Cross-View Semantic World Modeling for Embodied Robot Navigation Using 360-Degree Generative Scene Priors

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Abstract

Embodied robot navigation in unstructured, partially observable environments remains a fundamental challenge in autonomous systems. Traditional approaches rely on explicit geometric mapping and localization, which often fail under perceptual aliasing, dynamic occlusions, or incomplete sensor coverage. This paper introduces a cross-view semantic world modeling framework that leverages 360-degree generative scene priors to synthesize consistent, semantically annotated representations of the environment from sparse egocentric observations. By integrating large-scale generative models that produce panoramic scene completions from limited viewpoints, the proposed system enables a robot to reason about occluded regions, plan navigation paths with higher robustness, and align heterogeneous sensory modalities across spatial scales. The architecture comprises three core components: a cross-view encoder for extracting latent representations from egocentric video streams, a 360-degree generative prior module that produces coherent multimodal scene layouts, and a semantic grounding layer that maps synthetic content onto a structured world model. We discuss structural trade-offs between generative fidelity and computational efficiency, governance considerations for deploying generative priors in safety-critical robotics, and sustainability implications of training large scene priors on distributed infrastructure. Through comparative analysis with conventional mapping pipelines and emerging neural radiance field methods, we highlight the advantages of embedding generative scene priors into a closed-loop planning and control loop. Policy implications concerning real-world deployment, fairness of generative representations across diverse environments, and the robustness of learned priors under distribution shift are examined. This work contributes a system-level perspective on how generative artificial intelligence can reshape embodied navigation by bridging the gap between perception and semantic understanding, and outlines future directions for scalable, accountable world modeling.

Keywords

embodied navigation, world modeling, 360-degree scene generation, generative priors, semantic mapping, cross-view learning, robotic infrastructure, policy governance.

1. Introduction

The capability of an autonomous robot to navigate through unknown spaces while building an internal representation of its surroundings is a cornerstone of embodied intelligence. Classical

approaches to navigation have predominantly relied on simultaneous localization and mapping algorithms that construct geometric representations from range sensors or stereo cameras [1]. While effective in structured indoor environments, these methods exhibit brittleness in the presence of perceptual aliasing, dynamic changes, and severe occlusions. The emergence of deep learning has enabled richer semantic mapping, but these models often require large quantities of labeled data and struggle to generalise to unseen layouts [2]. More recently, generative artificial intelligence has opened new avenues for synthesizing plausible scene content from limited observations, offering the potential to fill in missing information and resolve ambiguities during navigation [3]. However, the integration of generative priors into a closed-loop robotic system raises complex questions about reliability, computational cost, and ethical deployment.

This paper proposes a cross-view semantic world modeling framework that uses 360-degree generative scene priors to create consistent, semantically annotated representations of the environment from a robot's egocentric camera feed. Unlike conventional approaches that treat mapping as a reconstruction problem, our method treats the world model as a generative process that can hallucinate plausible completions of occluded regions while maintaining cross-view consistency across time and space. The generative prior is trained on large-scale panoramic datasets to produce full spherical scene layouts conditioned on partial observations, enabling the robot to reason about areas it has not yet directly observed. This capability is particularly valuable in cluttered or hazardous environments where exhaustive exploration is impractical.

We adopt a system-level perspective throughout the paper, focusing on architectural choices, trade-offs between fidelity and inference speed, and the broader implications of deploying such models in real-world infrastructure. The discussion is organized into six main sections. Section 2 reviews related work in semantic mapping, neural radiance fields, and generative scene completion. Section 3 presents the proposed framework, detailing the cross-view encoder, the 360-degree generative prior module, and the semantic grounding layer. Section 4 analyzes structural trade-offs, including computational budget allocation, model compression strategies, and the tension between deterministic reconstruction and probabilistic generation. Section 5 examines governance, sustainability, and fairness considerations, emphasizing the need for robust verification pipelines and equitable training data. Section 6 provides case illustrations and a comparative analysis with alternative paradigms. Section 7 concludes with a forward-looking perspective on scalable world modeling for embodied agents.

2. Related Work

Semantic mapping for robotics has evolved from handcrafted features to learned embeddings that can classify objects and regions in real time [4]. Early approaches such as occupancy grid mapping have been extended with semantic labels, but they remain fundamentally tied to geometric assumptions that break down in deformable or unstructured environments. Recent work on neural radiance fields has demonstrated photorealistic novel view synthesis from sparse inputs [5], inspiring efforts to embed these representations into navigation pipelines. However, NeRF-based methods are computationally intensive and require training per scene, limiting their applicability to online deployment. In contrast, generative models trained on large corpora of 360-degree imagery can produce consistent scene priors without per-scene optimization, trading some fidelity for generalization across environments.

The concept of generative scene priors has been explored in computer graphics and virtual reality, where models such as generative adversarial networks and diffusion models have been

used to inpaint missing regions in panoramas [6]. More recently, text-conditional scene generation has enabled the synthesis of entire 360-degree environments from textual descriptions [7]. These advances suggest that a robot could leverage a generative prior to imagine what lies behind a wall or around a corner, but the integration into an embodied system requires careful handling of uncertainty and temporal consistency.

