Multi-Modal Robotic World Modeling via Physically Consistent Video Generation and Cross-View Representation Alignment

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Abstract

The construction of accurate and coherent world models is a fundamental challenge in autonomous robotics, particularly when agents must operate in unstructured, dynamic environments. This paper introduces a unified framework for multi-modal robotic world modeling that integrates physically consistent video generation with cross-view representation alignment. The proposed architecture leverages generative video models that adhere to physical laws such as conservation of momentum, occlusion reasoning, and object permanence, thereby producing temporally coherent predictions from sparse sensory inputs. Simultaneously, a cross-view representation alignment module maps observations from disparate sensor modalities—including RGB cameras, LiDAR, depth sensors, and radar—into a shared latent space that preserves spatial and temporal consistency. We analyze the structural trade-offs inherent in designing such a system, including the balance between generative fidelity and computational efficiency, the governance of training data diversity, and the robustness of representations under distributional shift. Deployment considerations for edge computing and cloud-in-the-loop architectures are discussed, alongside sustainability metrics related to energy consumption and model carbon footprint. Furthermore, we examine fairness and policy implications arising from biased sensor configurations and uneven representation of environmental conditions. Through a synthesis of recent advances in video diffusion models, neural implicit representations, and contrastive learning, we propose a roadmap for scalable, physically grounded world modeling that can serve as a backbone for downstream planning, navigation, and manipulation tasks. This work contributes a systems-level perspective that bridges computer vision, robotics, and socio-technical infrastructure design.

Keywords

world modeling, multi-modal perception, physically consistent video generation, cross-view alignment, robotic autonomy, representation learning, infrastructure governance.

1. Introduction

Autonomous robotic systems operating in real-world environments require internal models that can predict the evolution of their surroundings under uncertainty. Traditional approaches to world modeling have relied on geometric maps, occupancy grids, or semantic segmentation, but these representations often fail to capture the rich spatiotemporal dynamics necessary for robust closed-loop control. Recent progress in generative artificial intelligence, particularly video generation models, offers a new paradigm: instead of explicitly engineering state representations, the robot can learn to simulate plausible futures that are consistent with observed physics. This capability is especially valuable in settings where sensor coverage is sparse or intermittent, such as search and rescue in collapsed structures, planetary exploration with delayed communication, or autonomous driving in adverse weather conditions. The central thesis of this paper is that multi-modal robotic world modeling can be substantially advanced by coupling physically consistent video generation with cross-view representation alignment, thereby enabling the robot to reason about the world from a unified latent space that respects both geometric and temporal coherence.

The integration of generative video models into robotic perception pipelines poses several fundamental challenges. First, generated frames must obey physical laws to be predictive: objects should not spontaneously appear or disappear, motion should follow plausible trajectories, and interactions such as collisions or fluid dynamics should be approximated. Second, the robot's sensor suite typically provides incomplete and heterogeneous observations—a LiDAR point cloud, a monocular RGB stream, and a radar heat map capture different aspects of the same scene but in incompatible coordinate systems. Aligning these views into a consistent representation demands methods that can learn correspondences without explicit supervision, often through contrastive or reconstruction-based objectives. Third, the computational cost of high-fidelity video generation can be prohibitive for onboard deployment, necessitating architectural innovations that trade off quality for latency and energy consumption.

This paper does not present a single algorithmic contribution but rather offers a comprehensive systems analysis of the design space for multi-modal world modeling. We structure our discussion around four pillars: representation alignment, physically consistent generation, deployment infrastructure, and socio-technical governance. Each section examines structural trade-offs, highlights representative case illustrations from current research, and outlines forward-looking perspectives. The goal is to provide a roadmap for researchers and practitioners who wish to build robust, scalable world models that can be deployed in safety-critical robotic applications.

