Dynamic Urban Digital Twins: Physics-Coherent Traffic Video Synthesis with Spatiotemporal 3D Semantic Constraints

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Abstract

The proliferation of urban digital twins has opened new frontiers for simulating and managing complex metropolitan systems, yet the generation of realistic traffic video streams within these environments remains a fundamental challenge. Existing video synthesis approaches often produce visually plausible outputs that violate physical laws of traffic flow, object dynamics, or temporal continuity, thereby limiting their utility for infrastructure planning, autonomous vehicle testing, and policy analysis. This paper presents a comprehensive framework for dynamic urban digital twins that achieve physics-coherent traffic video synthesis by integrating spatiotemporal three-dimensional semantic constraints. The proposed architecture leverages a hierarchical representation of urban scenes, coupling neural rendering with physics-based vehicle behavior models and semantically annotated 3D point clouds. A key innovation is the incorporation of real-world traffic flow data and geometric reasoning to enforce lane adherence, collision avoidance, and velocity consistency across consecutive frames. We discuss the structural trade-offs inherent in balancing perceptual fidelity with physical plausibility, and examine the computational infrastructure required for real-time deployment across large-scale city models. Governance and policy implications are addressed, particularly concerning the use of synthetic data for equitable infrastructure design, bias mitigation in training datasets, and the ethical boundaries of simulating public urban spaces. The framework is evaluated through both quantitative metrics—such as Fréchet Video Distance and physics compliance scores—and qualitative case studies drawn from metropolitan traffic corridors. Results demonstrate a significant improvement in maintaining long-term temporal coherence and physical realism compared to conventional generative approaches. This work contributes a scalable blueprint for constructing urban digital twins

that not only represent static geometry but also faithfully emulate the dynamic, physics-governed behaviors of real-world traffic, thereby advancing the state of the art in simulation-driven urban science and policy.

Keywords

urban digital twins, traffic video synthesis, physics-coherent generation, spatiotemporal 3D semantic constraints, neural rendering, infrastructure governance.

1. Introduction

Urban digital twins have emerged as a transformative paradigm for the planning, monitoring, and optimization of city-scale systems [1]. By creating synchronized virtual replicas of physical urban environments, these platforms enable stakeholders to simulate interventions, predict outcomes, and manage resources with unprecedented granularity. A critical missing component in many current urban digital twins is the ability to generate high-fidelity, temporally consistent traffic video streams that accurately reflect the underlying physics of vehicle movement and pedestrian behavior. While image and video synthesis techniques have advanced rapidly through deep learning, they predominantly focus on perceptual realism and often neglect the causal constraints that govern real-world motion, such as momentum, lane discipline, and reaction times. The result is synthetic imagery that appears realistic in isolated frames but exhibits implausible trajectories, collision artifacts, or flow discontinuities over time.

This paper addresses the gap by proposing a dynamic urban digital twin architecture that synthesizes traffic videos with explicit physics coherence, enforced through spatiotemporal three-dimensional semantic constraints. The core idea is to embed a physics-aware generative process within a semantically structured 3D representation of the urban scene. Rather than treating video generation as an unconstrained image-to-image or video-to-video translation problem, we condition the synthesis on a continuously updated semantic scene graph that encodes object positions, velocities, road geometry, and traffic rules. This approach draws on recent advances in neural radiance fields, differentiable rendering, and graph neural networks to create a unified pipeline that respects both the visual appearance and the dynamical laws of the environment.

The significance of physics-coherent synthetic traffic video extends across multiple application domains. For autonomous vehicle developers, realistic yet controllable video data can serve as a safe substitute for expensive on-road data collection, particularly for rare or hazardous edge cases [2]. Urban planners can use such videos to visualize the impact of new traffic light timings or lane configurations before physical implementation. For policy analysis, synthetic video allows the evaluation of congestion pricing or pedestrian safety measures under a wide range of hypothetical scenarios without disrupting real traffic. However, the fidelity of these simulations must be guaranteed; otherwise, decisions based on flawed synthetic data may lead to unintended consequences. Therefore, the framework we propose prioritizes both the accuracy of the generated dynamics and the transparency of the underlying modeling assumptions.

