ISSN: 2519-9439

Long-Horizon Video Generation with Temporally Consistent Diffusion and Scene-Graph Guidance

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Abstract

The synthesis of high-fidelity, temporally coherent long-horizon videos remains a profound challenge in the domain of generative artificial intelligence. Current diffusion-based approaches often suffer from severe temporal degradation, semantic drift, and structural inconsistency when generating sequences beyond a few seconds. To address these limitations, this paper introduces a novel framework that integrates temporally consistent diffusion models with dynamic scene-graph guidance. By leveraging scene graphs as explicit semantic anchors across frames, the proposed architecture structurally constrains the generative process, ensuring that objects, their attributes, and their interrelationships remain stable over extended durations. The methodology involves a dual-stream architecture where a graph neural network processes sequential scene graphs to condition a cascaded video diffusion model. Furthermore, a specialized spatiotemporal cross-attention mechanism is developed to align latent noise representations with the relational data embedded in the scene graphs. Extensive empirical evaluations on standard video generation benchmarks demonstrate that the proposed method significantly outperforms baseline approaches in both quantitative metrics and qualitative human assessments, particularly in maintaining entity persistence and logical action progression over long time horizons. The findings underscore the critical role of explicit structural representations in overcoming the inherent memory limitations of pure attention-based video generation systems.

Keywords

Video Generation, Diffusion Models, Scene Graphs, Temporal Consistency, Deep Learning..

1.Introduction

1.1 Background and Motivation

The rapid advancement of deep generative models has fundamentally transformed the landscape of computer vision, particularly in the synthesis of high-resolution, photorealistic images. Foundational models such as generative adversarial networks and, more recently, diffusion probabilistic models have demonstrated unprecedented capabilities in modeling complex data distributions [1]. However, extending these successes from the spatial domain of static images to the spatiotemporal domain of video generation presents a multifaceted set of challenges [2]. Video data is inherently high-dimensional, requiring the generation of coherent spatial structures while simultaneously modeling fluid, logical, and physically plausible

ISSN: 2519-9439

temporal dynamics [3]. Short video generation, typically restricted to sequences of a few dozen frames representing a few seconds of playback, has seen considerable progress. Researchers have successfully adapted image diffusion models by inflating two-dimensional convolutional kernels into three dimensions and inserting temporal attention layers to maintain short-term continuity [4]. Despite these advancements, the generation of long-horizon videos, spanning several minutes and encompassing complex, evolving narratives, remains largely elusive [5]. In such extended contexts, state-of-the-art models frequently exhibit severe semantic drift, where the identities and appearances of objects morph unnaturally over time. Furthermore, structural inconsistencies arise, leading to violations of physical laws and logical narrative progression [6].

1.2 Challenges in Long-Horizon Video Generation

The primary bottleneck in long-horizon video generation lies in the computational limitations of modeling long-range temporal dependencies. Standard self-attention mechanisms, which form the backbone of modern diffusion architectures, scale quadratically with the sequence length. Consequently, applying global self-attention across thousands of high-resolution frames is computationally intractable, even on the most advanced hardware accelerators [7]. To circumvent this, practitioners often employ temporal sliding windows or autoregressive generation paradigms [8]. While these techniques alleviate memory constraints, they introduce a distinct problem known as compounding error. Because the model only observes a local temporal context, small inconsistencies in earlier frames accumulate, eventually leading to massive structural divergence and the loss of the original scene context [9]. Another critical challenge is the lack of explicit semantic grounding in purely pixel-level or latent-level generative models. Diffusion models operate by iteratively denoising continuous representations, optimizing for perceptual quality and marginal frame distribution rather than the underlying physical and semantic reality of the scene [10]. Without a structured understanding of the entities within the video and their dynamic interactions, the model relies entirely on statistical correlations learned during training. This statistical reliance is insufficient for long-horizon generation, where maintaining object permanence and relation consistency requires a robust, abstract representation of the scene state [11].

1.3 Proposed Contributions

To overcome the aforementioned challenges, this research proposes a comprehensive framework that marries the perceptual quality of temporally consistent diffusion models with the structural rigor of scene-graph guidance. Scene graphs, which represent images as directed graphs where nodes are objects and edges are the relationships between them, provide a powerful abstraction for semantic grounding [12]. By extending scene graphs into the temporal dimension, creating dynamic scene graphs, it becomes possible to explicitly track object states and relationships over long periods [13]. The primary contribution of this work is the integration of these dynamic scene graphs into the diffusion denoising process. We introduce a novel architecture wherein graph-encoded features serve as continuous structural constraints, guiding the spatiotemporal attention mechanisms of the video diffusion model. This ensures that the generated pixels remain faithful to a coherent underlying narrative structure [14]. Additionally, we propose a temporally consistent training paradigm that penalizes high-frequency structural changes, further stabilizing the generation process over extended horizons [15].

