Dream World Model (DreamWM): A World-Model-Guided 3D-to-Video Framework for Immersive Narrative Generation in VR

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***Abstract*—The creation of immersive and dynamically evolving narratives for Virtual Reality (VR) remains a challenge, primarily due to the inherent constraints in maintaining spatial and temporal coherence during generative processes. Current Text-to-Video models excel in visual quality but fail to ground narratives in a consistent 3D world, leading to visual inconsistencies and narrative logic violations when scaling to multi-segment stories. We introduce the Dream World Model (DreamWM), a novel, closed-loop framework that transforms abstract narrative descriptions (e.g., dreams or story scripts) into high-fidelity, spatially-grounded, and temporally coherent VR video experiences. DreamWM's core is a Narrative Latent World Model that manages high-level story progression, emotion, and causal logic through a latent state $\mathbf{z}_t$. This state drives a Text-to-3D Scene Generator (Marble) to produce consistent 3D geometry priors ($\mathbf{S}_t$) like Gaussian Splats, which are then used as multi-view control signals for a high-quality Video-to-Video Model (VACE) to synthesize the final expressive video segment $\mathbf{V}_t$. The crucial innovation is the World Model–Driven Closed Loop, where the generated video $\mathbf{V}_t$ feeds back to update the latent state $\mathbf{z}_{t+1}$, enabling dynamic scene transitions, emotional modulation, and dreamlike transformations with unparalleled coherence. DreamWM establishes a new paradigm for generative storytelling, bridging the gap between high-fidelity 3D geometry and dynamic, emergent narrative content.**

***Index Terms*—World Models, Generative AI, 3D Reconstruction, Video Generation, Virtual Reality, Immersive Storytelling, Computational Narrative, Gaussian Splatting.**

I. Introduction

The convergence of generative AI and Extended Reality (XR) promises a new era of interactive, personalized content creation [16], [17]. However, current generative models are typically specialized: Text-to-Image models lack temporal dynamics [11], while state-of-the-art Text-to-Video systems like Sora [9] and Lumiere [10] often struggle with maintaining **long-range temporal consistency and spatial grounding** across sequential story segments. Specifically, when generating a narrative where a user object must remain structurally consistent across diverse camera angles or dramatic scene shifts, these models frequently introduce object hallucinations or geometric inconsistencies [15], [20]. This geometric drift is fatal for immersive applications where user expectations of physical consistency are high, a core focus of CHI research on system plausibility [16], [18].

The concept of a **World Model** (WM), pioneered in reinforcement learning and cognitive science [3], [4], [5], offers a powerful solution. A WM provides a predictive, latent representation of the environment's dynamics, allowing an agent to plan and anticipate outcomes. We adapt this principle to narrative generation: instead of predicting agent actions, our World Model predicts **narrative state evolution**—the changes in plot, setting, and emotional tone—ensuring logical causality and coherence [6], [7].

We introduce the **Dream World Model (DreamWM)**, a novel 3D-to-Video framework designed explicitly for emergent, immersive narrative generation in VR. DreamWM addresses the core challenge of coherence by strictly separating the **geometry (the world's structure) from the appearance (the visual style and lighting)**, a design principle critical for robust generative synthesis [13].

DreamWM's Core Components and Loop. The user's input narrative initializes a **Narrative Latent State** $\mathbf{z}_t$. This state is decoded by a Text-to-3D Generator, which we term **Marble**, into a structured, geometrically consistent 3D scene $\mathbf{S}_t$ (e.g., using 3D Gaussian Splatting [2]). Multi-view geometric priors (RGB, depth, normals) are rendered from $\mathbf{S}_t$. These priors, along with the narrative state, condition a high-fidelity Video-to-Video model (VACE) to generate the expressive video segment $\mathbf{V}_t$. Crucially, $\mathbf{V}_t$ is then re-encoded by the WM to compute the next state $\mathbf{z}_{t+1}$, completing the closed loop that drives the narrative evolution. This structure allows the system to generate complex narrative dynamics, including non-linear, *dreamlike* scene transitions (e.g., a room melting into a forest) while preserving the 3D-grounded nature of the scene.