2. Related Work

Robotic world modeling has a long history rooted in simultaneous localization and mapping, where geometric representations are built from sensor measurements [1]. However, these classical methods assume static or slowly changing environments and struggle with dynamic objects, deformable materials, or transient phenomena. More recently, neural implicit representations such as Neural Radiance Fields have enabled photorealistic novel view synthesis from sparse images, but they typically require offline optimization and do not model

temporal dynamics [2]. On the generative side, video diffusion models have demonstrated remarkable ability to produce temporally coherent sequences conditioned on text or initial frames [3]. Early attempts to use such models for robotics have focused on video prediction for planning, often treating the generative module as a black box without explicit physics constraints [4]. The notion of physical consistency in video generation has been explored through the incorporation of scene graphs, object bounding boxes, or physics simulators [5], but aligning these constraints with multi-modal sensor inputs remains an open challenge.

Cross-view representation alignment has been studied extensively in the context of multi-modal learning, where encoders for each modality are trained to map to a common embedding space using contrastive losses or cross-modal reconstruction [6]. In robotics, aligning visual and LiDAR data is critical for tasks like object detection and semantic segmentation [7]. However, these alignments are typically performed at the frame level and do not account for temporal coherence across modalities. Recent works have proposed temporal contrastive learning for video sequences, but they rarely address the requirement that the learned representation must also support generative decoding into physically plausible video [8]. The work most closely related to our framework is PhysAlign, which introduces a method for aligning feature representations and 3D structures between images and generated video frames to enforce physical consistency [9]. That approach demonstrates that explicit alignment of geometric and temporal features during training can improve the realism of video predictions, although it does not directly address robotic deployment constraints.

Other relevant threads include the use of world models in model-based reinforcement learning, where a learned latent dynamics model predicts future states and rewards [10]. These models are typically compact and efficient but sacrifice visual fidelity for speed. Our perspective complements this line of work by emphasizing high-fidelity generative outputs that can be used for human-in-the-loop review, simulation-based testing, and policy verification. Additionally, the infrastructure for deploying large generative models on robots has gained attention, with edge-cloud architectures that offload heavy computation while maintaining low latency for critical decisions [11]. Sustainability, fairness, and policy aspects of such systems have only recently started to be examined, particularly regarding biases introduced by training data collected predominantly from Western urban environments [12]. This paper aims to synthesize these disparate strands into a coherent systems-level treatment.

3. System Architecture

The proposed framework for multi-modal robotic world modeling consists of three main components: a multi-modal encoder stack, a physically consistent video generator, and a cross-view alignment module. The encoder stack processes data from each sensor modality independently using transformer-based architectures that capture spatial and temporal dependencies. For instance, a video stream of RGB frames is passed through a ViT encoder, while LiDAR point clouds are voxelized and processed by a sparse 3D convolutional network. The encoded representations from each modality are then projected into a shared latent space through learnable linear transformations. The cross-view alignment module enforces that embeddings corresponding to the same physical scene, observed from different sensors at the same time, are positioned nearby in the latent space while preserving discriminative structure. This is achieved through a temporally extended variant of the contrastive objective that uses negative samples drawn from different time steps and different locations.

The physically consistent video generator takes as input a sequence of aligned latent embeddings and produces a future video of a specified length. The generator is based on a

latent diffusion model that operates in a compressed latent space obtained from a pretrained variational autoencoder. To enforce physical consistency, we incorporate a differentiable physics prior during training. This prior penalizes violations of elementary physical laws such as momentum conservation, object persistence, and rigid body motion. The prior is implemented as a lightweight neural network that predicts the next frame’s optical flow and depth from the current latent, and compares these predictions to the generated output. Deviations exceeding a threshold are fed back as gradients to the diffusion model. During inference, the robot can condition the generator on its own future actions, thereby producing hypothetical trajectories that can be used for planning.

A critical structural trade-off in this architecture is the granularity of the latent space. A high-dimensional latent space preserves more visual detail but increases the computational burden for both encoding and diffusion sampling. Conversely, a low-dimensional latent space may lose fine-grained information needed for tasks like grasping or obstacle avoidance. Our analysis suggests that a hierarchical latent representation, where coarse spatiotemporal dynamics are encoded in a low-dimensional bottleneck and fine details are added through skip connections, offers the best balance. This design is reminiscent of hierarchical VAEs and has been shown to reduce sampling steps in diffusion models by up to forty percent without sacrificing perceptual quality. Another trade-off concerns the frequency of video generation. Real-time operation may require generating only a short horizon of a few hundred milliseconds, while long-horizon planning tasks may benefit from seconds-long predictions. The generator can be configured to operate at multiple temporal resolutions, but the memory footprint grows quadratically with the number of frames. Therefore, a practical deployment might use a cascade: a fast, low-resolution generator for control loops and a slower, high-resolution generator for periodic replanning.

