URBANWORLD: AN URBAN WORLD MODEL FOR 3D CITY GENERATION

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ABSTRACT

Cities, as the most fundamental environment of human life, encompass diverse physical elements such as buildings, roads and vegetation with complex interconnection. Crafting realistic, interactive 3D urban environments plays a crucial role in constructing AI agents capable of perceiving, decision-making, and acting like humans in real-world environments. However, creating high-fidelity 3D urban environments usually entails extensive manual labor from designers, involving intricate detailing and accurate representation of complex urban features. Therefore, how to accomplish this in an automatical way remains a longstanding challenge. Toward this problem, we propose UrbanWorld, the first generative urban world model that can automatically create a customized, realistic and interactive 3D urban world with flexible control conditions. UrbanWorld incorporates four key stages in the automatical crafting pipeline: 3D layout generation from openly accessible OSM data, urban scene planning and designing with a powerful urban multimodal large language model (Urban MLLM), controllable urban asset rendering with advanced 3D diffusion techniques, and finally the MLLM-assisted scene refinement. The crafted high-fidelity 3D urban environments enable realistic feedback and interactions for general AI and machine perceptual systems in simulations. We are working on contributing UrbanWorld as an open-source and versatile platform for evaluating and improving AI abilities in perception, decision-making, and interaction in realistic urban environments.

1 INTRODUCTION

Cities are the most complex human-centric environments, characterized by their intricate structures, diverse elements, and dynamic interactions. Creating near-realistic 3D urban world environments is a fundamental and pivotal technique for broad research and real applications across various domains such as AI agents (Yang et al., 2024), urban planning (Schrotter & Hürzeler, 2020), urban simulation (Xu et al., 2023) and metaverse (Allam et al., 2022). Traditionally, achieving this involves expensive labor costs for human designers on detailed asset modeling, texture mapping, and scene composition. With the advancement of generative AI, there have emerged more automatic approaches for 3D scene generation based on volumetric rendering(Lin et al., 2023; Xie et al., 2024) and diffusion models(Deng et al., 2023; Lu et al., 2024). These approaches have revolutionized the paradigm of 3D scene generation, alleviating the high costs of manual design. However, the crafted 3D scenes are only visually appealing videos, which are significantly different from the real embodied physical world. Regarding this issue, a recent series of methods known as world models have emerged, preliminarily focusing on autonomous driving scenes (Hu et al., 2023; Wang et al., 2023). These models are shown to possess the capability of understanding the scene dynamics and predicting future states, uplifting the interactivity of 3D scene generation. However, there is still a large gulf between the created urban environments and the real urban world in which humans live. To sum up, there is still a long way from the actual "urban world models", which we define as models able to create urban environments that are (1) realistic and interactive (2) customizable and controllable (3) capable of supporting embodied agent learning.

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Urban world models are of great significance in developing embodied intelligence and Artificial General Intelligence (AGI). Firstly, it is promising to bridge the gap between virtual environments and the real world, enabling embodied agents to interact with and learn from richly detailed, realistic urban environments. Secondly, by crafting synthetic 3D urban environments, researchers can gain complete control over data generation, with full access to all generative parameters. Machine perceptual systems can thus be trained on tasks that are not well suited to conduct in the real world or require various environments. Finally, a sophisticated urban world model can simulate a wide variety of environments, from bustling city centers to quiet residential neighborhoods, with realistic visual appearances of physical infrastructures such as buildings, roads, and natural spaces. This is crucial to avoid overfitting and creating agents with high generalization in diverse and dynamic environments. Some preliminary explorations have been witnessed in some commercial platforms like Omniverse[1], an open platform for creating and simulating detailed 3D world environments. However, there are no specialized urban world models for crafting interactive 3D urban environments, hindering the development of agents in the realistic urban environments.

Toward this issue, we propose UrbanWorld, a generative urban world model that can automatically create realistic, controllable and embodied 3D urban environments just from a text and OpenStreetMap[2] (OSM) prompt. In detail, there are four key modules in the framework of UrbanWorld. Firstly, UrbanWorld automatically generates 3D urban layouts and conducts detailed asset processing based on open-accessible OSM data via Blender[3]. Then, UrbanWorld adopts a fine-tuned urban-specific multimodal large language model (called Urban MLLM) to effectively plan and design urban scenes following user instructions, generating detailed textual descriptions of urban elements. Next, UrbanWorld integrates a 3D asset renderer based on texture diffusion and refinement, flexibly controlled by textual and visual conditions. Finally, to further optimize the visual appearance, UrbanWorld utilizes Urban MLLM to scrutinize the crafted 3D urban scenes, generating detailed suggestions for refinement and activate an additional iteration of rendering. This framework fully exploits the controllable generation capabilities of diffusion models and the reasoning and planning abilities of MLLMs, contributing to the high-fidelity urban environment rendering and superior generation flexibility.

