Position: Interactive Generative Video as Next-Generation Game Engine

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Abstract

Modern game development faces significant challenges in creativity and cost due to predetermined content in traditional game engines. Recent breakthroughs in video generation models, capable of synthesizing realistic and interactive virtual environments, present an opportunity to revolutionize game creation. In this position paper, we propose Interactive Generative Video (IGV) as the foundation for Generative Game Engines (GGE), enabling unlimited novel content generation in next-generation gaming. GGE leverages IGV's unique strengths in unlimited high-quality content synthesis, physics-aware world modeling, user-controlled interactivity, long-term memory capabilities, and causal reasoning. We present a comprehensive framework detailing GGE's core modules and a hierarchical maturity roadmap (L0-L4) to guide its evolution. Our work charts a new course for game development in the AI era, envisioning a future where AI-powered generative systems fundamentally reshape how games are created and experienced.

1 Introduction

Computer games have witnessed an ever-growing market demand, yet the gaming industry faces three critical challenges. First, current game engines rely heavily on pre-made assets and fixed logic scripts, leading to predetermined content that players will eventually exhaust, even in modern open-world games. Second, existing game engines cannot provide adaptive, personalized gaming content tailored to individual players' preferences, habits, and backgrounds. Third, developing high-quality games, especially AAA games, requires substantial human resources and extensive development time. How to rapidly create high-quality games with unlimited personalized content while minimizing costs remains a fundamental challenge for the entire gaming industry.

During the past year, video generation models have made remarkable progress [77, 117, 52, 22, 87, 94, 85, 2, 8, 99, 54], demonstrating unprecedented capabilities in large-scale motion dynamics, semantic understanding, concept composition, 3D consistency with physical laws, and long-term temporal coherence in both object structure and appearance. These advances show great potential for effectively simulating real-world physics [77, 115, 113], suggesting that these models could serve as capable world models for generating physically plausible videos.

Building upon these advances in video generation, we propose Interactive Generative Video (IGV), a new paradigm that extends video generation capabilities with interactive features. IGV centers around video generation while incorporating four key characteristics: user control over the generated content, memory of video context, understanding and simulation of physical rules, and causal reasoning intelligence. By combining these elements, IGV effectively constructs an explorable and interactive virtual world through video generation, functioning similarly to a simulator.

The virtual worlds created by IGV naturally align with video games as they provide interactive environments where players can explore and engage with dynamically generated content, representing a promising direction for next-generation gaming. Recent works [9, 21, 3, 98, 13, 27, 114, 121, 20, 48, 29, 35, 15, 107] have demonstrated this potential by training action-conditioned video generation

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models using action-video pairs collected from classic games like Atari [3], DOOM [98, 114], CS:GO [3], Minecraft [121, 20, 35, 107], and Super Mario Bros [114]. These models create interactive gaming experiences by iteratively generating predicted video frames in response to user action inputs.

However, as pointed out by some works [121, 27, 21], merely replicating existing games through IGV offers limited value over traditional game engines. The revolutionary potential of IGV lies in its ability to create infinite entirely new games through its powerful generative capabilities. Imagine a future where everyone can become a game designer, creating their own games by simply providing design instructions to video generation models, which then generate limitless explorable virtual worlds. This will fundamentally transform both game development and gaming experiences.

In conclusion, this position paper argues that **Interactive Generative Video (IGV) serves as the core technology for Generative Game Engine (GGE)**. GGE will reduce technical barriers in game development while boosting productivity and creativity through infinite AI-driven content generation.

In this position paper, we first introduce preliminary knowledge about video generation and AI-driven game applications in Sec. 2. Sec. 3 analyzes the core capabilities required for next-generation Generative Game Engines (GGE) and demonstrates why Interactive Generative Video (IGV) is uniquely positioned to fulfill these requirements. Sec. 4 presents our comprehensive framework for GGE, providing detailed definitions, analysis, and future prospects for each module within the framework. To guide future research and development, Sec. 5 proposes a hierarchical roadmap that outlines progressive milestones toward fully functional GGE systems. Finally, Sec.6, Sec.7 and Sec. 8 discuss alternative perspectives, address potential ethical issues and provide concluding remarks.

2 Preliminaries

A more detailed preliminary section can be found in Appendix A.

Video Generation Models. Video generation models have achieved significant breakthroughs with the rise of diffusion models [41, 91, 90, 61, 64], which have become the mainstream approach due to their superior generation quality [77, 117, 52, 22, 87, 94, 85, 2, 8, 99, 54]. The field has also made substantial progress in conditional video generation [36, 72, 109], particularly in camera control [116, 104, 38, 28, 5], where methods like MotionCtrl [104] and CameraCtrl [38] enable precise manipulation of camera movements. For autoregressive video generation, which is crucial for creating variable-length or infinite video sequences, two representative approaches have emerged: GPT-like next-token prediction methods [53, 24, 102] and Diffusion Forcing [14, 89].

AI-driven Game Applications. AI technologies have demonstrated diverse applications in game creation. In game video generation, recent works leveraging diffusion models [3, 98, 20] have achieved high-quality results, with open-domain methods [21, 27, 121] even enabling the creation of novel game content. AI-powered design assistants have enhanced the game development process by automating design completion [88] and generating multiple design suggestions [59, 70], thereby streamlining development and fostering creativity. Furthermore, intelligent game agents have evolved from traditional reinforcement learning approaches [10, 46] to more sophisticated LLM-based methods [100, 105], significantly improving performance in long-horizon tasks.

3 Why IGV for Generative Game Engine?

Computer games have witnessed an ever-growing market demand, yet developing high-quality games, especially AAA games, requires substantial human resources and extensive development time. Traditional game engines like *Unreal* and *Unity* rely heavily on pre-made assets and fixed logic scripts, which not only limits game creation to predefined scenes and plots, but also means players will eventually exhaust all content. Even in open-world games like *The Legend of Zelda: Breath of the Wild*, while offering extensive freedom, players will ultimately experience all predetermined content. How to rapidly create high-quality and innovative games at scale while minimizing human costs remains a critical challenge for the entire gaming industry.