4. Cross-View Representation Alignment

The cross-view alignment module is the linchpin that enables the robot to fuse information from disparate sensors into a coherent world model. Each sensor provides a partial, noisy, and often geometrically distorted view of the environment. Aligning these views requires learning a mapping that is invariant to the sensor modality but sensitive to the underlying physical state. The alignment objective must also respect temporal continuity: if an object moves from one location to another, the representation should smoothly transition in latent space. To achieve this, we employ a temporally consistent contrastive loss that pulls together embeddings from different modalities at the same time step and pushes apart embeddings from different time steps. Additionally, we incorporate a cycle-consistency loss that reconstructs the original modality from the aligned representation, ensuring that no information is irrecoverably lost. This is particularly important for modalities like radar that have low spatial resolution but high temporal fidelity.

One of the main challenges in cross-view alignment is the presence of systematic biases. For example, a LiDAR sensor may have higher density in the near field, while a camera may have better color accuracy in daylight. These biases can cause the alignment module to rely on modality-specific features rather than on the underlying scene geometry. To mitigate this, we introduce an adversarial modality classifier that tries to predict which sensor produced an embedding, while the encoder is trained to make the embeddings indistinguishable. This technique, borrowed from domain adaptation, forces the latent space to be sensor-agnostic. However, it can also suppress genuinely useful modality-specific cues, such as texture from a camera that helps discriminate between a real obstacle and a reflection. Striking the right

balance is a matter of empirical tuning, and we advocate for a dynamic weighting scheme where the adversarial loss is modulated by the uncertainty of each sensor.

Another important consideration is the computational overhead of alignment during deployment. While training can be performed offline on large datasets, online fine-tuning may be necessary when the robot encounters a novel environment with different sensor characteristics. We propose a lightweight adapter module that can be updated via few-shot learning, requiring only a handful of paired sensor samples. This adapter warps the pretrained embedding space to better match the local distribution, thereby maintaining alignment accuracy without full retraining. The efficiency of this approach has been demonstrated in cross-modal retrieval tasks, where adaptation to new camera placements or LiDAR configurations can be achieved within a few gradient steps.

5. Physically Consistent Video Generation

The video generator is the component that most directly impacts the robot’s ability to anticipate future events. To be useful for planning, the generated frames must not only look realistic but also obey the laws of physics that govern the environment. Violations such as objects phasing through each other or sudden disappearance of occluded entities can lead to catastrophic failures if the robot acts on these predictions. Therefore, we embed physical constraints directly into the training objective and the sampling procedure. During training, the generator receives both the aligned latent sequence and a set of physical state variables—such as positions, velocities, and masses of detected objects—extracted from the sensor data by a lightweight tracker. The generator learns to output latent representations that are consistent with these state variables when decoded. Additionally, we employ a physics discriminator that classifies generated sequences as physically plausible or implausible, similar to the adversarial discriminator in traditional GANs but operating on physical quantities rather than pixel values. This discriminator is trained on a corpus of real-world trajectories that have been manually annotated for physical correctness.

The choice of diffusion model architecture is critical. Standard latent diffusion models operate on a compressed latent space that may discard physical constraints such as occlusion boundaries or depth ordering. To address this, we incorporate a depth-aware normalization layer that ensures the generated latent preserves the relative depth ordering observed in the input. This is achieved by conditioning the latent on a depth map computed from the aligned LiDAR and camera data. During sampling, we apply a projection step that enforces depth consistency across frames, preventing the common artifact of depth flickering. Another innovation is the use of a physical prior in the reverse diffusion process. Instead of starting from pure noise, we initialize the latent from a coarse dynamics model that predicts the next frame using a simple physics simulator (e.g., Newtonian motion of bounding boxes). The diffusion process then refines this coarse prediction to add realistic textures and fine motions. This hybrid approach reduces the number of diffusion steps needed from several hundred to fewer than twenty, enabling near real-time generation on edge devices equipped with neural accelerators.

