	A worm's eye view is an extreme low-angle shot taken from below the subject, almost directly upwards. This perspective can make subjects appear overwhelmingly large or powerful, or it can capture towering structures from ground level.
Diagonal Angle	A diagonal angle, is a camera angle that captures the subject from a non-frontal or backside, non-profile perspective. The camera is positioned at an intermediate angle between the subject's side and front or back, typically ranging from approximately 30° to 60° off-axis. This versatile angle allows the viewer to perceive multiple dimensions of the subject simultaneously, offering a more dynamic and three-dimensional representation.
Profile Shot	A profile shot is captured with the camera positioned to the side of the subject, showing the subject's profile or side view. This framing emphasizes the subject's silhouette, facial contours, and gestures.

Continued on next page

Table 7 – continued from previous page

Category	Definition
Back Shot	A back shot is a camera angle taken from behind the subject, typically showing the subject's back or shoulders while they face away from the camera. This can also include over-the-shoulder shots.
Composition Category	**Definition**
Symmetrical	Symmetrical composition is a technique where elements within the frame are arranged in a balanced and mirror-like manner, creating a sense of harmony and equilibrium. This can be achieved through vertical, horizontal, or radial symmetry.
Central	Central composition is a technique where the main subject is positioned at the exact center of the frame, drawing immediate attention to it. This approach uses the inherent strength of central focus, often resulting in a powerful and direct visual impact.
Diagonal	Diagonal composition is a technique that uses diagonal lines or elements within the frame to guide the viewer's eye and create a sense of movement, depth, and dynamism. These diagonal lines can be naturally present in the scene (such as a leaning tree) or can be intentionally created by tilting the camera (known as a dutch angle). This approach allows for a dramatic and visually engaging effect.
Rule of Thirds	The rule of thirds is a guideline that divides the frame into nine equal sections with two horizontal and two vertical lines. The main subjects are placed along these lines or at their intersections, creating a balanced and naturally pleasing composition.
Framing	Framing is a technique where elements within the scene are used to naturally frame the subject, directing the viewer's focus towards it. These framing elements can include natural objects (such as trees), architectural elements (such as windows), or other elements within the environment.
Curved Line	Curved line composition uses naturally occurring or deliberately arranged curved lines within the frame to guide the viewer's eye, create a sense of flow, or emphasize the softness of the scene. These lines can be literal (such as a winding road) or implied (such as a subject's pose).
Horizontal	Horizontal Composition is a technique where the main visual elements are arranged along a horizontal axis, emphasizing width and creating a sense of stability. This can be achieved using the horizon line, landscapes, or other horizontally aligned subjects.
Colors Category	**Definition**
Red	Red is a warm, highly intense color often associated with strong emotions, including passion, love, anger, danger, and urgency. In cinematography, it is used to draw attention, create tension, or symbolize strong emotional states.
Yellow	Yellow is a bright, warm color that is often associated with happiness, optimism, energy, and warmth. However, it can also represent caution, anxiety, or deceit, depending on the context.
Blue	Blue is a cool, calming color commonly associated with tranquility, stability, melancholy, and introspection. It is widely used to convey a sense of calmness, sadness, or detachment.
Green	Green is a color often associated with nature, growth, freshness, and harmony. However, in certain contexts, it can also represent envy, corruption, or toxicity.
Purple	Purple is a color traditionally associated with royalty, luxury, mystery, and spirituality. It is a color that can evoke both sophistication and fantasy, depending on the context.
Black and White	Black and white is a monochrome color scheme that removes all hues, focusing on contrasts between light and dark. This style emphasizes texture, composition, lighting, and shadow, often creating a timeless, dramatic, or nostalgic aesthetic.
Lighting Category	**Definition**
High Key	High key lighting is a technique characterized by bright, even illumination with minimal shadows and a high level of ambient light. This style is achieved using multiple light sources or a large, soft light source to reduce contrast.
Low Key	Low key lighting is a dramatic lighting technique that emphasizes strong contrast between light and dark areas, with deep shadows and minimal fill light. It is achieved using a primary light source with little to no fill light.
Hard Light	Hard light is a type of lighting that produces sharp, well-defined shadows and high contrast between illuminated and dark areas. It is created using a small, direct light source such as a spotlight or bare bulb.
Soft Light	Soft light is a technique that produces diffused, gentle illumination with gradual transitions between light and shadow. This effect is achieved using large light sources, diffusion panels, softboxes, or indirect lighting.
Back Light	Back light is a technique where the light source is positioned behind the subject, often creating a rim or halo effect around the subject's outline. This light separates the subject from the background and adds depth to the scene.
Side Light	Side light is a technique where the light source is placed at a 90-degree angle to the subject, illuminating one side while leaving the other side in shadow. This creates a strong contrast between light and darkness.