We propose Generative Game Engine (GGE) as a next-generation solution that dynamically generates both assets and logic. This paradigm shift offers several key advantages: (1) lower development costs for game studios through automated content generation; (2) reduced entry barriers for individual developers by eliminating the need for extensive asset creation; and (3) truly open-world experiences with unlimited, dynamically generated content that provides endless unique gameplay experiences.

Building upon recent advances in video generation, we propose Interactive Generative Video (IGV) as a promising foundation for GGE implementation. As illustrated in Fig. 4 (a), IGV is not the entirety of GGE. From a definitional perspective, IGV is viewed from a technical angle, while GGE is viewed from an application angle. Specifically, IGV represents video generation technology that supports interactive user input control, while GGE represents a game engine that utilizes generative AI to create games. IGV, as a potential realization of GGE, offers four key advantages: (1) powerful generalizable generative capabilities, (2) physics-aware world modeling, (3) user-controlled generation for interactive experiences, and (4) leveraging vast video data for training. In the following subsections, we elaborate on these advantages in detail.

3.1 Generalizable Generation for Unlimited Games

Video generation models excel at creating not just high-quality content, but novel and diverse game content. Pretrained on vast real-world video collections, these models develop comprehensive understanding of visual elements and relationships. Their novelty manifests in two aspects: (1) generalization ability to transfer skills to unprecedented scenarios, as shown by GameFactory [121] generating action-controllable videos in open-domain settings (Fig. 1), and (2) compositional creativity to combine learned elements innovatively, demonstrated by Sora [77]'s "origami undersea" scenes[†]. This compositional capability has become a key research focus, with dedicated evaluation benchmarks [43, 92] measuring such abilities.

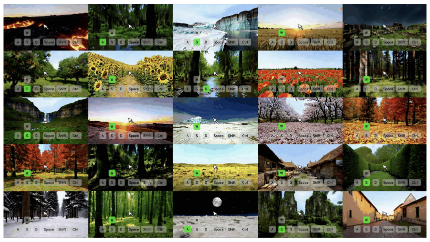


Figure 1: Demonstration of GameFactory [121]'s ability to generalize action control abilities learned from Minecraft data to open-domain scenarios.

3.2 Physics-aware World Modeling

Video generation models demonstrate remarkable potential in understanding the inherent rules of the real world, particularly physical knowledge [77, 115, 113]. During training, to ensure accurate video prediction, these models naturally learn implicit physical priors embedded in training videos. These priors encompass various common physical phenomena, including gravity, elasticity, explosions, collisions, as well as complex motion patterns of humans and animals. While traditional game engines typically rely on predefined physical formulas, extensive manual annotations, or motion capture, IGV leverages its learned physical priors to directly generate physically plausible content. This capability significantly simplifies game engine design and reduces the technical expertise required from developers, thereby enhancing game production efficiency. As shown in Figure 2, the generated video examples demonstrate IGV's physics-aware capabilities, highlighting its potential value for game development.

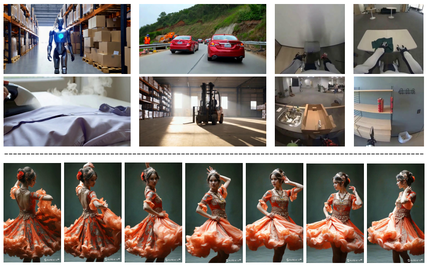


Figure 2: Physics-aware generation capabilities of video models. Top: Examples from Cosmos [73] demonstrating physical understanding in diverse scenarios including robotics, autonomous driving, manufacturing, and home environments. Bottom: Human motion examples generated by Kling [52].

3.3 Interactive Generation with User Control

Precise control of visual generation models has made significant progress [71, 124, 17, 78]. Current video generation models support various control signals essential for gaming interactions. These control capabilities excel in intuitive operations such as camera viewpoint adjustment [104, 38, 28, 5] and character movement control [42].

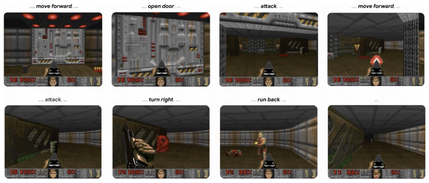
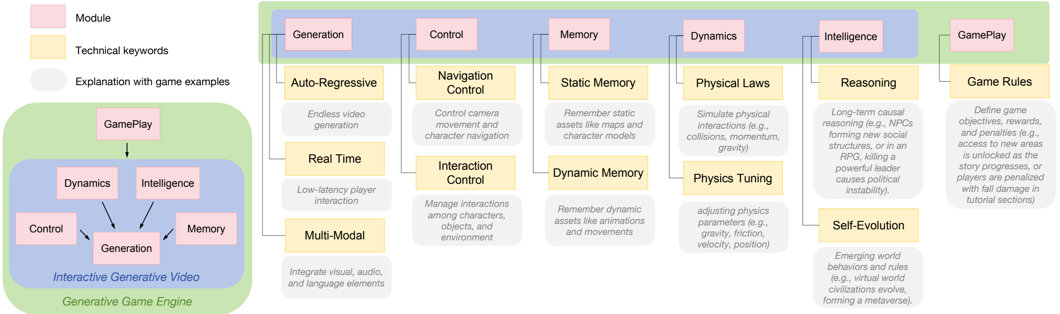


Figure 3: GameNGen [98] shows interactive gameplay in generated videos.