A. Contributions

In summary, our paper makes the following three key contributions:

1) We propose the **Dream World Model (DreamWM)**, a novel, world-model-guided generative narrative framework that bridges high-level narrative logic with low-level visual synthesis for immersive experiences.
2) We introduce a **Geometry-Grounded Video Generation Pipeline** that uses structured 3D representations (e.g., Gaussian Splatting) to render multi-view, scene-consistent geometric priors, ensuring spatial and temporal coherence in the generated video segments.
3) We establish a **Narrative World-Model Closed Loop**, where the generated visual output directly updates the

latent narrative state, enabling dynamic, emergent story evolution, emotional modulation, and complex scene transformations guided by a cognitive planning mechanism.

II. Related Work

Our work synthesizes research across multiple disciplines: World Models, 3D Scene Generation, High-Fidelity Video Synthesis, and Computational Narrative.

A. World Models and Latent Dynamics

World Models (WMs) originated in Reinforcement Learning (RL) as a method to learn a compressed, predictive model of the environment dynamics [22]. Key advancements include PlaNet [23] and the seminal Dreamer series [3], [4], [5], which use a Recurrent State-Space Model (RSSM) to learn a compact latent state $\mathbf{z}_t$ that predicts future states given actions $\mathbf{u}_t$. More recently, WMs have been scaled up to handle general video data. WorldDreamer [6] and LWM [7] demonstrate the capacity of WMs to understand complex visual sequence dynamics by predicting masked tokens, allowing them to handle the non-linear, multi-modal nature of real-world videos. Genie [8] further pushed WMs into interactive environments. Our work adapts the WM paradigm from acting within a fixed physical environment to **planning and controlling a high-level narrative arc**, where the "action" is the narrative transition and the "environment" is the generated story segment. This is aligned with the cognitive perspective of WMs for general AI [19].

B. Text-to-3D and 3D Scene Generation

The ability to generate 3D assets from text is critical for grounding narratives. Early methods relied on optimizing Neural Radiance Fields (NeRFs) [1] using Score Distillation Sampling (SDS) [12], but suffered from slow generation and geometry ambiguities (the Janus problem). The introduction of **3D Gaussian Splatting (3DGS)** [2] revolutionized the field by enabling real-time rendering and providing a more explicit, optimizable geometric primitive. Subsequent work, including DreamGaussian [13] and GaussianDreamer [14], leveraged 3DGS to significantly accelerate text-to-3D generation while improving geometric consistency. Our component, **Marble**, is a derivative of these 3DGS-based generative models, tailored to produce full, large-scale scenes $\mathbf{S}_t$ rather than just individual objects, focusing on the quality and richness of the geometric priors (depth, normals) necessary for downstream video conditioning. Other related techniques include Zero123 [25] for view-consistent image generation and text-to-mesh methods [26].

C. High-Fidelity Video Generation

Recent advances in video synthesis are dominated by diffusion models. The key challenge is balancing spatial fidelity with temporal coherence. Models like Imagen Video [20] and Stable Video Diffusion (SVD) [24] address this via factorized or space-time attention mechanisms. Lumiere [10] uses a Space-Time U-Net to generate the entire video duration in a single pass, enhancing global consistency. Sora [9] introduced scalable patch-based modeling that generalizes across diverse video durations and aspect ratios. Our **VACE** (Video-to-Video Appearance and Coherence Engine) component is a diffusion-based model optimized for control. Unlike typical text-to-video models, VACE is conditioned primarily on **multiple geometric prior frames** (RGB, depth, normal, segmentation) rendered from $\mathbf{S}_t$, allowing it to focus its generative capacity on synthesizing texture, lighting, and style $\mathbf{p}_t$ (appearance) while strictly adhering to the input 3D geometry [27]. This decouples structure from appearance, mitigating the temporal drift problem.

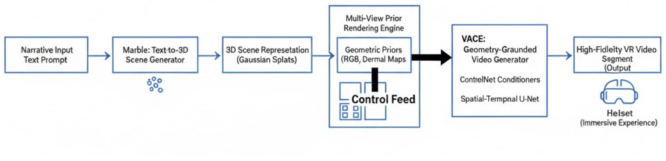

Fig. 1. Overview of our system pipeline.

