FILMAGENT: AUTOMATING VIRTUAL FILM PRODUCTION VIA MULTI-AGENT COLLABORATION

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ABSTRACT

Virtual film production requires intricate decision-making processes, including scriptwriting, virtual cinematography, and precise actor positioning and actions. Remarkable progress in automated decision-making have utilized agent societies powered by large language models (LLMs). This paper introduces FilmAgent, a novel LLM-based multi-agent collaborative framework designed to automate and streamline the film production process. FilmAgent simulates key crew roles—directors, screenwriters, actors, and cinematographers, and integrates efficient human workflows within a sandbox environment. The process is divided into three stages: planning, scriptwriting, and cinematography. Each stage engages a team of film crews providing iterative feedback, thus verifying intermediate results and reducing errors. Our evaluation of generated videos shows that the collaborative FilmAgent significantly outperforms individual efforts in line consistency, script coherence, character actions, and camera settings. Further analysis highlights the importance of feedback and verification in reducing hallucinations, enhancing script quality, and improving camera choices. We also explore the strengths and limitations of FilmAgent and suggest directions for future research on integrating LLMs into creative multimedia tasks. For more information, including open-source Unity environment, codes and videos, please visit our main project page at `https://filmagent.github.io/`.

1 INTRODUCTION

Virtual film production entails a methodical and disciplined approach to the directing, camera placement and actor positioning (He et al., 2023). Recent advancements in deep learning have started to revolutionize film production practices, where sophisticated neural networks enable the movement of virtual cameras through 3D environments (Jiang et al., 2020). However, films are not only about moving pictures; they are crafted through language. They are produced through the dialogues spoken by the characters, the screenplays that outline the story, the shooting scripts that instruct the cinematographers, and, undeniably, the guidance given by directors (Jiang et al., 2024). Therefore, filmmaking is fundamentally a communication-driven collaborative task, motivating our design of a multi-agent system based on large language models (LLMs).

In recent years, LLMs have shown remarkable proficiency in language understanding, instruction following, reasoning and planning (Bubeck et al., 2023). By harnessing the capabilities of LLMs, autonomous agents can make more nuanced decisions and execute actions with an unprecedented degree of autonomy (Chen et al., 2024; Xi et al., 2023). However, solving complex real-world tasks often requires cooperation among individuals to achieve better effectiveness (Guo et al., 2024). For example, both ChatDev (Qian et al., 2023) and MetaGPT (Hong et al., 2024) have implemented a multi-agent collaborative scheme throughout the software development process, simulating key stages such as requirement design, coding and testing. Collaborative efforts among multiple agents can accomplish more complex tasks than a single agent can, leading to enhanced performance in reasoning and factuality (Du et al., 2023; Xu et al., 2023; Zhang et al., 2024), demonstrating the emergence of collective intelligence.

Inspired by these developments, we propose **FilmAgent**, the first LLM-based multi-agent collaborative framework designed to automate virtual film production. In this framework, LLM-based agents

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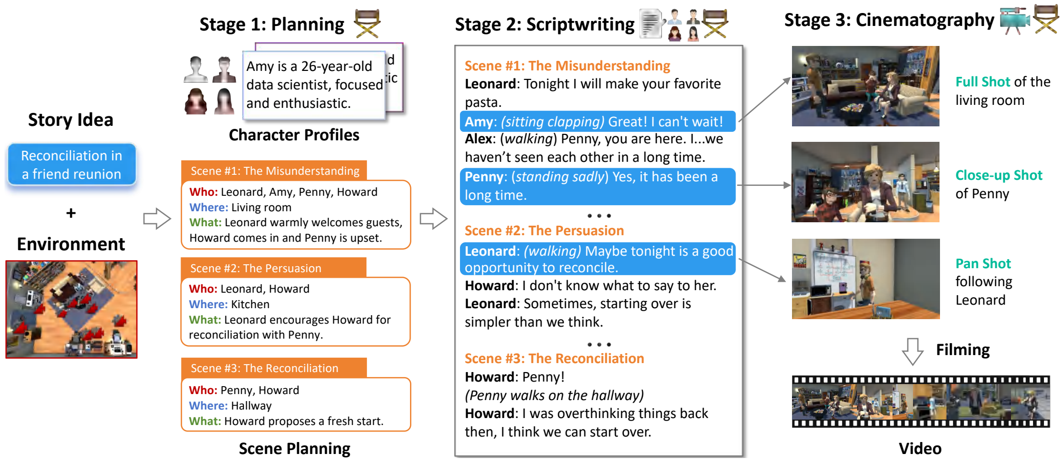


Figure 1: **The workflow of FilmAgent, our LLM-based multi-agent collaborative framework for virtual film production.** Given a 3D environment and a story idea, the director first creates potential character profiles, and converts the idea into a scene outline. Next, actors, the screenwriter and the director collaborate to develop the dialogue and choreograph movements. Cinematographers then annotate the camera setups for each line. Finally, the film is shot within our meticulously designed 3D environment.