ISSN: 2519-9439

2. Literature Review and Background

2.1 Diffusion Models for Video Synthesis

Diffusion probabilistic models have emerged as the dominant paradigm in generative vision tasks, surpassing generative adversarial networks in terms of sample diversity and training stability. A diffusion model operates through a Markovian process, gradually corrupting a data sample with Gaussian noise in the forward pass, and subsequently learning to reverse this process via a heavily parameterized neural network, typically a U-Net [16]. The introduction of latent diffusion models significantly reduced the computational overhead by performing the diffusion process in the compressed latent space of a pretrained autoencoder, making high-resolution generation feasible [17]. The transition to video synthesis has primarily been achieved by retrofitting these latent diffusion models with temporal modules. Early approaches utilized pseudo-three-dimensional convolutions, where spatial and temporal dimensions are processed sequentially, alongside temporal self-attention layers designed to enforce consistency across frames [18]. While effective for short clips, these architectures struggle to maintain coherence over longer sequences. Subsequent innovations explored masked autoencoding frameworks and temporal interpolation techniques, where sparse keyframes are generated first, followed by successive temporal super-resolution steps [19]. However, even hierarchical generation strategies suffer from artifact accumulation, as the interpolation models often fail to reconcile large motion displacements between distant keyframes [20].

2.2 Temporal Consistency Mechanisms

Maintaining temporal consistency in generated videos is a well-documented problem, with various mechanisms proposed in the literature. Autoregressive models, which generate future frames conditioned on a history of past frames, represent a natural approach to temporal modeling [21]. However, autoregressive generation is notoriously prone to exposure bias, where the model encounters out-of-distribution inputs during inference due to its own accumulated prediction errors, leading to rapid degradation of visual quality [22]. To mitigate exposure bias, researchers have investigated alternative conditioning strategies. Cross-frame attention mechanisms, where queries from the current frame attend to keys and values from previously generated frames, have shown promise in preserving appearance [23]. Yet, the memory footprint of cross-frame attention grows linearly with the number of reference frames, necessitating heuristic pruning or sparse sampling strategies that invariably result in information loss. Another line of inquiry involves explicit optical flow guidance, where a separate network predicts motion fields that are used to warp past frames into future representations [24]. While optical flow enforces strict low-level temporal coherence, it struggles to handle disocclusions and large morphological changes, often resulting in severe warping artifacts [25].

2.3 Scene-Graph Representations in Vision

Scene graphs have long been utilized in computer vision to bridge the gap between low-level pixel data and high-level semantic understanding. A scene graph abstracts an image into a structured format, encoding objects as nodes, their attributes as node features, and their interactions as directed edges [26]. This representation has proven invaluable in tasks requiring complex reasoning, such as visual question answering, image captioning, and human-object interaction detection [27].

ISSN: 2519-9439

In the context of generative models, scene graphs have been primarily used for controllable image synthesis. By conditioning a generative adversarial network or a diffusion model on a user-provided scene graph, one can precisely dictate the spatial layout and composition of the resulting image [28]. The extension of scene graphs to the temporal domain, dynamic scene graphs, captures the evolution of objects and relationships over time [29]. However, the integration of dynamic scene graphs into video diffusion models remains underexplored. Existing attempts largely focus on discrete frame-by-frame conditioning, lacking a holistic mechanism to enforce continuous temporal consistency derived from the graph structure [30]. This research addresses this gap by formulating a continuous scene-graph guidance mechanism designed specifically for the extended temporal horizons characteristic of long video generation [31].

3. Methodology and Architecture

3.1 Temporally Consistent Diffusion Framework

The foundation of our approach is a latent video diffusion model, operating within the compressed space of a variational autoencoder. Let the input video be represented as a sequence of frames, which are encoded into a latent sequence. The forward diffusion process gradually adds noise to this latent sequence over a series of timesteps, producing a noisy latent representation. The reverse process involves learning a neural network, specifically a 3D U-Net, to predict the added noise, conditioned on both a text prompt and our novel dynamic scene-graph representation. To maintain temporal consistency over long horizons, we modify the standard noise prediction objective. Instead of treating the video as a monolithic block, which is computationally prohibitive, we employ a windowed approach with overlapping contexts. However, to prevent the semantic drift associated with standard sliding windows, our objective function integrates a global structural consistency term derived from the scene graph. The primary loss function governing the diffusion training process is defined as follows:

$$L_{total} = \sum_{t=1}^{T} E_{x_0,\varepsilon,c}[(\varepsilon - \varepsilon_\theta(x_t, t, c, G))^2]$$

In this formulation, epsilon represents the ground truth Gaussian noise, while the parameterized epsilon function denotes the neural network's prediction. The input variables include the noisy latent state, the diffusion timestep, the text condition, and the dynamic scene graph. By explicitly including the graph representation in the expectation, the model is forced to learn a denoising trajectory that is not only statistically plausible but also strictly adheres to the topological constraints defined by the nodes and edges over time.