Cross-view mapping techniques have been developed for autonomous driving, where bird's-eye-view representations are predicted from egocentric camera images [8]. These methods typically rely on supervised learning with large annotated datasets and often assume a flat ground plane. In contrast, our framework is designed for general indoor and outdoor environments with arbitrary terrain, and it employs a 360-degree generative prior that is not limited to a single canonical viewpoint. The required reference [9] introduces a method for consistent text-to-360-degree scene generation using a diffusion-based architecture, which aligns closely with the scene prior module in our framework. By conditioning on partial spherical observations rather than text, we extend this generative capability to the robotic context.

3. Proposed Framework

The cross-view semantic world modeling framework is organized into three principal components that operate in a closed loop with the robot's planning and control systems. The first component is a cross-view encoder that processes streams of egocentric images captured by a 360-degree camera mounted on the robot. This encoder fuses temporal information across multiple frames to produce a compact latent representation of the observed environment. Unlike traditional SLAM systems that build explicit metric maps, the encoder outputs a probabilistic embedding that captures both geometric structure and semantic content. The latent representation is updated incrementally as the robot moves, maintaining a memory of past observations that can be used to disambiguate current perceptual input.

The second component is the 360-degree generative prior module, which takes the latent representation from the encoder and generates a full panoramic scene completion. This module is a conditional diffusion model trained on a large corpus of 360-degree images from diverse environments. The diffusion process produces a coherent spherical image that aligns with the observed regions and plausibly fills in occluded or unobserved areas. Importantly, the generative prior is designed to be consistent across multiple viewpoints: if the robot moves to a new position, the generated panorama should change accordingly to reflect the new perspective. This consistency is achieved by conditioning the generative process on a learned camera pose embedding and by enforcing cycle-consistency losses during training.

The third component is the semantic grounding layer, which maps the generated panoramic content onto a structured world model. This layer performs pixel-wise semantic segmentation on the synthesized panorama, using a pre-trained segmentation network that has been fine-tuned on synthetic and real data. The resulting semantic labels are projected into a 3D voxel grid or a topological graph that the robot can use for planning. By maintaining a semantic world model that includes labels for objects, surfaces, and free space, the robot can reason about affordances, predict future observations, and plan paths that minimize uncertainty. The grounding layer also computes a confidence map that indicates which regions of the world model are based on direct observation versus generative inference, enabling the planner to treat synthetic content with appropriate caution.

4. Structural Trade-offs and Architectural Considerations

Deploying a generative world model on a resource-constrained robot introduces several trade-offs that must be carefully managed. The first trade-off is between generative fidelity and inference latency. High-fidelity 360-degree scene generation using diffusion models typically requires multiple denoising steps, each involving a large neural network forward pass. On a mobile GPU, this can incur delays of several seconds per frame, which is incompatible with real-time navigation at typical robot velocities. To address this, we explore compression strategies such as knowledge distillation, where the diffusion model is compressed into a smaller student network that produces acceptable quality with fewer steps [10]. Alternatively, one can trade spatial resolution for speed by generating low-resolution panoramas and then upsampling with a lightweight super-resolution network. The appropriate trade-off depends on the navigation scenario: slow-moving inspection robots can tolerate higher latency, while fast-moving drones require near-instantaneous predictions.

A second trade-off concerns the granularity of the world model. A dense 3D voxel grid allows precise geometric reasoning but consumes large amounts of memory and computation. Sparse representations, such as topological graphs or object-centric maps, are more scalable but may lose information needed for fine-grained obstacle avoidance. Our framework supports an adaptive representation that switches between dense and sparse modes based on the robot's current task and the confidence of the generative prior. For example, when the robot is traversing a narrow corridor, the world model defaults to a high-resolution grid; in open spaces, it switches to a topological abstraction.

A third trade-off involves the training data for the generative prior. To generalize across many environments, the prior should be trained on a diverse dataset spanning indoor, outdoor, urban, and natural scenes. However, collecting and curating such a dataset raises governance issues. Biases in the training data can lead to systematic failures when the robot encounters environments under-represented in the training set, such as non-Western building layouts or extreme weather conditions [11]. This highlights the need for fairness-aware dataset construction and continuous model monitoring after deployment.

The architecture also must address the challenge of temporal consistency. A generative model that synthesizes each panorama independently may produce sudden changes in the generated content as the robot moves, leading to spurious objects appearing or disappearing. To mitigate this, we incorporate a recurrent latent dynamics model that predicts how the scene evolves over time, amortizing the generative cost across frames [12]. The encoder outputs not just a static latent but also a velocity embedding that the generative prior uses to warp previous predictions forward, reducing flicker and improving coherence.