fulfill various film crew roles, including director, screenwriter, actor, and cinematographer, to collectively create a film. As shown in Figure 1, the collaborative method emulates the human workflow and divides the process into three sequential stages: planning, scriptwriting, and cinematography. In the planning stage, given a brief story idea, the director develops character profiles and expands the idea into a detailed scene outline, specifying the where, what, and who of each segment. During scriptwriting, the director, screenwriter, and actors collaborate on dialogue development and choreograph movements. In the cinematography stage, the cinematographers and director work together to design camera setups for each line, selecting between static and dynamic shots to effectively convey the narrative visually. Finally, once the script is fully annotated, the film is shot within our meticulously constructed 3D environment. This virtual environment includes 15 locations, 21 actor actions depicting expressive gestures and emotions, 65 designated actor positions, 272 shots covering 9 types of static and dynamic shots, and speech audio generation. In addition, we propose two multi-agent collaboration algorithms, *Critique-Correct-Verify* and *Debate-Judge*, applied in scriptwriting and cinematography stages respectively, to refine the script and camera settings.

Comprehensive human evaluations of the generated videos validate the effectiveness of our framework. The results show that the collaborative FilmAgent significantly outperforms single-agent efforts across four aspects: plot coherence, alignment between dialogue and actor profiles, appropriateness of camera setting, and accuracy of actor actions. Further preference analysis underscores the importance of feedback and verification in correcting hallucinations, enhancing plot coherence and improving camera choices. This project lays the groundwork for automated virtual film production, showing the potential of collaborative AI agents in this creative domain.

In summary, our main contributions are as follows:

- We present FilmAgent, a novel LLM-based multi-agent collaborative framework for automating virtual film production, which mirrors the traditional film set process within a meticulously crafted 3D environment.
- We incorporate two collaboration strategies within the workflow, which substantially reduces hallucinations and enhances the quality of scripts and camera settings.
- Extensive human evaluations validate the effectiveness of FilmAgent, indicating LLM-based multi-agent collaboration as a promising avenue for automating film production.

2 RELATED WORK

2.1 VIRTUAL PRODUCTION

Virtual production is defined as "a broad term referring to a spectrum of computer-aided production and visualization filmmaking methods" (Bodini et al., 2024). This method supports remote collaboration and enhances accessibility due to its virtual nature (Nebeling et al., 2021). It has gained substantial attention in the film and entertainment industry, following its prominent use in *The Mandalorian* television series (Kavakli & Cremona, 2022). Recently, game engines are revolutionizing filmmaking with Virtual Camera Plugin, which allows real-time rendering of simulated environments. This enables filmmakers to play around in a virtual environment before shooting, potentially replacing traditional pre-visualization methods like storyboards (Legato & Deschanel, 2019).

Deep learning-based virtual production. Virtual film production covers a wide spectrum of problems, from narrative aspects (de Lima et al., 2009), camera control (Li & Cheng, 2008; Christie et al., 2008) and even cutting and editing problems (Leake et al., 2017). In recent years, the field has embraced deep neural networks due to their remarkable generalization ability. When applying cinematography in computer graphics environments, Jiang et al. (2020) combine the Toric coordinate system (Lino & Christie, 2015) with a Mixture-of-Experts model to generate styled camera motions based on different video references. Jiang et al. (2021) further introduce keyframing for finer control of camera motions with an LSTM-based backbone. In this work, based on the understanding that filmmaking is a communication-driven collaborative process (Jiang et al., 2024), we design a multi-agent system that uses large language models (LLMs) to enhance this collaboration.

Preliminary exploration with LLMs. Recent works in virtual production have begun to utilize the emergent reasoning and planning capabilities of LLMs (Wei et al., 2022). Qing et al. (2023) address the Story-to-Motion task, which requires characters to navigate to locations and perform specific actions based on textual descriptions. Here, LLMs are utilized as text-driven motion schedulers, extracting sequences of (text, position, duration) tuples from long text. VideoDirectorGPT (Lin et al., 2023) employs LLMs to plan videos, generating detailed scene descriptions, along with the positioning and layout of entities, for consistent multi-scene video production. Anim-Director (Li et al., 2024) leverages the understanding, reasoning, and verification capabilities of LLMs to produce long animated videos, allowing LLMs to interact with external generative tools deeply. In our work, we expand the use of LLMs to cover all aspects of virtual production, fully automating tasks from plot planning to cinematography within a simulated 3D environment.

2.2 MULTI-AGENT FRAMEWORK

Recently, LLM-based autonomous agents have gained tremendous interest in both industry and academia (Wang et al., 2024). AutoGPT (Significant Gravitas, 2023), Voyager (Wang et al., 2023) and AppAgent (Zhang et al., 2023) are typical task-oriented agents that can autonomously interacts with the environment and solve simple tasks. However, they struggle to achieve effective, coherent, and accurate problem-solving processes, particularly when there is a need for meaningful collaborative interaction (Zhuge et al., 2023; Qian et al., 2023).