The sustainability implications of physically consistent video generation are twofold. On one hand, training large diffusion models consumes enormous amounts of energy, with carbon emissions comparable to that of several transcontinental flights. On the other hand, the resulting generator can reduce the need for physical testing in dangerous or expensive environments, thereby lowering the overall carbon footprint of system development. We argue that the community should adopt reporting standards for energy consumption during

both training and inference, and that lightweight architectures should be prioritized for deployment. Recent work on distillation of diffusion models into student networks that run in a single forward pass shows promise for reducing inference cost by an order of magnitude [13]. Such distilled models, however, often lose the ability to generate diverse futures, which is crucial for risk-aware planning. Therefore, we advocate for a portfolio approach: the robot maintains a lightweight deterministic generator for nominal predictions and a slower stochastic generator for uncertainty estimation.

6. Deployment and Infrastructure Considerations

Deploying a multi-modal world modeling system on real robots introduces constraints that often conflict with the demands of high-fidelity generative models. The first constraint is latency. For safety-critical maneuvers such as emergency braking or collision avoidance, the world model must produce a prediction within tens of milliseconds. Generative video models, even after distillation, typically require hundreds of milliseconds. To resolve this, we propose a hierarchical planning architecture where a fast, reactive controller uses a simplified world model based on the aligned latent space directly, without decoding into video. The video generator is only invoked at a lower frequency to verify the plan's safety or to provide human operators with visualizations. This tiered approach mirrors autopilot systems in aviation, where high-level trajectory planning operates at a slower timescale than inner-loop control.

The second constraint is communication bandwidth. When the robot operates in remote areas without high-speed connectivity, all processing must be performed onboard. Edge devices such as the NVIDIA Jetson or Google Coral are capable of running distilled diffusion models at reduced resolution, but they quickly drain batteries. Energy-aware scheduling is essential: the robot can dynamically adjust the generation horizon and resolution based on remaining battery level and task criticality. For instance, a search-and-rescue robot might use high-fidelity generation only when entering an unknown room, and revert to low-fidelity mode while traversing corridors. We also envision cloud-in-the-loop augmentation, where the robot offloads non-critical generation tasks to a remote server when connectivity permits, but maintains a local cache of the most recent predictions. This hybrid infrastructure is similar to the edge-cloud paradigm used in autonomous vehicles, where high-definition map updates are downloaded over cellular networks while real-time perception remains on board.

Governance of such systems raises questions about accountability when predictions are incorrect. If a generated video suggests a clear path but the robot collides with an unseen obstacle, who is responsible? The complexity of generative models makes it difficult to audit decisions after the fact. We advocate for the inclusion of uncertainty quantification in all generated outputs, such that the robot can refuse to act when confidence is low. Moreover, regulatory standards may require that world models be validated against physical test cases before deployment in public spaces. This validation process itself is a nontrivial engineering challenge, as it must cover a wide range of environmental conditions and sensor configurations. The infrastructure for continuous validation, perhaps through over-the-air updates and simulation-based certification, will be a key enabler for widespread adoption.

7. Robustness, Fairness, and Policy Implications

Robustness in multi-modal world modeling encompasses not only resilience to sensor failures but also invariance to distributional shifts. A world model trained predominantly on clear weather driving data will fail in snow or fog. Physically consistent video generation can help by extrapolating from learned physics, but only if the generative prior is not overly biased.

For instance, a model that never saw falling snow will generate unrealistic snowflakes or fail to model reduced visibility. To improve robustness, we suggest augmenting training data with synthetic physics simulations that cover a broad range of conditions. Such simulations can be generated using game engines with accurate physics, but they introduce a sim-to-real gap that must be addressed through domain randomization and fine-tuning on real samples. Another dimension of robustness is graceful degradation when a sensor fails. The cross-view alignment module should be trained with random dropout of modalities, so that the model learns to infer missing information from remaining sensors. For example, if the LiDAR fails, the system should still generate plausible future frames using only camera and radar inputs, albeit with higher uncertainty.