[†] https://www.youtube.com/watch?v=KGcLSTFEgSk


Module
Technical keywords
Explanation with game examples
GamePlay
Dynamics
Intelligence
Control
Generation
Memory
Interactive Generative Video
Generative Game Engine
Generation
Control
Memory
Dynamics
Intelligence
GamePlay
Auto-Regressive
Endless video generation
Real Time
Low-latency player interaction
Multi-Modal
Integrate visual, audio, and language elements
Navigation Control
Control camera movement and character navigation
Interaction Control
Manage interactions among characters, objects, and environment
Static Memory
Remember static assets like maps and character models
Dynamic Memory
Remember dynamic assets like animations and movements
Physical Laws
Simulate physical interactions (e.g., collisions, momentum, gravity)
Physics Tuning
adjusting physics parameters (e.g., gravity, friction, velocity, position)
Reasoning
Long-term causal reasoning (e.g., NPCs forming new social structures, or in an RPG, killing a powerful leader causes political instability).
Self-Evolution
Emerging world behaviors and rules (e.g., virtual world civilizations evolve, forming a metaverse).
Game Rules
Define game objectives, rewards, and penalties (e.g., access to new areas is unlocked as the story progresses, or players are penalized with fall damage in tutorial sections)

(a) Framework of Generative Game Engine

(b) Technical Keywords of Each Module in Generative Game Engine

Figure 4: Proposed framework of Generative Game Engine (GGE). (a) Architecture and interactions between modules of GGE. (b) Technical keywords and their explanation of each module.

Such precise and responsive control enables players to naturally interact with generated content, creating engaging gaming experiences. With rapid development, more control signal types are being supported, further expanding interactive possibilities [47, 95]. Fig. 3 demonstrates IGV's strong interactive control capabilities and validates its potential for game development.

3.4 Video Data Accessibility Enables Scaling

Video data offers unique advantages for training generative game engines through its accessibility and unified representation format [115]. Unlike traditional game engines that require various heterogeneous assets (3D models, textures, animations, etc.) with substantial manual effort, videos are widely available across internet platforms and continuously growing through social media and streaming services. Moreover, videos naturally capture diverse real-world phenomena and human experiences, enabling models to learn comprehensive world knowledge through large-scale training. This abundant video data facilitates training powerful video generation models at scale, while using video as a unified representation simplifies the development process by avoiding the complexity of managing different asset formats, making it an ideal foundation for generative game development.

4 Framework of Generative Game Engine

We decompose our IGV-centered Generative Game Engine into six functional modules. Fig. 4 (a) demonstrates the relationships between these modules, while Fig. 4 (b) presents their key technical components and explanation. IGV consists of five core modules: First, the **Generation** module represents the basic generative capability of the video generation model. Four extension modules are built upon it: the **Control** module supports different modal control signals and is key to achieving interactivity; the **Memory** module maintains historical generation content from both dynamic and static aspects, crucial for ensuring temporal consistency; the **Dynamics** module models the internal rule logic of the game's virtual world, especially physical rules; while the **Intelligence** module enables advanced capabilities including causal reasoning and self-evolution. These five modules, through their video interface, create an independent virtual world with its own emergent properties and behaviors. However, a virtual world alone does not constitute a complete game experience, as games require external rules that embody game designers' intentions, providing players with clear objectives and feedback that create gaming enjoyment. Therefore, we propose an additional **GamePlay** module based on IGV, which serves as the key differentiator between GGE and IGV and is responsible for implementing these external rule logic within the virtual game world.

4.1 Generation

❑ **Concept.** The Generation Module handles video generation, the fundamental functionality of IGV. While ensuring basic video generation requirements like visual quality and motion coherence, this module encompasses three crucial functionalities to achieve optimal interactive experience: (1) **Streaming Generation** enables continuous video synthesis with frame-level control frequency. This supports endless procedural worlds in *No Man's Sky* where players can seamlessly explore for hundreds of hours, real-time weather and day-night cycles in *Red Dead Redemption 2* that evolve continuously, and instant response to rapid player inputs in rhythm games like *Beat Saber* where every frame matters. (2) **Real-time Processing** facilitates low-latency interaction with users. This is essential in competitive games like *Counter-Strike*, *Forza Motorsport*, and *League of Legends* where instant visual feedback is crucial. (3) **Multi-modal Generation** complements the video output with other modalities like text and audio. This includes dynamic music that responds to gameplay in *Journey*, positional audio cues for enemy locations in *PUBG*, ambient sound effects in *Minecraft*, and real-time dialogue subtitles in *Mass Effect*.

❑ **Technical Approaches and Future Directions.**

(1) **Streaming Generation**:

Diffusion-based methods [77] excel at generating high-quality visual content. A straightforward way to achieve streaming generation is to use different noise levels across frames. The variable noise levels mechanism means that later frames (with higher noise) can depend on previous frames (with lower noise), implementing autoregressive generation. Representative methods like Diffusion Forcing [14, 89, 119, 93, 23] have been widely used in game video generation [27, 98, 20, 121].

Next token prediction offers another approach to autoregressive video generation [53, 102], though its visual quality currently lags behind diffusion methods. However, its potential for integration with LLM, which could enable strong causal reasoning abilities [126, 108], makes it a promising direction.

Recent attempts to combine diffusion models with next token prediction aim to maintain quality while modeling frame causality [57, 24]. While these hybrid approaches show promise, they are still in early stages and their potential to surpass established diffusion-based methods remains to be seen.

(2) **Real-time Generation**:

Recent works have demonstrated promising advances in efficient video generation through various algorithmic techniques. These include lightweight model distillation [49], ODE-based diffusion step reduction [101], high-compression VAEs [16], and causal architectures like CausVid [119] with distribution matching distillation and Cosmos [73] with Medusa speculative decoding, key-value caching, and tensor parallelism. These advances, coupled with hardware optimizations like GPU parallelization and quantization, suggest that real-time video generation will soon be accessible to game developers on common hardware. While large companies can provide cloud computing support, we expect future personal developers to run these models on accessible machines.