In the transition from single-agent frameworks into multi-agent frameworks, the pioneering research on Generative Agents (Park et al., 2023) has laid the groundwork for the development of "Simulated Society". These societies are conceptualized as dynamic systems where multiple agents engage in intricate interactions within a well-defined environment (Xi et al., 2023). This approach aligns with the Society of Mind (SoM) theory (Minsky, 1988), which suggests that intelligence arises from the interaction of computational modules, achieving collective goals beyond the capabilities of individual modules. To this end, many works (Xu et al., 2023; Zhang et al., 2024; Cohen et al., 2023) have improved reasoning and factuality of LLMs by integrating discussions among multiple agents. Furthermore, both ChatDev (Qian et al., 2023) and MetaGPT (Hong et al., 2024) have successfully implemented multi-agent collaborative schemes throughout the software development process, simulating standard practices such as requirement design, coding and testing. Motivated by the promising outcomes of multi-agent collaboration, we have developed a multi-agent system called FilmAgent to replicate human workflows and automate the virtual production process.

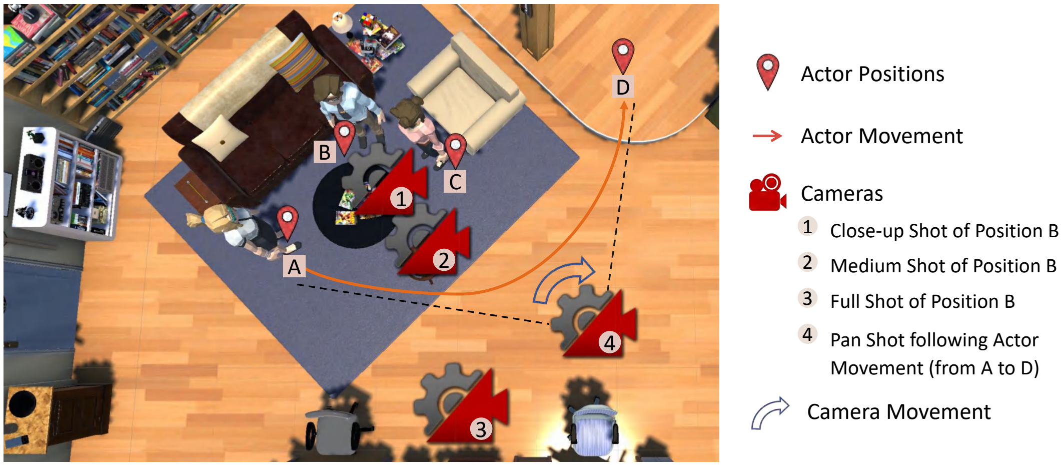


Figure 2: **A vertical view of one of the 3D environments (the living room)** in FilmAgent built with Unity. The environment is pre-configured with designated positions for actors and various camera setups for cinematography. These include static shots from multiple distances and dynamic shots that either follow or orbit around characters.

3 FilmAgent

FilmAgent is an LLM-based multi-agent framework for automated virtual film production in a sandbox environment. The basic process is illustrated in Figure 1. An introduction of our constructed 3D environment for filmmaking is in Sec. 3.1. We describe the overview of FilmAgent in Sec. 3.2, the core collaboration strategies in Sec. 3.3, and the production workflow in Sec. 3.4.

3.1 Environment Setup

We have meticulously built a 3D environment ready for filmmaking. This Unity environment includes 15 locations that reflect everyday settings, such as living rooms, kitchens, offices and roadside, thus providing versatile backdrops for a wide range of narratives. A screenshot of the living room is presented in Figure 2. Each scene is pre-configured with actor positions and camera setups. All locations are listed in Figure 6 in Appendix.

Positions. The environment includes 32 standing points and 33 sitting points, each accompanied by a human-written description indicating its location. For example, Position B in Figure 2 is described as "near the sofa, sittable, between Positions A and C, allowing easy communication with characters at these positions".

Actions. Each character can perform 21 different actions, selected from Mixamo[1]. These actions range from basic movements like sitting down and walking to more expressive gestures, such as joyful jumping and annoyed head-shaking. All actions are listed in Appendix A.

Cameras. Following the principles of the "language of film" (Wohl, 2004), we define 9 types of shots, including 3 static shots from various distances (e.g., close-up, medium, and long shots as shown by Camera 1-3 in Figure 2) and 6 dynamic shots that track or orbit around a character (e.g., pan shot represented by Camera 4 in Figure 2, zoom shot, arc shot, etc..) In total, the environment contains 165 static shots and 107 dynamic shots. The examples of different camera settings are provided in Appendix A.

Audio. To create more natural and expressive audio, we utilize ChatTTS[2] to generate the speech for each line in the script. The duration of each camera shot and action in the video is synchronized with the length of the corresponding audio segment.

With these configurations in place, our 3D scenes can support automatic virtual film production.