D. Computational Narrative and VR Storytelling

The field of computational narrative investigates algorithms for generating coherent story structures, from early plot-based systems [28] to modern LLM-driven story generation [29]. In XR, the focus shifts to interactive and immersive experiences [16], [32]. Systems like Storycaster [31] explore generative AI for room-based storytelling, but typically rely on 2D projections or pre-authored 3D assets. The key challenge, recognized by CHI/UIST literature, is enabling **emergent narratives** that respond dynamically to user input while maintaining the structural logic necessary for perceived coherence [28]. DreamWM contributes to this domain by providing a framework where the narrative planner (the World Model) is inherently aware of the underlying spatial structure, allowing for physically-grounded yet dynamically evolving plots, reminiscent of dream logic [30].

III. System Overview

As shown in Fig. 1, the Dream World Model (DreamWM) framework is designed as an iterative, closed-loop generation pipeline that translates abstract narrative input $\mathbf{I}$ into a sequence of high-fidelity, VR-ready video segments $\mathbf{V}_0, \mathbf{V}_1, \ldots, \mathbf{V}_T$. The system is structured into four main components operating over a time step t: the World Model, the Marble 3D Scene Generator, the Multi-View Rendering Engine, and the VACE Video-to-Video Model.

A. The DreamWM Closed Loop

The process begins with the user input $\mathbf{I}$ at $t = 0$, which is encoded to initialize $\mathbf{z}_0$. The system then cycles through the following steps for each narrative segment:

1) **Narrative Decoding:** The World Model decodes the latent state $\mathbf{z}_t$ into a detailed textual prompt P_t, which

includes scene description, camera parameters, and emotional tone.

2) **3D Scene Synthesis:** P_t is passed to the Marble module, which generates a 3D geometric representation $\mathbf{S}_t$.
3) **Prior Rendering:** The Multi-View Engine renders a set of geometry priors $R_t = \{\mathbf{G}_{\text{RGB}}, \mathbf{G}_{\text{Depth}}, \mathbf{G}_{\text{Normal}}\}$ from $\mathbf{S}_t$.
4) **Video Generation:** R_t and the stylistic prompt P_t are fed into VACE, which synthesizes the final video segment $\mathbf{V}_t$.
5) **State Update (Closed Loop):** The World Model processes the generated video $\mathbf{V}_t$ and the previous state $\mathbf{z}_t$ to compute the next narrative latent state $\mathbf{z}_{t+1}$:

$$\mathbf{z}_{t+1} = g_\phi(\mathbf{V}_t, \mathbf{z}_t)$$

This closed-loop feedback mechanism, g_ϕ, ensures that the visual output constantly modulates and informs the future narrative trajectory, maintaining a dynamic, self-correcting story logic.

IV. Method Details

The successful operation of DreamWM hinges on the synergistic design of its components, particularly the interplay between the abstract world model and the concrete 3D geometry engine.

A. Narrative Latent State and World Model (f_θ, g_ϕ)

The World Model uses a specialized Recurrent Neural Network (RNN) structure, such as a Gated Recurrent Unit (GRU) or LSTM, to maintain the latent state $\mathbf{z}_t$. The state $\mathbf{z}_t \in \mathbb{R}^D$ is highly structured, composed of sub-vectors:

1) **Event Embeddings ($\mathbf{z}_{\text{event}}$):** Encodes the current plot point, entities, and relationships.
2) **Emotion Vectors ($\mathbf{z}_{\text{emotion}}$):** Captures the dominant emotional valence (e.g., tension, surprise, tranquility) to guide the visual style [30].
3) **Spatial Intent ($\mathbf{z}_{\text{spatial}}$):** A vector describing the scene's required topological features (e.g., proximity of objects, type of environment).

The narrative progression is governed by the state transition function f_θ:

$$\mathbf{z}_{t+1} = f_\theta(\mathbf{z}_t, \mathbf{u}_t)$$

where $\mathbf{u}_t$ is an optional manual intervention or a high-level plot point sampled from a narrative policy (e.g., "introduce a conflict").