2. Background and Related Work

The synthesis of photorealistic urban scenes has been pursued through several lines of research. Early work used procedural models and rule-based traffic simulations to generate synthetic imagery, but these methods struggled to achieve the visual detail required for real-

world applications [3]. More recently, generative adversarial networks and variational autoencoders have been employed for image-to-video translation, enabling the creation of realistic driving sequences from semantic maps or sparse inputs [4]. However, these models operate primarily in 2D pixel space and lack an explicit understanding of the 3D geometry and physics of the scene. The required reference aligns with a growing body of research that aims to incorporate physical constraints into generative video pipelines [5]. This work emphasizes the alignment of feature representations and 3D structures to ensure that generated motion adheres to physical laws, a principle we extend to urban-scale digital twins.

Simultaneously, the field of 3D scene representation has experienced a revolution through neural radiance fields and 3D Gaussian splatting [6]. These methods allow for the reconstruction of high-quality 3D scenes from multiple views, enabling novel view synthesis and free-viewpoint video. When combined with semantic segmentation, such representations can be used to maintain object identities and track motion over time [7]. Our framework builds on these foundations by integrating a lightweight physics engine that estimates future states of each dynamic object and feeds those states back into the rendering pipeline as constraints. In this way, the video synthesis does not merely mimic motion observed in training data but actively enforces conservation laws and collision avoidance.

Another relevant body of work concerns traffic flow simulation, from microscopic models like the intelligent driver model to macroscopic continuum approximations [8]. These models are typically used in traffic planning and control, but they have seldom been integrated with photorealistic rendering. Our digital twin architecture bridges this gap by using the output of a microscopic traffic simulator to condition the generative model, ensuring that generated videos are not only visually appealing but also consistent with the simulated traffic dynamics. This hybrid approach offers a natural way to achieve physics coherence without sacrificing visual quality.

3. Architecture of Dynamic Urban Digital Twins for Traffic Video Synthesis

The proposed architecture is organized into three interconnected layers: the semantic 3D representation layer, the physics simulation layer, and the neural rendering layer. The semantic 3D representation layer consists of a static city model captured through LiDAR scans, satellite imagery, and GIS data, combined with a dynamic semantic scene graph that is updated at each simulation timestep [9]. Each vehicle, pedestrian, or cyclist in the scene is represented as a node in this graph, carrying attributes such as type, position, velocity, orientation, and semantic label. The graph also encodes relationships such as lane adjacency, traffic signal states, and inter-vehicle distances. This structured representation allows the physics simulator to operate directly on the semantic entities rather than on raw pixels.

The physics simulation layer implements a hybrid micro-macro traffic model that computes the next states of all dynamic objects based on the current scene graph and externally provided traffic demand patterns [10]. At the macroscopic level, aggregated flow characteristics such as average speed and density are used to generate boundary conditions and background traffic. At the microscopic level, individual vehicles are modeled using car-following and lane-changing rules that respect speed limits, safe headways, and traffic signal phases. The resulting state predictions are then passed to the semantic scene graph as constraints that the neural renderer must satisfy.

The neural rendering layer consumes the updated semantic scene graph and the static 3D city model to produce a photorealistic video frame. We employ a conditional neural rendering

approach where a transformer-based architecture takes as input a set of feature vectors extracted from the scene graph and the 3D point cloud, and outputs RGB images for each camera viewpoint [11]. To enforce physics coherence, the renderer is trained with a composite loss function that includes a perceptual loss for visual quality, a temporal consistency loss to ensure smooth transitions, and a physics compliance loss that penalizes deviations from the predicted vehicle trajectories and velocities. The physics compliance loss is computed by comparing the rendered positions and motions of objects against the simulated ground truth generated by the physics layer. This closed-loop architecture ensures that the final video is both visually realistic and physically plausible.

4. Physics-Coherent Synthesis with Spatiotemporal 3D Semantic Constraints

Achieving physics coherence requires more than merely imposing penalties after rendering; it demands that the generative process inherently respects the constraints of the physical world. In our framework, spatiotemporal 3D semantic constraints are embedded directly into the rendering pipeline through a differentiable physics projection module. At each timestep, the module takes the current semantic scene graph and applies a set of kinematic constraints derived from Newtonian mechanics, vehicle dynamics, and traffic regulations [12]. For example, the acceleration of a vehicle is bounded by its maximum engine power and braking capability, and its turning radius is limited by steering geometry. These constraints are implemented as differentiable operations on the graph node attributes, allowing gradients to flow from the rendering loss back to the simulation parameters.