[1] `https://www.mixamo.com/`
[2] `https://github.com/2noise/ChatTTS`

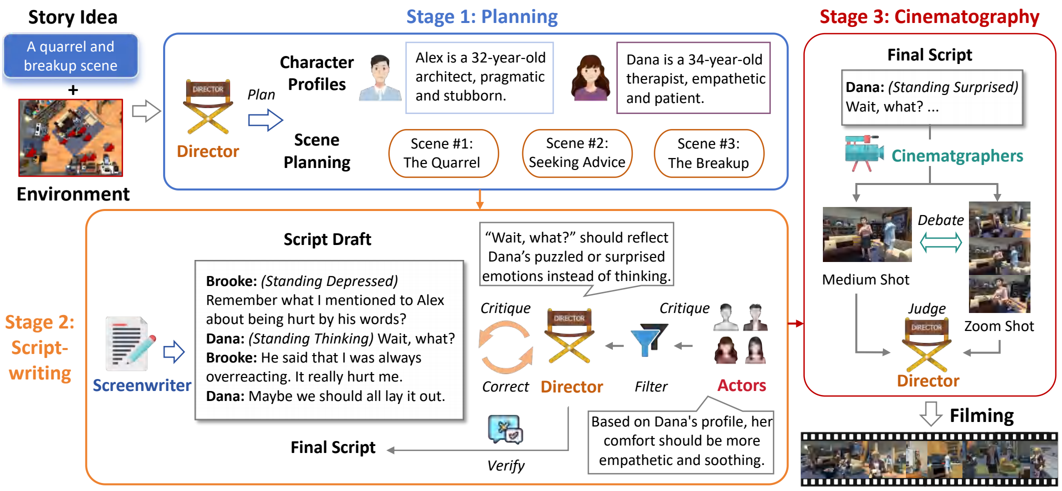


Figure 3: FilmAgent replicates the human workflow by completing the planning, scriptwriting, and cinematography stages sequentially. The process involves LLM-based agents fulfilling diverse film crew roles and collaborating through *Critique-Correct-Verify* and *Debate-Judge* strategies.

3.2 Overview

Clear role specialization allows for the breakdown of complex work into smaller and more specific tasks (Li et al., 2023; Hong et al., 2024). In our film studio FilmAgent, we define four main characters: **Director, Screenwriter, Actor** and **Cinematographer**, as shown in Figure 3. Each of these roles carries its own set of responsibilities.

The **Director** initiates and oversees the entire filmmaking project. This role includes setting character profiles, planning video outlines, providing feedback on the script, engaging in discussions with other crew members, and making final decisions when conflicts arise. The **Screenwriter** works closely under the Director's guidance. Its responsibilities go beyond writing dialogue; they also specify the positioning and actions for each line, and continuously update the script to ensure it is coherent, captivating, and well-structured, based on the Director's critiques. **Actors** are responsible for making minor adjustments to their lines based on their character profiles, ensuring the dialogue aligns with the characters, and communicating any necessary changes to the Director. **Cinematographers** select the camera settings for each line according to shot usage guidelines, collaborate with peer cinematographers to compare and discuss these choices, and ensure the appropriateness of camera settings.

3.3 Agent Collaboration Strategies

In this section, we introduce two collaboration strategies used in this work, including *Critique-Correct-Verify* (Algorithm 1) and *Debate-Judge* (Algorithm 2).

Critique-Correct-Verify Collaboration. As outlined in Algorithm 1, this strategy involves two agents working collaboratively. First, the *Action agent* $\mathbf{P}$ generates a response $\mathbf{R}$ based on the given context $\mathbf{C}$ and instruction $\mathbf{I}$. Next, the *Critique agent* $\mathbf{Q}$ reviews the response $\mathbf{R}$ and writes critiques $\mathbf{F}$ highlighting potential areas for improvement. The Action agent $\mathbf{P}$ then integrates the critiques and corrects the response. Finally, the *Critique agent* $\mathbf{Q}$ evaluates the updated response $\mathbf{R}$ to determine whether the critiques $\mathbf{F}$ have been adequately addressed or if further iterations are necessary.

Debate-Judge Collaboration involves multiple agents who propose their responses and then engage in a debate to persuade each other. A third-party agent ultimately summarizes the discussion and delivers the final judgment. We present the details of our collaboration strategy in Algorithm 2. During each iteration, two *peer agents* $\mathbf{P}$ and $\mathbf{Q}$ independently generate their responses and then critique each other's work. Based on the critiques received, each agent may revise their response or maintain the original. After several rounds of debate, the *Judgment agent* $\mathbf{J}$ concludes the discussion and makes the final decision $\mathbf{R}$.