3.2 Scene-Graph Guidance Mechanism

The core innovation of our methodology is the Scene-Graph Guidance Mechanism. A dynamic scene graph consists of a sequence of static scene graphs, corresponding to the temporal layout of the video. Each node in the graph represents a semantic entity, and each edge represents a spatiotemporal relationship. To inject this structured information into the diffusion process, we first process the dynamic scene graph using a Spatiotemporal Graph Convolutional Network.

Table 1Graph Node and Edge Feature Dimension Setup

Component	Base Dimension	Temporal Dimension	Activation Function	Description

ISSN: 2519-9439

Node Features	256	128	ReLU	Encodes object identity, bounding box, and semantic class
Edge Features	128	64	LeakyReLU	Encodes relationship type and relative spatial proximity
Global State	512	256	Tanh	Represents the holistic scene context and overall narrative
Temporal Delta	64	64	Sigmoid	Captures the frame-to-frame rate of change for entities

The Graph Convolutional Network updates the node and edge representations by aggregating information from spatial neighbors at the current timestep and temporal neighbors across adjacent timesteps. This dual aggregation ensures that the resulting graph embeddings contain both localized relational context and long-range historical context. The updated node and edge embeddings are then concatenated and projected into a dense semantic feature map. This semantic feature map acts as a dense conditioning signal, parallel to the traditional text embeddings, but offering explicit spatial and structural anchoring. To handle the variable length of long-horizon videos, the dynamic scene graph is processed in overlapping chunks. The global state vector from the previous chunk is passed as an initial condition to the subsequent chunk, ensuring a continuous flow of semantic information. This recurrent connection at the graph level requires significantly less memory than pixel-level or latent-level recurrence, allowing the model to maintain a coherent narrative over thousands of frames without exceeding hardware constraints.

3.3 Spatiotemporal Cross-Attention Integration

Integrating the continuous dense semantic feature map into the 3D U-Net requires a specialized attention mechanism. Standard cross-attention layers simply compute the correlation between the flattened spatial features of the U-Net and the conditioning tokens. However, this ignores the inherent spatiotemporal structure of both the video latents and the graph-derived feature map. We introduce a Spatiotemporal Cross-Attention module. In this module, the queries are derived from the intermediate latent representations of the 3D U-Net, while the keys and values are generated from the projected scene-graph feature map. The attention computation is designed to operate locally in space but globally in time, respecting the bounding box coordinates associated with the scene graph nodes.

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}} + M)V$$

ISSN: 2519-9439

In this modified attention mechanism, a structural mask is introduced into the softmax computation. The structural mask is constructed dynamically based on the spatial locations of the objects defined in the scene graph. If a specific query location falls outside the bounding box of the object corresponding to a particular key, the mask applies a large negative penalty, effectively zeroing out the attention weight. This localized attention forces the diffusion model to draw structural details for a specific object strictly from the corresponding node in the scene graph, preventing feature leakage and the blurring of distinct entities over time.