B. 3D Scene Generation (Marble)

The Marble module is a **Text-to-3D Scene Generator** based on 3D Gaussian Splatting (3DGS) [2], trained to decode the latent state $\mathbf{z}_t$ into a set of 3D Gaussians $\mathcal{G}_t$.

1) **Geometry Representation:** We use a set of N 3D Gaussians, where each i-th Gaussian $\mathcal{G}_i$ is defined by its mean $\mathbf{p}_i \in \mathbb{R}^3$, covariance matrix $\mathbf{\Sigma}_i$, opacity α_i, and a diffuse color $\mathbf{c}_i$. The geometric stability of 3DGS under different views makes it superior to implicit fields like NeRF for our purpose [13].
2) **Multi-view Rendering Process:** The Marble output $\mathcal{G}_t$ is used to render a set of K synthetic control frames R_t from strategically sampled camera poses $\mathbf{C} = \{\mathbf{C}_k\}_{k=1}^K$. These frames strictly enforce the geometric consistency for the subsequent VACE stage. The rendered priors include:
   - $\mathbf{G}_{\text{RGB}}$: The raw color rendering of the scene's structure.
   - $\mathbf{G}_{\text{Depth}}$: A depth map crucial for maintaining spatial layout.
   - $\mathbf{G}_{\text{Normal}}$: Surface normals, critical for VACE to synthesize plausible lighting and shadows.

Fig. 2. 3D scene generated by Marble

Fig. 3. 3D scene generated by Marble

C. Geometry-Grounded Video Generation (VACE)

The Video-to-Video Appearance and Coherence Engine (VACE) is a customized Latent Diffusion Model (LDM) [11]. It takes the low-fidelity geometric priors R_t from Marble and the detailed textual prompt P_t (derived from $\mathbf{z}_t$) to generate a high-fidelity video segment $\mathbf{V}_t$.

1) **Conditioning Signals:** VACE utilizes a Spatial-Temporal U-Net architecture [10], where the geometric priors R_t are injected into the U-Net through specialized **ControlNet-like conditioning layers** [21] at multiple

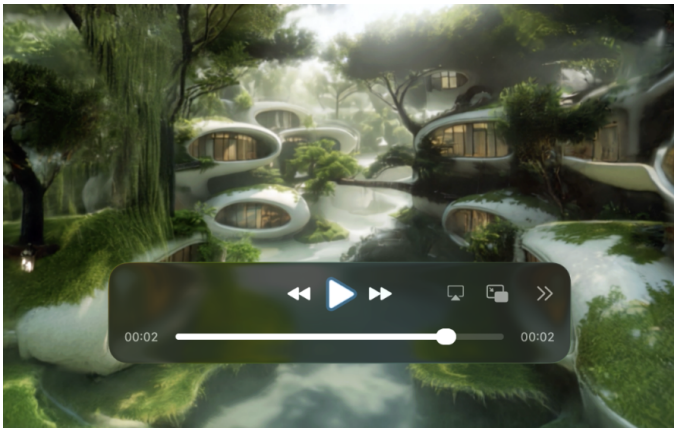

Fig. 4. VACE generated video

scales. This forces the generated video to respect the input depth and normal maps.

2) **Spatial-Temporal Fusion:** Temporal attention layers are modulated by the **Emotion Vector** $\mathbf{z}_{\text{emotion}}$ from the latent state $\mathbf{z}_t$. This enables stylistic consistency (e.g., using a dark, high-contrast style for a 'fear' segment) across the entire video segment $\mathbf{V}_t$ and ensures smooth temporal blending.
3) **Style Control:** The appearance information, which includes textures, realistic details, and cinematic lighting, is primarily generated by VACE, effectively isolating the dynamic elements (appearance/style) from the static elements (geometry/structure).