Algorithm 1: Critique-Correct-Verify Collaboration

Input : Context $\mathbf{C}$; Instruction $\mathbf{I}$; Maximum number of iterations M; Action agent $\mathbf{P}$; Critique agent $\mathbf{Q}$;
Output: The final response $\mathbf{R}$ that is approved by the Critique agent $\mathbf{Q}$;
$\mathbf{H} \leftarrow [\mathbf{C}; \mathbf{I}]$ ▷ Initialize the conversation history;
$m \leftarrow 0$ ▷ Current round;
while $m \leq \mathrm{M}$ **do**
    $m \leftarrow m + 1$;
    $\mathbf{R} \leftarrow \mathbf{P}(\mathbf{H})$ ▷ Generate response;
    if $m > 1$ **then**
        $\mathbf{D} \leftarrow \mathbf{Q}(\mathbf{C}, \mathbf{I}, \mathbf{R}, \mathbf{F})$ ▷ The Critique agent $\mathbf{Q}$ verifies whether the response has addressed critiques;
        if $\mathbf{D} = \textit{TRUE}$ **then**
            Break ▷ Stop iterating if the Critique agent $\mathbf{Q}$ thinks the response is already of high quality;
    $\mathbf{F} \leftarrow \mathbf{Q}(\mathbf{H}, \mathbf{R})$ ▷ Generate critiques;
    $\mathbf{H} \leftarrow \mathbf{H} + [\mathbf{R}; \mathbf{F}]$ ▷ Append $\mathbf{R}$ and $\mathbf{F}$ to the conversation history $\mathbf{H}$;
Return the final response $\mathbf{R}$;

Algorithm 2: Debate-Judge Collaboration

Input : Context $\mathbf{C}$; Instruction $\mathbf{I}$; Number of iterations M; Peer agents $\mathbf{P}$, $\mathbf{Q}$; Judgment agent $\mathbf{J}$;
Output: The final judgment $\mathbf{R}$ that concludes the debate;
$\mathbf{H} \leftarrow [\mathbf{C}; \mathbf{I}]$ ▷ Initialize the conversation history;
$m \leftarrow 0$ ▷ Current round;
$\mathbf{R_P} \leftarrow \mathbf{P}(\mathbf{H})$
$\mathbf{R_Q} \leftarrow \mathbf{Q}(\mathbf{H})$ ▷ Agents $\mathbf{P}$ and $\mathbf{Q}$ generate responses;
while $m < \mathrm{M}$ **do**
    $m \leftarrow m + 1$;
    $\mathbf{F_P} \leftarrow \mathbf{Q}(\mathbf{C}, \mathbf{I}, \mathbf{R_P})$
    $\mathbf{F_Q} \leftarrow \mathbf{P}(\mathbf{C}, \mathbf{I}, \mathbf{R_Q})$ ▷ Agents $\mathbf{P}$ and $\mathbf{Q}$ exchange feedback;
    $\mathbf{H} \leftarrow \mathbf{H} + [\mathbf{R_P}; \mathbf{R_Q}; \mathbf{F_Q}; \mathbf{F_P}]$ ▷ Append responses and corresponding feedback to the conversation history $\mathbf{H}$;
    $\mathbf{R_P} \leftarrow \mathbf{P}(\mathbf{C}, \mathbf{I}, \mathbf{R_P}, \mathbf{F_P})$
    $\mathbf{R_Q} \leftarrow \mathbf{Q}(\mathbf{C}, \mathbf{I}, \mathbf{F_Q}, \mathbf{F_Q})$ ▷ Agents $\mathbf{P}$ and $\mathbf{Q}$ update their responses;
$\mathbf{R} \leftarrow \mathbf{J}(\mathbf{H} + [\mathbf{R_P}; \mathbf{R_Q}])$ ▷ Judgment agent $\mathbf{J}$ synthesizes the debate and formulates the final judgment;
Return the final judgment $\mathbf{R}$;

3.4 WORKFLOW

As shown in Figure 3, following the traditional film studio workflow, we divide the whole virtual film production process into three sequential stages: planning, scriptwriting and cinematography, and apply the collaboration strategies in Sec. 3.3.

Planning. From a brief story idea, the director generates various character profiles that could be relevant to the story. The profiles include key attributes such as gender, occupation, and personality traits. Using these profiles and a set of 15 predefined locations in our 3D environment, the director expands the initial story idea into a detailed scene outline, specifying the where, what, and who of each segment (as illustrated in Figure 1).

Scriptwriting involves three key roles: the screenwriter, the director and the actors. The scriptwriting stage can be divided into three parts: (1) *Initial Draft*: The screenwriter drafts the initial script, including character dialogue, positioning and actions. Positioning refers to assigning each character to specific positions (e.g., Position A-D in Figure 2). Actions are annotated from the action space for each line, as shown in Figure 4. (2) *Director-Screenwriter Discussion*: The director and screenwriter

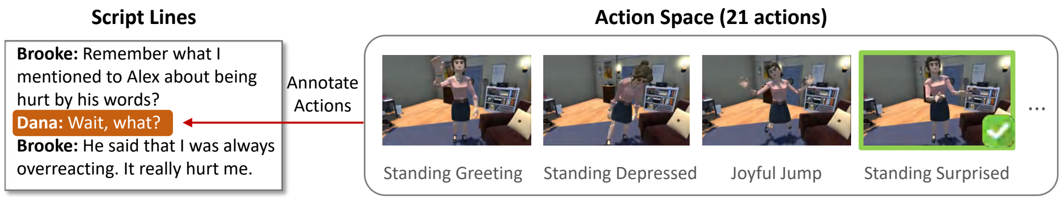


Figure 4: The screenwriter's responsibilities extend beyond writing dialogues; they also need to annotate the corresponding action for each line.