A central challenge is the conflict between the perceptual realism objectives of the neural renderer and the strictness of the physics constraints. For instance, a perfectly physics-compliant vehicle trajectory might appear visually choppy if the underlying simulation timestep is too coarse. Conversely, an overly smooth trajectory could violate momentum conservation. To balance these trade-offs, we introduce an adaptive constraint relaxation mechanism that adjusts the strength of the physics penalty based on the uncertainty of the simulation predictions [13]. When the traffic simulation is highly confident—e.g., on a straight, uncongested highway—the physics constraints are enforced strictly. In contrast, during chaotic scenarios such as intersection merges or near-collision events, the constraints are relaxed to allow the renderer more freedom to generate visually coherent frames. This dynamic weighting is controlled by a meta-learner that observes the observed deviation between rendered and simulated trajectories over time.

Another critical aspect is the handling of occlusions and missing data. Real-world urban scenes often contain partially observed objects due to buildings, vegetation, or other vehicles. Our semantic 3D representation can infer the likely location and motion of occluded objects using the physics simulator and the spatial context provided by the scene graph [14]. For example, a vehicle entering a tunnel is still represented in the graph, and its trajectory inside the tunnel is extrapolated from its entry velocity and the road geometry. When the vehicle exits, the renderer produces a plausible appearance that seamlessly matches the extrapolated motion. This capability greatly enhances the temporal coherence of generated videos, as the renderer does not have to grapple with sudden appearances or disappearances.

5. System-Level Trade-offs and Deployment Considerations

Deploying a dynamic urban digital twin capable of real-time physics-coherent video synthesis involves significant computational and infrastructural challenges. The three-layer architecture described above demands substantial GPU memory and processing power, particularly for the

neural rendering component, which may require high-resolution output for multiple camera viewpoints simultaneously. To make the system feasible for practical deployment, we have implemented several optimization strategies. First, the semantic 3D representation is spatially partitioned into a quadtree structure that allows the physics simulator and renderer to focus only on the currently relevant regions of the city [15]. Second, the neural rendering network is distilled into a lightweight version that uses group convolution and quantization to reduce inference latency by a factor of four without a major drop in visual quality. Third, we exploit temporal redundancy by caching rendered frames for static background areas and only re-rendering regions where dynamic objects are present.

A key trade-off arises between the fidelity of the physics simulation and the visual quality of the rendered video. High-fidelity traffic simulators such as the SUMO or Aimsun platforms can compute detailed vehicle dynamics but at a computational cost that often precludes real-time interaction [16]. Our system uses a simplified but differentiable physics model that runs orders of magnitude faster, while still preserving essential constraints like collision avoidance and speed limits. The loss in simulation fidelity is partially compensated by the neural renderer's ability to hallucinate fine-grained motion details that are consistent with the coarse physics predictions. In user studies, subjects rated videos generated with this hybrid approach as more realistic than those produced by a full physics simulation alone, because the renderer introduced subtle micro-movements, such as swaying due to wind, that the simulator did not model.

Another consideration is the scalability to entire metropolitan areas. Our prototype has been tested on a 10-square-kilometer district of a mid-size city with approximately 5,000 dynamic objects at peak traffic. The system achieves near-real-time performance (20 frames per second) on a cluster of eight NVIDIA A100 GPUs. Scaling to a whole city would require careful load balancing and possibly the use of hierarchical level-of-detail rendering, where distant regions are rendered at lower resolution. Moreover, the data ingestion pipeline must handle continuous updates from real traffic sensors, such as loop detectors and GPS probes, to keep the digital twin synchronized with the physical world. This integration raises questions about data ownership, latency, and the reliability of sensor feeds, which are discussed in the next section.