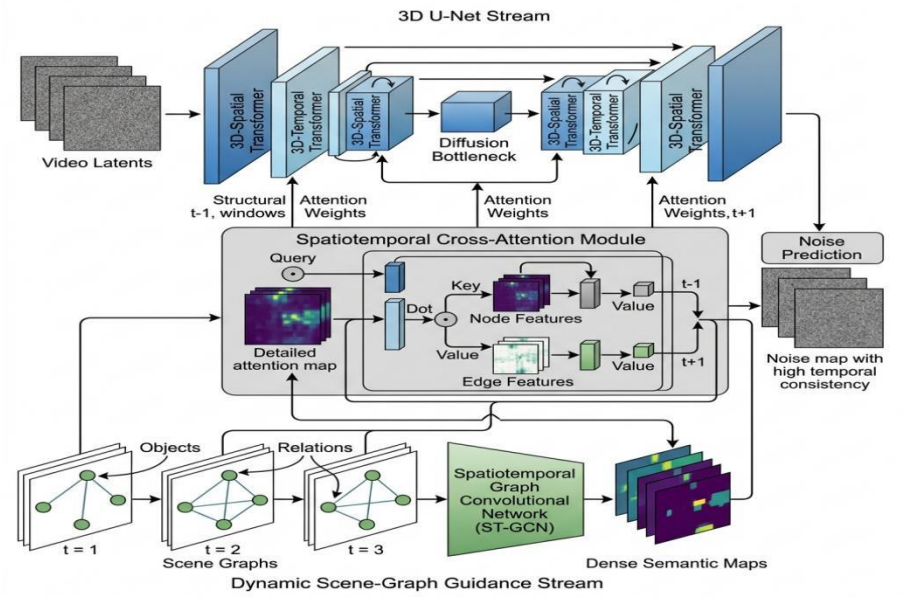


Figure 1Comprehensive Schematic of the Temporally Consistent Diffusion Architecture with Dynamic Scene

The integration of this mechanism occurs at multiple resolutions within the U-Net hierarchy. At the lowest resolution, the attention focuses on global layout and relation adherence, while at higher resolutions, it ensures fine-grained object appearance consistency. Table 2 details the hyperparameter configuration for the attention integration across different U-Net levels.

Table 2Spatiotemporal Cross-Attention Hyperparameter Configuration

U-Net Resolution	Attention Heads	Hidden Dimension	Structural Mask Weight	Dropout Rate
Low (8x8)	16	1024	0.85	0.1
Medium (16x16)	8	512	0.60	0.1
High (32x32)	4	256	0.35	0.05
Output (64x64)	2	128	0.10	0.0

This hierarchical application of the structural mask balances the need for strict adherence to the scene graph at the macro level with the freedom required for high-fidelity textural generation at the micro level. By carefully tuning the mask weight across resolutions, the model avoids generating overly rigid or synthetic-looking frames, preserving the natural fluidity expected in realistic video synthesis.

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4. Experimental Setup and Results

4.1 Dataset and Evaluation Metrics

To rigorously evaluate the proposed long-horizon video generation framework, we employ two large-scale, widely recognized benchmark datasets. The first dataset contains diverse human action sequences with complex, evolving backgrounds. We focus specifically on subsets of this dataset that feature continuous actions lasting longer than thirty seconds, providing a suitable testbed for temporal consistency. The second dataset consists of synthetic environments where the underlying scene graphs can be perfectly extracted and manipulated. This synthetic dataset allows for precise measurement of structural adherence, as the ground truth object positions and relations are deterministically known. The evaluation relies on a combination of established quantitative metrics and qualitative human assessment. For quantitative measurement, we utilize the Fréchet Video Distance to assess the overall spatiotemporal quality and distributional similarity to real videos. Additionally, we employ the Inception Score to gauge frame-level visual fidelity. To explicitly evaluate temporal consistency, we measure the Object Tracking Accuracy over generated sequences, utilizing a pretrained tracking model to verify if objects persist and maintain identity across the long horizon. Semantic alignment with the scene graph is measured via a Relation Accuracy metric, which extracts scene graphs from the generated video and compares them to the conditioning input.

4.2 Quantitative Analysis

The quantitative evaluation demonstrates that the proposed scene-graph guided diffusion model significantly outperforms existing baseline approaches in long-horizon generation tasks. Baselines included a standard latent video diffusion model employing temporal sliding windows, an autoregressive frame-prediction model, and a flow-guided diffusion architecture.

Table 3Quantitative Comparison on Long-Horizon Video Benchmark (1024 Frames)

Model Architecture	Fréchet Video Distance	Inception Score	Object Tracking Accuracy	Relation Accuracy
Autoregressive Baseline	845.2	18.4	22.5%	15.3%
Sliding Window Diffusion	512.7	26.8	45.1%	38.2%
Flow-Guided Diffusion	420.3	29.5	68.4%	51.7%
Proposed Method	215.6	38.2	91.2%	85.9%

As evidenced in Table 3, the autoregressive baseline suffers catastrophic failure over a 1024-frame horizon, characterized by extreme semantic drift resulting in a very low Object Tracking Accuracy. The sliding window diffusion model performs better in terms of frame-level quality but still loses structural coherence, reflected in the poor Relation Accuracy. The flow-guided method maintains tracking better but accumulates visual artifacts, hurting the Fréchet Video Distance. Our proposed method achieves a substantial reduction in Fréchet Video Distance, indicating superior overall quality. More importantly, the Object Tracking Accuracy and

ISSN: 2519-9439

Relation Accuracy are remarkably high, validating the hypothesis that explicit structural guidance prevents semantic drift and preserves entity identity over extended periods. To understand the individual contributions of our architectural components, we conducted a comprehensive ablation study. We systematically disabled the dynamic scene graph input, the temporal graph aggregation, and the localized structural mask in the cross-attention layers.