then engage in a *Critique-Correct-Verify* cycle. The director (the Critique agent Q) thoroughly reviews the script and provides critiques on the plot coherence and the appropriateness of character actions. Take Figure 3 as an example. the director identifies an inappropriate action and suggests a better one to convey the character's surprise. The screenwriter (the Action agent P) then revises the script based on the director's critiques. The director verifies the updated script to determine if further adjustments are needed. (3) *Actor-Director-Screenwriter Discussion*: Actors provide feedback based on their understanding of characters to ensure consistency between the script and character profiles. In the example in Figure 3, the actor Dana suggests a more empathetic tone to be align with her character profile. The director filters and aggregates this feedback, then, in collaboration with the screenwriter, employs the same *Critique-Correct-Verify* cycle to refine the script.

Cinematography involves a collaborative process among two peer cinematographers and the director in the *Debate-Judge* manner to ensure diverse and appropriate camera choices. Two cinematographers (agents P and Q) independently assign their camera choices to each line of the script. They then engage in a debate to address any discrepancies in their choices, refining their decisions as the discussion progresses. Considering Figure 3 as an example. through cinematographers debating over the best shot, with one preferring a medium shot to capture body language, while another favors a zoom shot to emphasize Dana's surprise. the pros and cons of each side are thoroughly explored. After several rounds, the director (the Judgment agent J) summarizes the debate process, resolves any remaining conflicts, and finalizes the camera setup based on the discussion.

After these stages, we can simulate the entire script within the constructed 3D environment and begin filming. Each line in the script is specified with the positions of the actors, their actions, and the chosen camera shots. The duration of each line in the video is determined by the length of the corresponding speech audio.

4 Experiments

4.1 Experimental Setup

Data. We manually brainstorm 15 story ideas that can be implemented in the locations and action spaces within our constructed 3D environment, such as "a quarrel and breakup scene", "late night brainstorming for a startup" and "casual meet-up with an old friend".

Evaluation Scheme. We evaluate the generated videos across five key aspects: the script's fidelity to the intended theme, the appropriateness of camera settings, the alignment of the script with actor profiles, the accuracy of actor actions, and the overall plot coherence. In our preliminary study, we observed that all scripts faithfully adhered to the intended story ideas. Therefore, we conduct comprehensive human annotations on the remaining four aspects of the videos. We use a 5-point Likert scale to assess the script's alignment with actor profiles, the appropriateness of camera settings, and the overall plot coherence. For evaluating the accuracy of actor actions, we randomly select 50 actions from the generated scripts and annotate their accuracy.

Baselines. Following the experimental setup of AgentVerse (Chen et al., 2024), to validate the superiority of FilmAgent in facilitating agent collaboration over standalone agents, we compare it against the following baselines: (1) **CoT:** A single agent generates the chain-of-thought rationale and the complete script. (2) **Solo:** A single agent is responsible for planning, scriptwriting, and cinematography, representing our FilmAgent framework without multi-agent collaboration algorithms. (3) **Group, i.e. the full FilmAgent framework,** utilizing multi-agent collaboration.

	Action	Plot	Profile	Camera
CoT	0.68	1.60	3.84	1.67
FilmAgent (Solo)	0.80	1.87	4.20	2.07
FilmAgent (Group)	**0.88**	**3.53**	**4.44**	**3.53**

Table 1: Comparison of baselines using human annotations for actor **actions**, overall **plot** coherence, script alignment with actor **profiles**, and appropriateness of **camera** settings. The evaluation metric for Action is accuracy (0-1), while the others use a 5-point Likert scale.

Implementation Details. All our experiments employ the "gpt-4o-2024-05-13" version of OpenAI API to simulate multi-agent virtual film production. The maximum number of iterations in multi-agent collaboration algorithms is set to 3.

4.2 RESULTS

The results in Table 1 show that agents configured using FilmAgent (both Solo and Group setups) consistently outperform the standalone CoT agent. This shows the efficacy of decomposing complex tasks into manageable sub-tasks. We find that the CoT agent struggles with generating accurate camera selections, and often suggests actor movements outside of the action space, leading to low camera and action scores. Comparative analysis between the Solo and Group configurations further highlights the benefits of the multi-agent framework. FilmAgent facilitates iterative feedback and revisions through multiple collaboration algorithms, leading to significant improvements in all aspects, especially in plot coherence and the appropriateness of camera settings.

4.3 PREFERENCE ANALYSIS

To further analyze the effectiveness of multi-agent collaboration, we compare 15 scripts before and after *Critique-Correct-Verify*, i.e. *Director-Screenwriter Discussion* (denoted as Scriptwriting #2) and *Actor-Director-Screenwriter Discussion* (denoted as Scriptwriting #3), and 50 randomly-selected modifications on the camera choices before and after *Debate-Judge* in the Cinematography Stage (denoted as Cinematography).