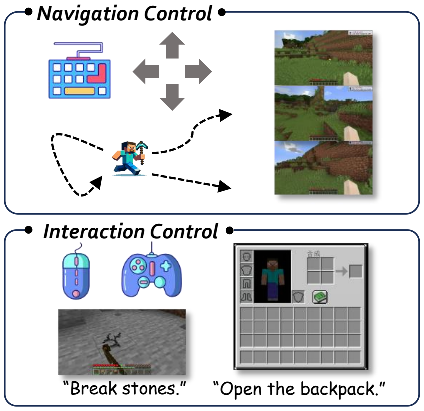


Figure 5: The Control module manages player control through two aspect: navigation and interaction control.

(3) **Multi-modal Generation**:

One approach is to develop unified large multimodal models that support understanding and generation across multiple modalities including text, vision, audio, human motion, depth maps, and so on. Recent works have started exploring this direction [126, 108, 53, 82], though significant challenges remain. An alternative strategy is to first develop specialized large models for individual modalities [25, 112, 45, 7] before integrating them into a unified system. Specifically, this requires designing pipeline relationships between different expert models within the unified system. For example, language models generate video generation instructions, the generated videos then serve as input for audio models to produce corresponding audio signals, ultimately leading to a unified output.

4.2 Control

❑ **Concept.** As shown in Fig. 5, the control module manages user control of the virtual world through two aspects: (1) **navigation control** enables players to navigate and explore the virtual world through camera and character movement. For example, in racing games, players use arrow keys or “WASD” for acceleration, braking, and steering, while in open-world games, players typically use “WASD” for character movement, mouse for camera rotation, and space bar for jumping or climbing. (2) **interaction control** allows players to manipulate objects within the virtual environment. For instance, in construction games, players use left mouse clicks to select and place buildings, right clicks to rotate structures, and keyboard shortcuts like ‘E’ to access inventory or ‘Q’ to demolish objects.

❑ **Technical Approaches and Future Directions.**

The technical implementation of control mechanisms has been well-studied. Common approaches include: (1) Cross Attention [121, 98, 27], where control signals are transformed into conditional features that serve as keys and values, while the video features serve as queries. (2) Another approach uses external Adaptors [13, 104], which directly fuses control features with video features.

While control is easily mastered in fixed scenes, it should generalize to open-domain scenarios. Some works [121, 27, 21] have leveraged video generation priors for this purpose, but generalizing complex actions with limited control annotations remains challenging and requires further exploration.

Learning control, especially for interaction control, goes beyond mechanical execution and requires understanding the underlying rules of how interactions change the environment (as part of physical laws). Following a data-driven approach, future work aims to collect large-scale datasets [121, 13] and improve the learning of these interaction rules. Physical laws will be further discussed in Sec. 4.4.

For game control signal design, the key design principle is to align with users' gaming intuitions. A promising research direction would be developing more natural control signals that better match human habits, such as using gesture recognition or brain-computer interfaces.

4.3 Memory

❑ **Concept.** Conventional video generation models rely solely on attention mechanisms, struggling to maintain scene layouts, object appearances, and other visual elements in long-duration or large-motion scenarios. As demonstrated in Fig. 6, the Memory module addresses these challenges through two aspects: (1) **static memory** encompasses scene-level and object-level memory, including game maps, buildings, character models, and object appearances. In construction games like *Minecraft* or *SimCity*, the module needs to consistently maintain the structure of player-built constructions; inconsistency in building layouts or designs between frames would severely impact player experience. (2) **dynamic memory** handles short-term motion and behavior patterns, such as character animations, vehicle trajectories, particle effects, and environmental changes like weather transitions. This is crucial in games requiring precise motion consistency, such as fighting games where character movements and attack animations must remain fluid and coherent, or rhythm games where dance movements need to maintain smooth transitions between frames.

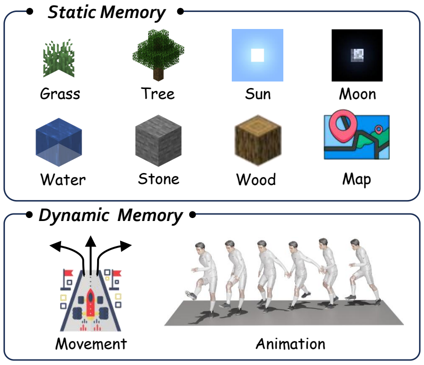


Figure 6: The Memory module consists of static and dynamic memory.

❑ **Technical Approaches and Future Directions.**

Current methods mainly rely on attention-based memory, utilizing attention's inherent ability to remember historical frames through cross-attention between historical and predicted frames [98, 20, 107]. However, this approach is unreliable and faces limitations in both precision of memory preservation and limited window size. Another promising solution is using dedicated memory structures, which can be implemented either as implicit high-dimensional features [51] or explicit 3D representations [66, 68, 120, 123, 65, 83]. These structures serve as conditional controls for the generation module, ensuring consistent preservation of static elements. The adaptation of these methods as memory mechanisms for game video generation requires further investigation.

4.4 Dynamics

❑ **Concept.** As demonstrated in Fig. 7, the Dynamics Module focuses on two key aspects: (1) **Physical Laws** specifically focuses on comprehending and generating videos that comply with fundamental physics, especially rigid body mechanics including gravity, collision, and acceleration. In racing simulators like *Forza Motorsport*, physics-based puzzle games like *Portal*, and platformers like *Super Mario Odyssey*, where precise physical interactions drive core gameplay mechanics. (2) **Physics Tuning** extends beyond **Physical Laws** by enabling control over physical parameters rather than simply replicating real-world physics. This includes adjusting gravity, friction coefficients, or directly modifying time, velocity, and mass values. In games like *Braid* where time manipulation is core to gameplay, *Superhot* where time moves only when the player moves, and *Control* where physics manipulation powers create unique gameplay experiences.

❑ **Technical Approaches and Future Directions.**

A data-driven approach learns physical laws from large-scale video data [77, 73], though this requires extensive high-quality videos demonstrating diverse physical phenomena [125]. Physics-based memory control offers an alternative by using video generation models as renderers on top of physics simulators [63, 31], ensuring perfect physics compliance but limited to mathematically formulated phenomena. Establishing appropriate benchmarks for evaluating physical accuracy remains crucial [79, 55] to identify limitations and guide improvements. Physics tuning capability, often overlooked in current research, is crucial for models to truly understand and manipulate physical knowledge, and we encourage future research to explore synthetic data with annotated physical parameters as a potential solution.