D. World Model–Driven Scene Evolution

The closed-loop mechanism is where the "dream" quality emerges. The update function $\mathbf{z}_{t+1} = g_\phi(\mathbf{V}_t, \mathbf{z}_t)$ uses a separate video encoder $\mathcal{E}_{\text{vid}}$ to extract salient visual features $\mathbf{v}_{\text{feedback}} = \mathcal{E}_{\text{vid}}(\mathbf{V}_t)$.

$$g_\phi(\mathbf{V}_t, \mathbf{z}_t) = \text{GRU}(\mathbf{v}_{\text{feedback}} \oplus \mathbf{z}_t)$$

- **Dynamic Scene Transitions:** If $\mathbf{v}_{\text{feedback}}$ indicates an unexpected visual element (e.g., a color shift, or object presence not in $\mathbf{z}_t$), the WM can trigger a non-linear narrative transition, such as the sudden "melting" of one scene into another, which is a hallmark of dream logic [30].
- **Updating Story Logic:** The feedback mechanism enables the WM to track **observable consequences**. If the generated scene $\mathbf{V}_t$ visually resolves a conflict in $\mathbf{z}_{\text{event}}$, the WM updates $\mathbf{z}_{t+1}$ to proceed to the next plot point, ensuring emergent yet causal progression.

E. Temporal Stitching Module

To ensure seamless transitions between segments $\mathbf{V}_t$ and $\mathbf{V}_{t+1}$, we implement a Temporal Stitching Module (TSM). This module uses an interpolation scheme on the latent space of VACE, applying noise scheduling across the final L frames of $\mathbf{V}_t$ and the initial L frames of $\mathbf{V}_{t+1}$. A keyframe-based transition mask is utilized to blend the style while the underlying 3D geometry from Marble maintains the structural link, preventing visual pops [33].

F. Design Rationale

- **Separating Geometry from Appearance:** By using Marble for structure (3DGS) and VACE for appearance (Diffusion), we gain explicit control. Geometric coherence is enforced by $\mathbf{S}_t$, while creative freedom and dynamic style are provided by VACE, solving the "consistent hallucination" problem in video generation [34].
- **World Model Ensures Coherence:** The WM acts as a **Narrative Planner and Validator**. It enforces high-level rules, mitigating the risk of the generative models producing locally pleasing but globally inconsistent or nonsensical output [28].
- **Video Alone is Insufficient:** Pure Text-to-Video models, even advanced ones [9], lack the internal 3D representation to guarantee multi-view, object-consistent videos necessary for immersive VR where the user's viewpoint is dynamic and unscripted.

V. Implementation Details

A. Training and Hardware

The DreamWM system is implemented using PyTorch. The World Model (f_θ, g_ϕ) is trained on a synthetic dataset of narrative transcripts paired with low-fidelity, stylized video simulations (rendered from pre-authored 3D scenes). Marble is a fine-tuned Gaussian Splatting generator initialized from a base model similar to DreamGaussian [13]. VACE is a customized SVD [24] model trained on a large dataset of high-resolution video clips conditioned on synthetic depth and normal maps. Training utilizes 8 NVIDIA A100 GPUs.

B. Hyperparameters and Integration

The latent state $\mathbf{z}_t$ dimension D is set to 256. The WM operates at a 3-second narrative chunk frequency. For Marble, the 3DGS representation is densified to approximately 10^6 Gaussians per scene. VACE generates videos at 512×512 resolution at 24 FPS, using $K = 4$ multi-view priors rendered at 128×128. The VACE model uses 4 ControlNet conditioning blocks for integrating the geometric priors R_t with a linear schedule for noise injection.

C. VR Environment Setup

The generated video segments $\mathbf{V}_t$ are projected onto a 360-degree cylindrical or cubemap surface using the camera poses $\mathbf{C}$ derived from Marble, enabling seamless presentation in standard VR headsets (e.g., Meta Quest 3). We use Unity for the final VR runtime, leveraging its high-performance video texture playback capabilities.

VI. Experiments and Evaluation

Our evaluation strategy combines rigorous quantitative metrics (ICCV style) for model performance and geometry coherence with qualitative user studies (CHI style) for narrative experience and immersion.

A. Quantitative Metrics

We compare DreamWM against four baselines: (1) **Sora** (simulated via high-quality open-source T2V [44]), (2) **VACE alone** (T2V without 3D priors), (3) **Marble + I2V** (generate 3D, render single keyframe, use I2V for motion), and (4) **WorldDreamer** (WM optimized for general video prediction). We use a test set of 100 narrative scripts.