The results in Figure 5 shows the winning rates of revised scripts, indicating a clear preference by human evaluators for the revised scripts over the original versions. This demonstrates the effectiveness of iterative feedback and verification. For the scriptwriting stage, as illustrated by Case #1 in Table 2, the *Director-Screenwriter discussion* reduces hallucinations in non-existent actions (e.g., standing suggest), enhances plot coherence, and ensures consistency across scenes. Case #2 shows that *Actor-Director-Screenwriter discussion* improves the alignment of dialogue with character profiles. For the *Debate-Judge* method in cinematography, Case #3 demonstrates the correction of an inappropriate dynamic shot, which is replaced with a medium shot to better convey body language. Case #4 replaces a series of identical static shots with a mix of dynamic and static shots, resulting in a more diverse camera setup.

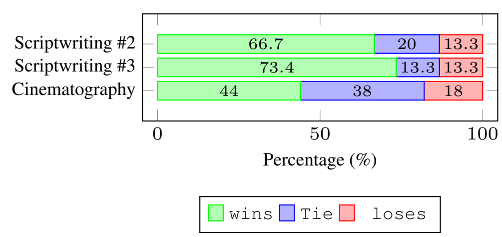


Figure 5: Compared with the original version, the win, tie, and lose rates of the updated script and camera choices after multi-agent collaboration.

5 LIMITATIONS

Our system operates in predefined 3D environments with limited action spaces and preset camera settings. Recent studies (Qing et al., 2023; Jiang et al., 2024) offer more adaptable motion and camera adjustments base on textual instructions. Future research could integrate these flexible components into the FilmAgent framework. Additionally, incorporating multimodal LLMs presents a promising direction for providing more accurate feedback and verification.

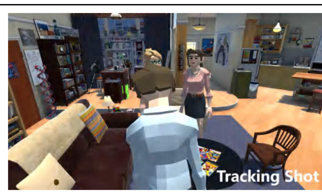
<table>
<tr><td rowspan="2">Case #1</td><td>Scene #1 (Roadside)
Emma: I’d love that. Where should we meet?
Alex: (Standing suggest) There’s a cafe just around the corner from here. How about tomorrow at 3?
Emma: (Standing happy) Perfect! See you tomorrow.
Scene #2 (Alex’s living room)
Alex: (Standing greeting) Welcome to my humble abode! Make yourself comfortable.</td><td>Scene #1 (Roadside)
Emma: I’d love that. Where should we meet?
Alex: (Standing thinking) How about at my place? Tomorrow at 3?
Emma: (Standing happy) Perfect! See you tomorrow.
Scene #2 (Alex’s living room)
Alex: (Standing greeting) Welcome to my humble abode! Make yourself comfortable.</td></tr>
<tr><td colspan="2">Critiques from the Director: For the reasonableness of actions, {"dialogue": "There’s a cafe . . . ?", "currect_action": "Standing suggest", "suggested_revision": "Standing thinking"}. For the fluency of the script, the dialogue in Scene 1 mentions meeting up in cafe, but Scene 2 shows them at Alex’s house instead. Consider changing Alex’s dialogue to mention catching up at his place to make Scene 2 more natural.</td></tr>
<tr><td rowspan="2">Case #2</td><td>Brooke: Alex said I was always overreacting. It really hurt me.
Dana: Sounds rough. There was a time I felt ignored too but I chose to let it go. Maybe we should all lay it out.</td><td>Brooke: Alex said I was always overreacting. It really hurt me.
Dana: That must have been really tough for you. There was a time I felt overlooked too, but talking about it openly could help us all.</td></tr>
<tr><td colspan="2">Dana’s profile: {"name": "Dana","age": "34","gender": "female","occupation": "therapist","personality traits": "empathetic, patient","speaking style": "soothing, deliberate, therapeutic"}.
Critiques from the Actor Dana: It would be more effective to say “That must have been really tough for you.” This reinforces my empathetic and patient traits.</td></tr>
<tr><td rowspan="2">Case #3</td><td></td><td></td></tr>
<tr><td colspan="2">The selected shots for the last line in Case #1. Debate from one Cinematographer: Tracking Shot is not applicable as Alex is not moving, violating the guideline of Tracking Shot usage. Instead, the Medium Shot correctly shows Alex’s body language.</td></tr>
<tr><td rowspan="2">Case #4</td><td>Mia: (Standing Arguing) What is this? I found messages between you and Lily. (Medium Shot of Mia)
Alex: (Standing Thinking) Mia, I can explain. These conversations were some unfinished matters from the past. (Medium Shot of Alex)
Mia: (Standing Angry) Past? These are from just last week! How could you hide this from me? (Medium Shot of Mia)
Alex: (Standing Deny) I didn’t think it was important. I didn’t want to upset you.(Medium Shot of Alex)</td><td>Mia: (Standing Arguing) What is this? I found messages between you and Lily. (Medium Shot of Mia)
Alex: (Standing Thinking) Mia, I can explain. These conversations were some unfinished matters from the past. (Pan Shot of Alex)
Mia: (Standing Angry) Past? These are from just last week! How could you hide this from me? (Pan Shot of Mia)
Alex: (Standing Deny) I didn’t think it was important. I didn’t want to upset you. (Close-up Shot of Alex)</td></tr>
<tr><td colspan="2">Debate from one Cinematographer about the third line: The Medium Shot is used again to capture Mia’s body language. However, having consecutive static medium shots might make the scene feel dull. Consider replacing this shot with a Pan Shot to create some dynamic tension.</td></tr>
</table>

Table 2: Comparisons of the scripts and camera settings **before (left)** and **after (right)** multi-agent collaboration, with excerpts from their discussion process. Case #1 and #2 are from the *Critique-Correct-Verify* method in Scriptwriting #2 and #3 stages respectively. Case #3 and #4 are from the *Debate-Judge* method in Cinematography.