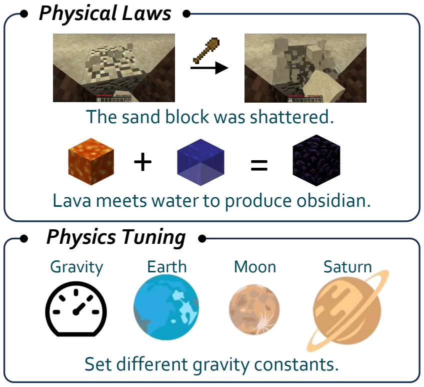

Physical Laws
The sand block was shattered.
+
=
Lava meets water to produce obsidian.
Physics Tuning
Gravity
Earth
Moon
Saturn
Set different gravity constants.

Figure 7: The Dynamics module focuses on physical laws and physics tuning.

4.5 Intelligence

❑ **Concept.** As Demonstrated in Fig. 8, the Intelligence module implements two key aspects: (1) **Reasoning**: This capability enables long-term causal inference based on initial conditions, creating immersive virtual worlds. For example, the system can predict how a kingdom's economy and social structure might evolve over centuries based on its initial resources and policies, or simulate wildlife migration patterns when environmental conditions change, such as animals seeking new water sources after a river dries up. Similar mechanics can be found in strategy games like *Crusader Kings* and ecosystem simulations like *Planet Zoo*. (2) **Self-Evolution**: This capability goes beyond generating continuous video streams with changing virtual worlds; it enables virtual worlds to continuously develop, evolve, and generate new knowledge, rules, and behaviors through emergent properties. In simulation games, civilizations could naturally emerge and form their own cultures, ecosystems could develop new species, and cities could grow and adapt organically. Such technology could eventually realize a metaverse similar to *The Matrix*, where countless agents and players live in self-evolving virtual worlds.

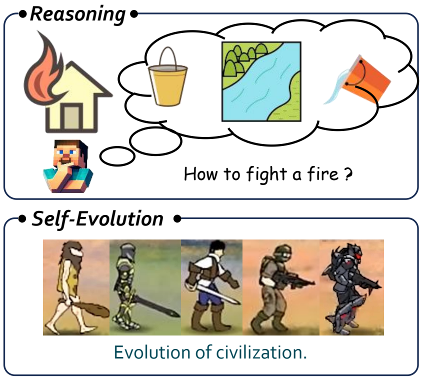


Figure 8: The Intelligence module implements reasoning and self-evolution.

❑ **Technical Approaches and Future Directions.**

Implementing reasoning capabilities requires video generation models to have a causal structure through autoregressive generation (as discussed in Generation Module in Sec.4.1) and large-scale long-context training [30], similar to large language models. Alternatively, leveraging (multimodal) large language models for causal reasoning alongside video generation models shows promise for unified understanding and generation[126, 108]. Furthermore, if all previously mentioned capabilities including physics understanding, physical simulation, and causal reasoning are successfully implemented and demonstrate powerful performance in the future, we might witness the emergence of remarkable self-evolution capabilities. This convergence of advanced capabilities could potentially lead to truly autonomous virtual worlds, such as metaverses inhabited by countless intelligent agents, or brain-in-a-vat worlds similar to those depicted in *The Matrix*.

4.6 Gameplay

❑ **Concept.** The GamePlay Module builds upon IGV by implementing external **Game Rules**, which are designer-imposed rules such as game objectives, rewards, penalties, and constraints that shape the virtual world's gameplay experience. These include scoring systems in *Tetris*, health and damage systems in *Dark Souls*, mission objectives and reward structures in *Grand Theft Auto*, achievement systems in *Minecraft*, time limits in *Mario*, competitive ranking systems in *League of Legends*, and quest completion rewards in *World of Warcraft*.

❑ **Technical Approaches and Future Directions.**

The implementation of the GamePlay module primarily relies on agent systems empowered by large language models [1, 97] or multimodal large models [62], enabling various gameplay aspects including level design, difficulty scaling, and NPC development. While existing single agents [56, 106] show promise, key research challenges remain in developing unified multi-agent frameworks for game environments. Another practical research direction is exploring how agents and agent systems can enable dynamic, adaptive game rules, including reward and penalty mechanisms. As players progress through games, their skill levels, capabilities, and experience continuously evolve, making it essential to adaptively adjust difficulty levels and reward-penalty systems accordingly.

5 Levels of Generative Game Engine

We propose a five-level maturity model (L0-L4) to evaluate GGE and guide their future development. This framework helps assess current technologies and identify key research directions in GGE. Below we detail each level, with the overview table presented in Appendix B.

Level 0: No AI-Assisted Assets Generation. At this foundational level, game engines rely entirely on manually crafted content without any AI-generated elements. All game assets and rules must be pre-designed during the development phase. Classic examples include *Super Mario*, where each level layout is carefully hand-crafted, and *Tetris*, where the game rules and piece designs are fixed. This approach enables precise control but requires heavy resources and restricts players to fixed content.

Level 1: AI-Assisted Assets Generation. Game development combines manual processes with AI-assisted creation of assets and logic during development and gameplay. AI tools generate diverse assets to reduce content creation workload. For instance, in *Cyberpunk 2077*, developers can utilize image generation models like Stable Diffusion [84] to create varied textures for neon billboards, trash piles, and urban details throughout Night City. During gameplay, the engine generates segments, such as unique explosion animations when a player destroys a bridge in an open-world game, or dynamic NPC dialogues in games like *AI Dungeon*. While this approach speeds up development and adds variety, the framework remains pre-designed and needs significant human intervention and curation.