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Category	Definition
Top Light	Top light is a technique where the light source is placed directly above the subject, casting shadows downward. This creates dramatic shadows on the subject's face and emphasizes the upper contours.
Focal Length Category	**Definition**
Standard Lens	A standard lens, also known as a Normal Lens, is a lens with a focal length that closely matches the human eye's natural field of view. In most cases, this ranges between 35mm to 50mm for full-frame cameras. Standard lenses provide a balanced perspective without significant distortion, making them highly versatile for various types of scenes.
Medium Focal Length	Medium focal length refers to lenses with a focal length slightly longer than standard lenses, typically between 50mm and 85mm for full-frame cameras. These lenses offer moderate compression and a slightly narrowed field of view, making subjects appear closer without the extreme effects of telephoto lenses.
Telephoto Lens	A telephoto lens is a long-focus lens with a focal length greater than 85mm, typically ranging from 85mm to 300mm or beyond for full-frame cameras. These lenses provide a narrow field of view and significant background compression, making distant subjects appear closer.
Fisheye Lens	A fisheye lens is an ultra-wide-angle lens with a focal length typically between 8mm and 16mm, designed to capture an extremely wide field of view, often with a 180° angle. It creates a distinctive curved, distorted image, which can be either circular (full-frame fisheye) or rectangular (rectilinear fisheye).
Macro Lens	A macro lens is a specialized lens designed for extreme close-up photography, capable of achieving a high level of magnification (typically 1:1 or greater). These lenses have a short minimum focusing distance, allowing detailed capture of small subjects.
Movement Category	**Definition**
Fixed Shot	A fixed shot is a static camera setup where the camera remains completely stationary throughout the shot. There is no movement in any direction (pan, tilt, or zoom). The composition and perspective are determined solely by the subject's movement within the frame.
Dolly In Shot	A dolly in shot is achieved by moving the camera towards the subject on a dolly track, creating a sense of gradual approach, increasing subject emphasis, or building tension.
Dolly Out Shot	A dolly out shot is achieved by moving the camera away from the subject on a dolly track, expanding the field of view, creating a sense of distancing, revelation, or release.
Crane Shot	A crane shot is a type of camera movement where the camera is mounted on a crane, allowing it to move vertically, horizontally, or in complex patterns across a scene. This technique provides sweeping, cinematic perspectives.
Trucking Left Shot	A trucking left shot is a lateral camera movement to the left, maintaining a consistent perspective of the subject. This is often used to follow a subject moving horizontally.
Trucking Right Shot	A trucking right shot is a lateral camera movement to the right, maintaining a consistent perspective of the subject. This is also used for tracking horizontal movement.
Pan Left Shot	A pan left shot is achieved by rotating the camera horizontally to the left from a fixed position, allowing a gradual reveal of the scene from right to left.
Pan Right Shot	A pan right shot is achieved by rotating the camera horizontally to the right from a fixed position, allowing a gradual reveal of the scene from left to right.
Tilt Up Shot	A tilt up shot is a vertical camera movement where the camera tilts upward from a fixed position, gradually revealing the upper part of the scene or subject.
Tilt Down Shot	A tilt down shot is a vertical camera movement where the camera tilts downward from a fixed position, gradually revealing the lower part of the scene or subject.
Rolling Clockwise Shot	A rolling clockwise shot is a dynamic camera movement where the camera rotates around its lens axis in a clockwise direction, creating a spiraling effect.
Rolling Counterclockwise Shot	A rolling counterclockwise shot is a dynamic camera movement where the camera rotates around its lens axis in a counterclockwise direction, creating an opposite spiraling effect.
Tracking Shot	A tracking shot is a camera movement that follows a subject along a path, maintaining consistent framing. It can be achieved using a handheld setup.
Zoom In Shot	A zoom in shot is an optical camera technique where the focal length of the lens is adjusted to bring the subject closer without moving the camera physically. This effect magnifies the subject within the frame.
Zoom Out Shot	A zoom out shot is an optical camera technique where the focal length of the lens is adjusted to increase the field of view, making the subject appear smaller within the frame.
Combinational Shot	A combinational shot, is a complex camera movement technique that combines two or more distinct camera movements within a single continuous take. This may include any combination of Dolly, Trucking, Pan, Tilt, Zoom, Crane, Rolling, or Tracking movements executed in sequence or simultaneously.