6 Conclusion

We present FilmAgent, an LLM-based multi-agent framework that automates virtual film production. This framework features a meticulously crafted 3D environment, simulates efficient human workflows, and employs multi-agent collaboration strategies. Extensive human evaluations demonstrate the effectiveness of FilmAgent, showing that it significantly enhances script quality, improves camera selection, and reduces hallucination errors. These results highlight the potential of FilmAgent to advance virtual film production through multi-agent collaboration.

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A Environment Details

There are 15 locations in our constructed sandbox environment. Figure 6 displays the screenshots of each location. Nine types of camera shots are annotated in Figure 7. The descriptions and views of these static and dynamic shots are shown in Table 3 and 4. Characters can perform 21 actions from the Mixamo website. The complete list of these actions is as follows:

"Joyful Jump", "Sit Down", "Sitting Clapping", "Sitting Laughing", "Sitting Talking", "Stand Up", "Standing Agree", "Standing Angry", "Standing Arguing", "Standing Bored", "Standing Crying", "Standing Deny", "Standing Depressed", "Standing Greeting", "Standing Happy", "Standing Normal", "Standing Puzzled", "Standing Surprise", "Standing Talking", "Standing Thinking", "Walking"

(a) Apartment kitchen
(b) Apartment living room
(c) Beverage Room
(d) Billiard room
(e) Dining Room
(f) Gaming room
(g) Large kitchen
(h) Meeting room
(i) Office
(j) Reception Room
(k) Relaxing Room
(l) Roadside
(m) Sofa Corner
(n) Storehouse
(o) Work room

Figure 6: Locations in our constructed environment.

Figure 7: A vertical view of the living room in FilmAgent, with additional annotations of more types of shots based on Figure 2. The views from different cameras are shown in Table 3 and 4.

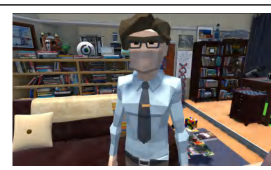
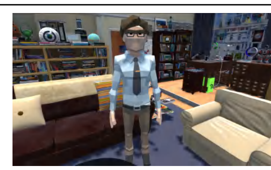
No.	Shot Type	Description	View
①	Close-up Shot	Close-up (CU) Shot should be close to the subject, typically including the collar, encapsulating the identity.	
②	Medium Shot	Medium Shot (MS) should include the posture (such as body language) and physical movement (like walking).	
③	Long Shot	Long shot (LS) contains the human body, showing where the subject is located.	

Table 3: Examples of 3 types of static shots in Figure 7, targeted at Position B.

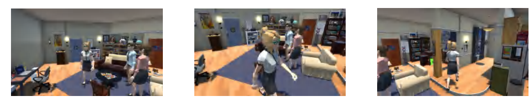
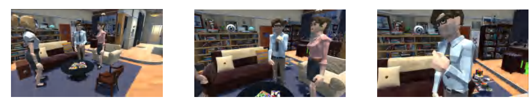
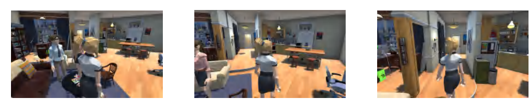
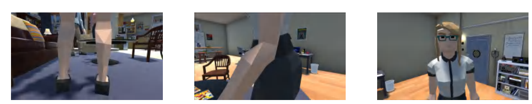
No.	Shot Type	Description	View
④	Pan Shot	A pan shot smoothly rotates horizontally from one side to the other while remaining stationary. The view follows the subject's movement from A to D.	
⑤	Zoom Shot	Zooming brings the subject closer, effectively magnifying a specific focus point in the frame. The view shows the zoom shot from position B.	
⑥	Tracking Shot	A tracking shot involves a moving camera that follows one or more characters. The view of the example follows the character's back from position A to D.	
⑦	Curve Surround Shot	Curve Surround Shot is an Arc Shot orbiting the camera around a character from feet to head. The character often makes an entrance as the camera circles it.	
⑧	360-Degree Arc Shot	A 360-degree Arc Shot revolves the camera around a character at a fixed height, typically with the character stationary as the camera circles it.	
⑨	Truck Shot	Trucking involves the camera moving side to side along a fixed point, effective for conveying scene dynamics. The view in the example provides a comprehensive view of the entire location.	

Table 4: Examples of 6 types of dynamic shots in Figure 7.