Level 2: Physics-Compliant Interactive World Generation. This level shifts from manual-centric development to interactive video generation, representing AI-Driven Generative Game Engines. The engine continuously generates physics-compliant content based on player interactions in real-time. For example, when a player sets fire to a wooden bridge, the engine dynamically generates not only the realistic blazing effects but also adapts the game world accordingly, such as rerouting enemy paths around the destroyed structure. While many works operate at this level [98, 121, 20], significant improvements are needed in physics understanding, simulation realism, and generalizable interaction.

Level 3: Causal-Reasoning World Simulation. Building on Level 2's physics-compliant generation, which focuses on immediate responses, this level adds causal reasoning across time to address short-term limitations. The engine maintains a world model that understands player actions and logic rules, generating content that reflects long-term cause-and-effect relationships. For example, when a player assassinates a faction leader in Act 1, the engine simulates the resulting political instability, leading to city-wide riots and power struggles that emerge in Act 3. Through this understanding, the game creates storylines where players' early choices shape the world's future development.

Level 4: Self-Evolving World Ecosystem. Building on Level 2's physics generation and Level 3's causal reasoning, as these capabilities continuously advance, the model emerges with self-evolution abilities. The game world becomes a self-evolving ecosystem where complex systems emerge from initial rules and interactions. For example, as the NPC population grows, they autonomously organize into governance structures and establish trade networks, exhibiting emergent social behaviors beyond their initial programming. At this stage, the engine will create virtual worlds similar to those in *Ready Player One* or *The Matrix*, where players can not only play but potentially live within these worlds. This advancement will revolutionize gaming and profoundly impact human society.

6 Alternative Views

Alternative View #1: While GGE represents an automated approach to game content generation, it is worth examining whether it shares the same limitations as Procedural Content Generation (PCG) methods, specifically the tendency to produce repetitive content and the presence of difficult-to-fix bugs that potentially limit their practical applications.

Potential Solution #1: GGE differs fundamentally from Procedural Content Generation (PCG). PCG creates infinite content by randomly combining limited assets and predefined logic rules. In contrast, GGEs learn from massive datasets, acquiring knowledge of unlimited assets and world logic rules. Unlike PCG's meaninglessly repetitive content generation, GGE can create truly diverse content, similar to how AI image generation has enabled diverse, high-quality artworks on Civitai [18]. Additionally, GGEs implicitly model logic rules and leverage control modules for precise control, avoiding PCG limitations such as difficult control, procedural bugs and debugging needs.

Alternative View #2: Given that traditional rendering pipelines in standard game engines offer efficient asset rendering and allow more resources to be allocated to gameplay enhancement, why should we adopt IGV instead of maintaining the traditional approach that prioritizes gameplay dynamics over graphical realism?

Potential Solution #2: Traditional rendering pipelines efficiently handle graphics, allowing developers to focus more resources on gameplay rather than graphics. This raises concerns that IGV might shift too many resources toward visual realism at the expense of gameplay quality, a trade-off that many developers would find unreasonable. However, IGV represents a paradigm shift that enhances both graphical realism and gameplay quality together, rather than trading off one for the other. We analyze this from four aspects: (1) **Complete system**: IGV is not just a generation model, but a system integrating Control, Memory, Dynamics and Intelligence. Beyond improving graphics, it enhances gameplay through, for example, personalized game content, infinite explorable experiences, and intelligent NPC behaviors. (2) **Enhanced gaming experience**: IGV enables dynamic, customized, and infinitely explorable experiences, which traditional game development with triangle rendering and added gameplay logic cannot easily achieve. (3) **Enhanced creative freedom**: IGV's vitual world generation capabilities free developers from focusing on graphics, allowing them to concentrate on gameplay design. Its controllability enables developers to freely exercise creativity in designing more innovative gameplay experiences. (4) **Positive industry impact**: IGV's efficiency and capabilities accelerate game development and lower entry barriers. This attracts more developers, resulting in more creative games and enriching the gaming experience industry-wide.

We also address an additional alternative view regarding the concerns about GGE costs in Appendix C.

7 Ethical Issues

Several key ethical issues need to be carefully considered in the development and application of GGE: copyright concerns (determining ownership and protection of AI-generated content), security issues (preventing the generation of harmful content), creativity concerns (whether AI enhances or limits human creative expression), democratization implications (the impact of lowering barriers to game creation), and labor concerns (potential effects on gaming industry workers). These critical issues require thorough discussion and resolution, which we address in detail in the Appendix D.

8 Conclusion

In this position paper, we have presented Interactive Generative Video (IGV) as a promising foundation for next-generation game engine. We proposed a comprehensive framework with six essential modules and established a five-level maturity model (L0-L4) to guide future research and development. Through our analysis, we demonstrated that IGV's unique capabilities in content generation, physics simulation, and interactive control make it an ideal candidate for revolutionizing the gaming industry. We believe this work provides a clear roadmap for advancing game engine technology while identifying key challenges and opportunities for future exploration.

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Appendix A Preliminaries

A.1 Video Generation Models

Video Generation Models aim to synthesize temporally consistent video sequences $\mathbf{x} = \{x_0, x_1, \ldots, x_t\}$, where x_i indicates the i-th frame. The video is generated by an autoregressive model [81, 110, 53, 102], a diffusion model [40, 77], or a masked transformer model [11, 122]. With the rise of diffusion models [41, 91, 90, 61, 64], which have now become the mainstream approach in video generation due to its high-quality generation performance, significant progress has been achieved in this field [77, 117, 52, 22, 87, 94, 85, 2, 8, 99, 54].

Conditional Video Generation is formulated as $p(\mathbf{x}|c)$ and it varies depending on the type of control signal c which denotes conditions such as text prompts or other control signal. Approaches such as [36, 72, 109] incorporate images as control signals for the video generator, improving both video quality and temporal relationship modeling. Methods such as Direct-a-Video [116], MotionCtrl [104], and CameraCtrl [38] use camera embedders to adjust camera poses, enabling control over camera movements in generated videos. 3DTrajMaster [28] extends this capability by transforming 2D camera signals into 3D for more advanced control. ReCamMaster [5] re-shoots the source video with novel camera trajectories.