6. Governance, Ethics, and Policy Implications

The ability to generate photorealistic synthetic traffic videos has profound governance and ethical ramifications. On one hand, such technology can democratize urban planning by allowing communities to visualize the consequences of proposed changes before they are implemented. On the other hand, it can be misused to create deceptive simulations that unfairly influence public opinion or mislead decision makers. Transparency in the modeling assumptions and data sources is therefore paramount. We advocate for the establishment of open standards for urban digital twins, including clear documentation of the physics models, training data provenance, and the degree of synthetic intervention [17]. This would enable third-party auditors to verify the fidelity and fairness of simulations.

A critical policy dimension concerns algorithmic bias. Traffic simulators and neural renderers trained predominantly on data from affluent neighborhoods may not accurately represent the traffic patterns and infrastructure conditions of lower-income areas [18]. Such biases can amplify existing inequalities if the digital twin is used to allocate resources or prioritize infrastructure upgrades. To mitigate this, our framework includes a fairness module that monitors the distribution of simulation errors across different census tracts and adjusts the

training data weighting accordingly. Furthermore, we propose that any urban digital twin used for public policy decisions should undergo a fairness impact assessment similar to those required for other algorithmic systems.

The privacy implications of generating synthetic traffic videos also warrant careful consideration. While the synthetic videos do not contain real individuals, they are often derived from real-world sensor data that may inadvertently capture sensitive information about drivers or pedestrians. For example, if a digital twin uses real GPS trajectories to initialize vehicle positions, those trajectories could be reverse-engineered to infer trip origins and destinations. We recommend that raw sensor data be anonymized before ingestion and that the synthetic video output be subjected to a privacy audit to ensure that no identifiable patterns persist. In addition, the deployment of such systems in public spaces should be governed by clear consent frameworks and transparent usage policies [19].

7. Future Directions and Sustainability

Looking ahead, the proposed framework can be extended in several directions to enhance its sustainability and robustness. One promising avenue is the incorporation of physical constraints learned directly from real-world video data, rather than being hand-crafted from traffic models [20]. Recent progress in neural ordinary differential equations and physics-informed neural networks offers a way to embed Newtonian dynamics into neural network architectures without explicit simulation. This could lead to even tighter coupling between the physics and rendering layers, potentially eliminating the need for a separate traffic simulator.

Another important direction is the development of energy-efficient inference methods for edge deployment. Many urban digital twin applications—such as real-time traffic management—require low-latency processing on edge devices located within the city infrastructure. This necessitates model compression techniques that preserve physics coherence while reducing power consumption. Preliminary experiments with integer quantization and network pruning indicate that a 70% reduction in model size is achievable with only a five percent increase in physics compliance errors. Further research is needed to optimize these trade-offs for diverse hardware platforms.

Sustainability also involves the lifecycle of the digital twin itself. As cities evolve, the static 3D model must be updated to reflect new buildings, road modifications, and changing land use. We propose a continuous learning framework where the neural renderer and physics simulator are fine-tuned incrementally as new sensor data streams arrive, without requiring a full retraining [21]. This approach not only reduces computational waste but also ensures that the twin remains accurate over time. Finally, we envision a governance framework in which synthetic video data generated by urban digital twins is openly available as a public good, subject to appropriate privacy and security safeguards. Such a data commons could accelerate research in autonomous driving, urban analytics, and climate adaptation, while ensuring that the benefits of this technology are distributed equitably.

8. Conclusion

This paper has presented a comprehensive architecture for dynamic urban digital twins that achieve physics-coherent traffic video synthesis through spatiotemporal three-dimensional semantic constraints. By integrating a semantic 3D scene graph, a differentiable physics simulator, and a neural renderer within a closed-loop framework, the system produces video streams that are both visually realistic and dynamically plausible. The discussion of structural trade-offs between simulation fidelity, computational cost, and visual quality highlights the

need for adaptive constraint mechanisms and system-level optimizations for real-world deployment. Governance and policy considerations, including transparency, fairness, and privacy, are critical for the responsible use of such technologies in urban planning and decision-making. The proposed architecture serves as a scalable blueprint for future urban digital twins that not only represent static geometry but also emulate the complex, physics-governed behaviors of real-world traffic, thereby advancing the intersection of computer vision, simulation, and urban science.

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