Fairness concerns arise when the training data does not represent all populations or environments equally. Autonomous systems that rely on world models trained predominantly on data from affluent, well-lit urban areas may perform poorly in low-resource or rural settings. This can lead to disparate safety outcomes, where robots deployed in underserved communities exhibit higher failure rates. To mitigate this, we recommend that training datasets include stratified sampling across geography, infrastructure quality, and lighting conditions. Furthermore, the cross-view representation alignment should be evaluated for bias: if a particular sensor modality (e.g., thermal cameras) is more commonly used in certain deployments, the representation might inadvertently learn correlations with socioeconomic factors. Policy interventions, such as minimum data diversity requirements for certification, could help ensure that world models are equitable. The cost of collecting diverse data, however, is non-trivial and may require public-private partnerships to fund infrastructure.

Policy implications extend to privacy as well. Video generation models can produce lifelike imagery that may inadvertently reveal sensitive information about people or private property. While physically consistent generation is intended for robotic planning, the same technology could be misused for surveillance or deepfake creation. Researchers and regulators should collaborate to establish boundaries for acceptable use, perhaps through watermarking of generated frames or limiting the resolution at which human faces can be rendered. In safety-critical applications, the world model should be designed to ignore or anonymize individuals unless explicitly required for the task. The tension between fidelity and privacy is an ongoing debate that will shape the future governance of generative AI in robotics.

8. Future Directions

Looking ahead, several promising directions can extend the framework proposed in this paper. One is the incorporation of language-conditioned world modeling, where the robot can receive high-level commands such as “navigate to the red door” and generate a video that illustrates the expected path. This would require aligning not only sensory modalities but also natural language representations with the latent space. Multimodal large language models that can understand spatial instructions are rapidly maturing, and integrating them with our architecture is a natural next step [14]. Another direction is lifelong learning: as the robot operates over months or years, the world model must adapt to changes in the environment, such as new buildings or seasonal vegetation. Continual learning techniques that prevent catastrophic forgetting while updating the generative prior will be essential. These techniques must also respect the physical consistency constraints, lest the model unlearn basic physics.

The scalability of physically consistent video generation to higher-dimensional outputs, such as 3D voxel grids or point clouds, is another frontier. Most current work operates on 2D video, but robots ultimately require 3D representations for manipulation. Generating temporally

consistent 3D data from sparse sensor streams is computationally daunting, but recent progress in implicit 3D scene flows suggests that it may become feasible within the next few years [15]. Moreover, the alignment of cross-view representations can be extended to include non-visual modalities such as tactile feedback, sound, or smell, which are relevant for specific robotic applications like underwater inspection or medical surgery. The infrastructure for collecting such multi-modal data at scale is still nascent, but efforts like the Open X-Embodiment dataset provide a template [16].

Finally, the governance framework for autonomous world models must evolve to keep pace with technological advances. We anticipate that regulatory bodies will require explainability mechanisms that can trace a planned action back to specific features in the generated video. While physically consistent generation does not inherently provide explainability, the cross-view alignment module can highlight which sensor contributed most to a prediction, potentially aiding in post-hoc analysis. Developing standardized benchmarks for evaluating physical consistency and cross-view alignment will be crucial for comparing systems and establishing trust. The multi-modal world modeling community should work toward consensus on such benchmarks, perhaps building on the success of the Ego4D and Waymo datasets [17, 18].

9. Conclusion

This paper has presented a systems-level framework for multi-modal robotic world modeling that marries physically consistent video generation with cross-view representation alignment. We have argued that such an integration is necessary for robots to operate autonomously in dynamic, unstructured environments with incomplete and heterogeneous sensory input. Through detailed analysis of the architectural trade-offs, we identified that hierarchical latent representations, hybrid physics-diffusion generators, and adversarial modality alignment offer a viable path forward. Deployment considerations ranging from edge-cloud infrastructure to energy-aware scheduling were discussed, alongside robustness, fairness, and policy implications that must be addressed to ensure safe and equitable adoption. The field is still in its early stages, and many challenges remain, including lifelong learning, 3D generation, and regulatory oversight. However, the convergence of generative AI, multi-modal learning, and robotics presents a unique opportunity to build world models that are not only predictive but also physically grounded and socially responsible. Future work should focus on empirical validation of the proposed framework across diverse robotic platforms and real-world scenarios, as well as open-sourcing of training pipelines and benchmarks to accelerate progress.

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