Autoregressive Video Generation Models. Since game videos require variable-length or even infinite-length generation to enable interactive game experience, autoregressive mechanism is necessary. Autoregressive video generation refers to a process where new frames are generated based on previously generated frames, which can be expressed as $p(x_1, x_2, ..., x_n) = \prod_{i-1}^{n} p(x_i|x_1, x_2, ..., x_{i-1})$, where x_i indicates the i-th frame. An intuitive approach is to adopt GPT-like next-token prediction methods [53, 24, 102]; however, this approach often falls short in terms of generation quality. Relying on the exceptional performance of diffusion models, Diffusion Forcing [14, 89] implements autoregression by applying different levels of noise to different frames, allowing the denoising of new frames with higher noise levels while conditioning on previous frames with lower noise levels. Methods [121, 27, 98, 20] leveraging Diffusion Forcing has achieved remarkable results.

A.2 AI-driven Game Applications

Game Video Generation. Previous works have utilized GANs [51, 50, 67] to generate game videos or used NeRF to reconstruct 3D scenes to simulate the game process [66, 68], but often fall short in terms of generation quality. Using the powerful generative capabilities of diffusion models, some works [3, 98, 114, 20, 27] have produced high-quality game videos. However, the content is typically confined to specific preexisting games. Open-domain Methods [21, 27, 121], by utilizing multi-stage training or large-scale training datasets, create new content for video games.

Game Design Assistant. AI-powered design assistants offer numerous advantages throughout the creative process, depending on the tool, the type of AI and the creative workflow. These systems can streamline development, reduce costs, reduce manual effort, improve team collaboration, and even inspire creativity [58]. In the gaming domain, most existing AI-driven design tools primarily assist by auto-completing an ongoing design [88] or generating multiple design suggestions for creators to evaluate [59, 70, 12, 96].

Intelligent Game Agent. Reinforcement learning has long been the predominant approach in this domain. Early efforts explored the use of hierarchical RL [10, 46, 26, 60, 74, 127, 4] in the context of MineRL competitions [37]. However, due to the absence of guidance from prior knowledge, such approaches often struggle to perform effectively on long-horizon tasks. With the advancement of LLM [1, 97], leveraging their prior knowledge to plan long-horizon tasks has shown promising results. Recent advancements in LLM-related research [100, 105, 128, 80, 111, 44] have significantly propelled the progress of agents in long-horizon tasks.

Appendix B Overview Table for Levels of GGE

In Table 1, we demonstrate the overview of different maturity levels for GGE.

Level	Name	Technical Features	Application Examples	Category
L0	No AI-Assisted Assets Generation	Manual creation and integration of all game assets and logic.	*Super Mario*: fixed levels; *Tetris*: fixed rules.	Traditional Manual Game Development
L1	AI-Assisted Assets Generation	Al-assisted creation and integration of game assets and logic.	*Cyberpunk 2077*: AI-generated assets; *AI Dungeon*: real-time NPC dialogues.	
L2	Physics-Compliant Interactive World Generation	Real-time **physics-compliant** video generation with user **interactions**, supported by the Dynamics module.	E.g., Player sets fire to wooden bridges, AI dynamically renders blazing spans and rerouted enemy paths	Next-Gen AI-Driven Generative Game Engine
L3	Causal-Reasoning World Simulation	World simulation with **causal reasoning** across time based on L2, incorporating the Intelligence module.	E.g., Killing a faction leader in Act 1 triggers city-wide riots in Act 3.	
L4	Self-Evolving World Ecosystem	Autonomous world **evolution** with **emergent** behaviors based on L2 and L3, requiring advanced Intelligence module.	E.g. NPCs self-organize governments and trade as population increases.	

Table 1: Proposed Maturity Levels (L0-L4) of Generative Game Engine. L0-L1 represent traditional manual game development with limited AI assistance, while L2-L4 showcase next-generation game engines featuring video-based world generation.

Appendix C Additional Alternative Views

> **Alternative View #3**: The economic costs of GGE appear to be significant. For instance, the computational overhead is substantial since GGE relies on IGV and LLMs, which are computationally intensive large models. Do these costs prevent IGV-centered GGE from becoming the next generation of game engines? Are these costs we incur for implementing GGE justified by the benefits it brings?

Potential Solution #3: Regarding the computational costs, we believe these can be effectively reduced through technological advancements. Recent works have demonstrated promising advances in efficient autoregressive video generation. On the algorithmic front, CausVid [119] achieves real-time frame generation through distribution matching distillation (DMD) [118], while Cosmos [73] enables real-time generation by combining Medusa speculative decoding, key-value caching, tensor parallelism, and low-resolution adaptation. Additionally, hardware optimizations like GPU parallelization, quantization, and knowledge distillation have significantly accelerated inference speeds for autoregressive models. With ongoing research in efficient models, we believe autoregressive video generation will eventually achieve real-time performance on commonly available hardware accessible to game developers.

Beyond computational costs, other economic considerations include:

- **Data Collection Costs**: These will be mitigated as more open-source datasets like GameGen-X [13] become available. While initial training incurs costs, trained models reduce future asset production costs, leading to overall savings.
- **Licensing Costs**: Generative models will lower the barrier for developers to create their own new IPs. Building a mutually beneficial ecosystem between developers and gaming companies is also advantageous.
- **Safety Control Costs**: While this affects all generative AI, not just IGV, the benefits of incorporating generative AI outweigh these costs, as demonstrated by successful products like Runway [85], Midjourney [69], and ChatGPT [76].

We believe that these costs will not impede GGE's development or future potential. The technology is continuously evolving, with costs decreasing while model capabilities become increasingly powerful, making the benefits more and more significant. This mirrors the trajectory of large language models. Compared to ChatGPT [76] released in 2022, today's LLMs demonstrate stronger performance (like DeepSeek-R1 [32]'s reasoning capabilities and GPT-4o's multimodal generation abilities [75]) while becoming cheaper and more accessible (open-source models like DeepSeek [32] and Qwen [6] now offer performance comparable to commercial models).