5. Governance, Sustainability, and Fairness

The integration of generative AI into robotic navigation raises governance challenges that extend beyond technical performance. One immediate concern is accountability: when a robot relies on a generative prior to infer the presence of an obstacle or a pathway, any errors in the generation can lead to collisions or entrapment. Safety-critical applications such as autonomous vehicles or search-and-rescue robots require that the system provide a confidence measure for every synthesized element and that the planner default to conservative behavior when confidence is low. Regulation in this domain is still nascent, but frameworks emerging from autonomous driving and medical robotics can be adapted, such as requiring a human-in-the-loop override for decisions based on generative inference [13].

Sustainability is another important dimension. Training a large-scale 360-degree generative prior consumes significant energy, with reported carbon footprints comparable to training large language models [14]. To reduce environmental impact, we advocate for federated training strategies that leverage idle compute across multiple institutions, and for model pruning that removes redundant parameters after initial training [15]. Furthermore, the on-robot inference must be optimized for energy efficiency, using techniques such as quantization and early-exit mechanisms that halt generation when the observed data already provides sufficient coverage. The carbon cost of frequent model updates should also be weighed against the benefits of improved performance.

Fairness concerns arise because the generative prior may perform poorly in environments that are underrepresented in its training data. For example, a model trained primarily on North American office spaces might fail to generate accurate scene completions in a market in Southeast Asia or a rural African village. This can lead to differential performance that exacerbates existing inequalities in access to robotic technology. One mitigation is to incorporate continual learning, where the model adapts online to novel environments by fine-tuning on locally collected data [16]. However, this raises privacy issues, as the collected data may contain sensitive information. Differential privacy techniques can be applied to protect individuals while still enabling model improvement. Policymakers should consider mandating bias audits for navigation systems deployed in public spaces, similar to emerging requirements for facial recognition [17].

6. Case Illustration and Comparative Analysis

To illustrate the practical utility of the proposed framework, consider a search-and-rescue scenario inside a partially collapsed building. The robot enters a room with only one visible doorway; the opposite wall is occluded by debris. A conventional mapping system would mark the occluded region as unknown and plan a path that avoids it, potentially missing a viable exit. The cross-view generative prior, however, synthesizes a plausible completion of the far wall, including a second door that is statistically likely given the building's layout [18]. The world model then contains a candidate exit with lower confidence, but the planner can incorporate this information into a risk-aware path. If the robot later moves to a position where the second door is visible, the generative prediction is either confirmed or corrected, updating the confidence.

A comparative analysis with three alternative approaches highlights the advantages of our method. The first alternative is a classical occupancy grid mapping system with frontier exploration [1]. While robust and predictable, this approach requires the robot to physically visit every region to update the map, resulting in lengthy exploration times. The second alternative is a neural radiance field approach that reconstructs the scene from sparse images [5]. This produces high-quality geometry but requires per-scene optimization that is too slow for real-time navigation. The third alternative is a learning-based semantic segmentation system that predicts occupancy directly from images without a world model [4]. This method is fast but cannot reason about occluded areas, leading to myopic decisions.

Our framework outperforms these alternatives in terms of path efficiency and adaptability, but it introduces higher computational demands and a risk of hallucination. To mitigate hallucination, we incorporate a novel consistency check: the generative prior's outputs are compared against a separate predictive model that estimates the likelihood of a scene layout given the robot's pose history [19]. Inconsistencies trigger a re-evaluation or a fallback to

conservative navigation. This layered verification mechanism is analogous to redundant sensor fusion in avionics.

From an infrastructure perspective, deploying the generative prior at scale requires a cloud-edge hybrid architecture. The heavy model training and periodic updates reside in the cloud, while a compressed student model runs on the robot's edge computer. Connectivity constraints in remote environments may necessitate local adaptation with on-board fine-tuning using small amounts of self-supervised data [20]. The system design must also account for communication latency and bandwidth limits; for example, sending high-resolution panoramic observations to the cloud for every frame is infeasible, so the encoder transmits only the latent representation.

7. Conclusion

Cross-view semantic world modeling using 360-degree generative scene priors represents a paradigm shift for embodied robot navigation, moving from reactive mapping to proactive synthesis of environmental structure. This paper has presented a comprehensive framework that integrates a cross-view encoder, a generative prior module, and a semantic grounding layer, enabling robots to reason about occluded areas and plan more efficient paths. We have analyzed the structural trade-offs between fidelity, latency, memory, and consistency, and discussed governance, sustainability, and fairness implications that are critical for responsible deployment. The comparative analysis demonstrates that while generative priors introduce new failure modes, they also open up capabilities unattainable with classical or purely reconstruction-based methods.

Future research should focus on online adaptation of generative priors to novel environments with minimal data, robust verification mechanisms that bound the risk of hallucination, and large-scale benchmarks for evaluating world modeling quality in complex scenes. The integration of such systems into critical infrastructure, such as autonomous delivery fleets or disaster response robots, will require close collaboration between engineers, policymakers, and ethicists to ensure that the benefits of generative world modeling are realized without compromising safety or equity. Our work provides a foundation for this interdisciplinary effort, and we hope it inspires further system-level investigations into the role of generative AI in embodied intelligence.

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