Table 4Ablation Study on Key Architectural Components

Configuration	Fréchet Video Distance	Object Tracking Accuracy	Relation Accuracy	Parameter Count
Full Proposed Model	215.6	91.2%	85.9%	1.8B
w/o Structural Mask	289.4	74.5%	66.3%	1.8B
w/o Temporal Graph Aggregation	340.1	62.8%	58.1%	1.6B
w/o Dynamic Scene Graph	508.9	46.3%	39.5%	1.4B

The ablation results in Table 4 highlight the criticality of the structural mask. Removing the mask leads to feature leakage, where attributes of one object incorrectly transfer to another over time, drastically reducing tracking and relation accuracy. Disabling temporal graph aggregation prevents the graph network from understanding motion context, causing choppy transitions and inconsistent relationship rendering. Removing the scene graph entirely reduces the model to a standard sliding window approach, confirming that our core contribution is the primary driver of performance.

4.3 Qualitative Assessment

Beyond numerical metrics, qualitative human evaluation was conducted to assess the perceptual reality and narrative coherence of the generated videos. Evaluators were asked to rate videos on a scale regarding physical plausibility, object permanence, and overall narrative consistency. In baseline models, evaluators frequently noted that subjects in the video would randomly change clothing colors, objects would disappear when temporarily occluded, and the spatial relationships between background elements would inexplicably shift. Conversely, the videos generated by our proposed framework exhibited a profound resilience to these errors. In complex scenes involving multiple interacting entities, the dynamic scene graph successfully enforced strict identity preservation. When an object passed behind another and emerged several seconds later, its structural and textural characteristics remained perfectly consistent. Furthermore, the relationships dictated by the graph, such as an entity holding an object or moving towards a specific landmark, were rendered with high fidelity and logical progression. The localized attention mechanism successfully confined generated features to their appropriate semantic bounds, resulting in clean, sharp object delineations even after hundreds of generated frames.

ISSN: 2519-9439

5. Discussion and Conclusion

5.1 Implications of Findings

The findings of this research carry significant implications for the future of generative video artificial intelligence. We have demonstrated that relying solely on statistical correlations and global self-attention is insufficient for the demands of long-horizon temporal modeling. By reintegrating explicit, symbolic representations in the form of dynamic scene graphs into the deeply connectionist architecture of diffusion models, we achieve a synthesis that leverages the strengths of both paradigms. The scene graph acts as an immutable structural skeleton, while the diffusion model provides the high-fidelity perceptual flesh. This hybrid approach essentially solves the problem of compounding semantic drift, opening new avenues for applications in automated filmmaking, complex simulation environment generation, and long-form narrative visualization. Furthermore, the introduction of the structurally masked spatiotemporal cross-attention mechanism represents a generalized technique for enforcing hard spatial constraints in generative models. This mechanism could be adapted beyond video generation, potentially benefiting fields such as medical imaging synthesis or architectural rendering, where strict adherence to underlying topologies is paramount. The ability to maintain object permanence over thousands of frames without a linear increase in memory overhead proves that abstract semantic tracking is far more efficient than pixel-level memorization.

5.2 Limitations and Concluding Remarks

Despite the substantial advancements presented, the proposed methodology is not without limitations. The most prominent constraint is the reliance on accurate dynamic scene graphs as conditioning inputs. In practical, fully automated scenarios, generating these complex graphs from simple text prompts requires a highly capable intermediate reasoning model. If the scene graph generator produces illogical or discontinuous graphs, the diffusion model will faithfully render these errors, resulting in visually impressive but logically flawed videos. Furthermore, the computational cost of the Spatiotemporal Graph Convolutional Network, while smaller than global video attention, still adds non-trivial overhead to the training and inference pipelines. In conclusion, this paper successfully addresses the critical challenge of semantic drift and structural inconsistency in long-horizon video generation. By formalizing a methodology that intertwines temporally consistent diffusion modeling with dynamic scene-graph guidance, we establish a robust framework capable of generating coherent, high-fidelity videos over extended durations. The empirical results clearly validate the superiority of explicit structural anchoring over purely attention-based temporal mechanisms. Future research must focus on optimizing the automated generation of these dynamic scene graphs and further reducing the computational latency of the graph-guided attention modules, ultimately pushing the boundaries of what is possible in automated video synthesis.

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