While GGE currently faces some cost-related concerns in the short term, these challenges are outweighed by its transformative value. As discussed in Alternative View #2 in Sec. 6, GGE offers significant advantages over traditional game engines, such as personalized gaming experiences, infinitely generated game content, and lowering the barrier to game development so that everyone can become a game designer. These compelling benefits, which are unattainable with traditional game engines, make GGE's economic costs worthwhile to address and overcome.

Appendix D Ethical Issues

Copyright Issues: How should we determine copyright ownership and protect legitimate copyright interests of all parties involved in GGE-generated games?

Copyright protection presents a new challenge in generative AI development, including IGV, which requires significant attention from both technical and legal perspectives. While this is a complex issue, the industry is actively working towards solutions that can foster the mutual development of AI technology and copyright protection. To address these challenges, we propose several approaches:

Training data for IGV should prioritize the use of copyright-free or properly licensed data sources to minimize legal risks. Game developers can build mutually beneficial partnerships with copyright holders to legally obtain data and share the copyright of the created content. For instance, while noting the Studio Ghibli's recent copyright concerns with OpenAI, we observe that Ghibli has successful experiences in collaborating with game companies (e.g., development of game "Ni no Kuni"). Such examples demonstrate the feasibility and value of proper copyright collaboration.

Technically, research works [34, 33] on dataset copyright protection and detection of unauthorized training data usage are progressing, which has positive implications for IGV in game development.

Security Issues: What measures can be implemented to prevent the generation of harmful content by generative models such as IGV?

IGV systems are built upon existing video generation models, thus inheriting their established safety measures. Current commercial video generation services like Runway and Sora have implemented comprehensive safety systems that filter out inappropriate content including violence, pornography, hate speech, and other harmful materials. From a technical perspective, safety measures can be implemented through various approaches: (1) Value alignment [19, 86] through techniques like RLHF during the model post-training phase would establish fundamental safety boundaries. This alignment with human preferences and values can effectively constrain the model's output content; (2) Real-time harmful content detection [103, 39] using VLMs can quickly analyze generated content, identify potential harmful elements, and block inappropriate content in real-time, which is particularly crucial in interactive gaming environments.

Creativity Issues: Can IGV serve as a creative tool, allowing for deep human creativity?

We believe IGV can enhance human creativity for the following reasons: (1) Interactive generative video technology eliminates mechanical and repetitive tasks in game development, such as debugging, writing basic code, and building standard scenes. By automating these uncreative aspects, developers can channel their energy into creative endeavors, focusing on innovative gameplay design and unique artistic expressions that truly matter to the gaming experience. (2) IGV breaks down technical barriers, making game development accessible to creators from professional studios to independent developers. This democratization enables more diverse voices to enter the gaming industry, each bringing their unique perspectives and creative visions. Like other AIGC applications, it enables creators to realize their ideas without technical constraints, as demonstrated by artist Sofia Crespo's work[†] that blends technology with organic art, showing how AI amplifies creativity.

Democratization Issues: Does democratizing game creation diminish its value?

We believe that democratizing game creation will not diminish its value, but rather enhance the overall value and creativity of the entire field. Here is our analysis and examples:

The democratization of gaming won't diminish creative value. The widespread availability of technology enables more people to enter this field, generating more diverse creative thinking and innovative designs. Creation value lies in innovation and personalization, not just technical difficulty. Through this technology, even ordinary users can create games with unique characteristics and

[†] `https://en.wikipedia.org/wiki/Sofia_Crespo`

personal style, which holds its own distinctive value. A good example is the opening up of image generation models, which hasn't diminished the value of artistic creation. People with varying levels of professional expertise have shared numerous new artistic works on Civitai [18], which has actually enhanced the creativity in this field and the value of its works.

Labor Issues: How should we view the potential negative impact of highly automated productivity tools like GGE on labor in the gaming industry?

We acknowledge the labor impact concern with generative AI. IGV aims to enhance productivity and creativity rather than replace human workers. We advocate for measures like education and support programs to help industry professionals leverage AI tools, ensuring positive industry transformation.

Appendix E Workflow Integration with GGE

It is important to emphasize that the introduction of generative game engines (GGE) will not lead to a single, rigid game development workflow. We provide below a framework example of how GGE can be incorporated into game development workflows

Phase #1: Pre-production Phase

- **Concept Design**: Define core game elements (gameplay mechanics, story, target audience, art style) through LLM consultation and convert to IGV condition prompts.
- **Prototype Development**: Select suitable base models based on computing power and performance requirements, and develop prototypes using initial prompts for feasibility testing.

Phase #2: Production Phase

- **Asset and Logic Requirements**: Create detailed prompts for specific assets and logic requirements (e.g., character model descriptions, area map sketches, level-up rule systems).
- **Training Data Collection and Model Fine-tuning**: Fine-tune models with targeted game data (e.g., collecting copyright-free space movie/game assets for a space exploration game).

Phase #3: Testing Phase

- **Functionality Testing**: Test prompt-based content generation and screen for harmful content.
- **Compatibility and Performance Testing**: Optimize performance across different devices with necessary algorithm/hardware acceleration.

Phase #4: Post-launch Maintenance

- **Content Updates**: Update model parameters and prompts for new content (DLCs, characters, events).
- **Data Analysis and Optimization**: Use player behavior data (with consent) for model fine-tuning and reinforcement learning.

Feasibility Requirements

The successful implementation of this workflow relies on these key factors:

- (1) **Model Capability**: Robust base IGV models that support efficient control, fine-tuning, and fast inference.
- (2) **Data Accessibility**: Well-established data sharing and copyright mechanisms that enable legal and cost-effective access to high-quality training data.
- (3) **Computing Resources**: Accessible AI computing infrastructure, either through local hardware resources or affordable cloud computing services.