1) **Geometry Consistency Score (GCS):** Measures the structural similarity of the generated video $\mathbf{V}_t$ to the original 3D scene $\mathbf{S}_t$. We use a 3D reconstruction network (e.g., monocular depth estimation [35]) to infer 3D geometry from $\mathbf{V}_t$ and compute the L_2 error against the ground truth depth of $\mathbf{S}_t$.
2) **Temporal Coherence Score (TCS):** Calculates the difference in feature embeddings (e.g., CLIP [36]) between adjacent frames within $\mathbf{V}_t$ and across the TSM boundaries, rewarding smooth transitions [37].
3) **Narrative Consistency Score (NCS):** An LLM-based metric that evaluates the generated narrative (extracted via video-to-text [38]) against the WM's planned plot points ($\mathbf{z}_{\text{event}}$), punishing logical contradictions or inconsistencies.
4) **Video Fidelity (FID, VBench):** Standard metrics for measuring visual quality and prompt adherence [39], [40].

VII. Discussion and Future Work

A. Cognitive Alignment and Controllability

DreamWM's success lies in its cognitive alignment: the World Model provides the high-level, persistent structure of "thought" (narrative logic), while the 3D-to-Video pipeline executes the visual rendering. This separation of concerns offers high **controllability**; a user or designer can directly modify the $\mathbf{z}_{\text{emotion}}$ vector to instantly apply a consistent, dynamic style shift across an entire segment without sacrificing structural stability [5].

B. Interpretability and Hallucination Mitigation

The explicit nature of the World Model's latent state $\mathbf{z}_t$ enhances **interpretability**. Since $\mathbf{z}_t$ is composed of decipherable sub-vectors ($\mathbf{z}_{\text{event}}$, $\mathbf{z}_{\text{emotion}}$), system behavior can be traced back to the narrative logic. Furthermore, enforcing 3D geometric constraints through Marble significantly mitigates the risk of visual **hallucination and geometric drift**, which plagues purely T2V systems.

C. Future Research

Future work will focus on integrating interactive agents. By incorporating an action space $\mathbf{u}_t$ controlled by a user, DreamWM can be extended to true interactive cinematic experiences, where the WM must learn to predict both narrative progression and agent behavior [41]. We also plan to explore alternative 3D representations beyond Gaussian Splatting, such as textured meshes, to optimize for VR rendering pipelines.

VIII. Limitations

1) **Marble Failure Cases:** As a generative 3D model, Marble can still produce geometrically ambiguous or "melted" objects from complex, highly novel prompts, which VACE cannot fully correct.
2) **VACE Temporal Drift:** While mitigated by 3D priors, VACE may still exhibit minor temporal inconsistencies in appearance (e.g., flickering textures) over very long sequences (10+ seconds) if the $\mathbf{z}_{\text{emotion}}$ conditioning is insufficient.
3) **World Model Hallucinations:** The WM ($\mathbf{z}_{t+1} = g_\phi(\mathbf{V}_t, \mathbf{z}_t)$) can occasionally misinterpret the video feedback $\mathbf{V}_t$, leading to a non-sequitur update to $\mathbf{z}_{t+1}$ and a sudden, unexpected story branch.
4) **VR Rendering Cost:** While 3DGS is fast for rendering priors, the VR presentation requires rendering high-resolution videos, which demands significant VRAM and CPU resources for real-time playback in the headset.

IX. Conclusion

We presented Dream World Model (DreamWM), a framework that leverages a World Model to guide coherent and expressive narrative generation, grounded in consistent 3D geometry. By linking the Narrative Latent State ($\mathbf{z}_t$) to a 3D Scene Generator (Marble) and conditioning a high-fidelity Video Model (VACE) with multi-view geometric priors, DreamWM overcomes the critical challenges of spatial inconsistency and temporal drift in generative storytelling. The World Model closed loop provides a powerful mechanism for dynamic story evolution and the realization of complex, dreamlike narratives within a stable 3D world, paving the way for the next generation of truly immersive and emergent content creation for Virtual Reality.

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