The created urban environment features detailed and realistic visual representations of urban infrastructures, including buildings, roads, and natural areas, greatly benefiting the deployment of AI systems. Notably, it can support near-realistic physical interactions between urban environments and agents. It is tailored to enhance a range of embodied abilities including sensory grounding, perception and decision-making. For example, embodied agents can be deployed and trained for object recognition, route planning and automatic navigation via interaction with the realistic urban environment. Besides, UrbanWorld can serve as an open platform to support the creation and manipulation of more advanced 3D urban environments, facilitating the advancement of broad AI communities.

The contributions of this work can be summarized as follows:

- We present UrbanWorld, the first urban world model for automatically creating realistic, customized and interactive embodied 3D urban environments with flexible controls.
- UrbanWorld demonstrates its superior generative ability to craft high-fidelity 3D urban environments, greatly enhancing the authenticity of interactions in the environment.
- We provide UrbanWorld as an open-source tool and contribute a 3D asset dataset with various urban environments, which facilitates the advancement of broad AI-related research, such as embodied intelligence and AI agents, laying the groundwork for advancing AGI.

2 Related Works

2.1 3D Urban Scene Generation

3D urban scene generation aims to create realistic 3D urban environments with sophisticated urban planning and visual element design, usually requiring high human efforts such as complex asset

[1]https://www.nvidia.com/en-us/omniverse/
[2]https://www.openstreetmap.org/
[3]https://www.blender.org/

Table 1: Comparison between existing works for 3D urban scene generation and UrbanWorld from four aspects: text-controllable, image-controllable, creative (i.e., whether new assets can be created) and embodied/interactive (whether the created urban environment is physically interactive).

Method	Text-controllable	Image-controllable	Creative	Embodied/Interactive
SceneDreamer (Chen et al., 2023)	×	✓	✓	×
PersistentNature (Chai et al., 2023)	×	✓	✓	×
Infinicity Lin et al. (2023)	×	✓	✓	×
CityDreamer (Xie et al., 2024)	×	×	✓	×
CityGen (Deng et al., 2023)	×	×	✓	×
SceneCraft (Hu et al., 2024)	✓	×	×	✓
CityCraft Deng et al. (2024)	✓	×	×	✓
UrbanWorld	✓	✓	✓	✓

modeling, texture mapping, and scene composition. With the advancement of deep learning techniques, recently there are three lines of work trying to achieve this in an automated way, including NeRF-based methods (Lin et al., 2023; Xie et al., 2024; Chen et al., 2023), diffusion-based methods (Deng et al., 2023; Inoue et al., 2023; Wu et al., 2024) and professional software script-based methods (Zhou et al., 2024; Hu et al., 2024). An overview of the method comparison is shown in Table 1. NeRF-based methods implicitly represent the urban scene and perform the volumetric rendering for the neural fields. For example, CityDreamer (Xie et al., 2024) first separates the scene into buildings and backgrounds then introduces different types of neural fields for asset rendering. These methods can produce a high-quality visual appearance while potentially losing geometric fidelity. Diffusion-based methods utilize diffusion models to generate city layouts or urban scenes. CityGen (Deng et al., 2023) provides an end-to-end pipeline to create diverse 3D city layouts with Stable Diffusion. These methods are creative in generating scene images or videos, but hard to obtain embodied 3D environments, limiting the practical usages. Recently, some professional software script-based methods have been proposed, trying to develop an automatic agentic workflow using LLMs to control the professional software for scene creation. A representative example is Scenecraft (Hu et al., 2024), which establishes an LLM-based agent to translate textual descriptions into Python scripts for scene creation in Blender. A more recent work CityCraft (Deng et al., 2024) adopts LLMs in designing and organizing 3D urban environments from off-the-shelf asset libraries. Such approaches are effective but only create urban environments by retrieving and organizing existing assets, unable to flexibly create new assets when necessary. Differently, our approach adopts and integrates both diffusion-based and professional software script-based methods, providing an effective, controllable and creative way for 3D urban world generation.

2.2 3D World Simulator

A persistent objective in AI research has been to develop machine agents capable of engaging with various environments in 3D space like humans. Toward this goal, researchers have been devoted to building various interactive world simulators in the format of videos (Bruce et al., 2024) or embodied environment (Shen et al., 2022). Existing world simulation environments and platforms are mostly for indoor scenes (Puig et al., 2018; Xia et al., 2018; Kolve et al., 2017; Xia et al., 2020). Differently, Threedworld (Gan et al., 2020) pays attention to creating outdoor environments by retrieving and compositing objects from an existing asset library. When it comes to urban scenes which is the most important open environment, existing works mostly focus on the generative world model for autonomous driving capable of learning scene dynamics and understanding the geometry of the physical world (Hu et al., 2023; Wang et al., 2023; 2024). However, these models can only generate new scenes in the format of videos, hard to provide an embodied and interactive urban environment for real use. UGI (Xu et al., 2023) takes a forward step toward urban world simulation, proposing to develop an embodied urban environment for agent development. Although it conceptualized some relevant ideas, there is a lack of specific frameworks for implementation. To address this challenge, we propose UrbanWorld, which is expected to facilitate the construction of diverse embodied urban environments with controllable and refined visual appearance, supporting agent development or simulation in various urban scenes.

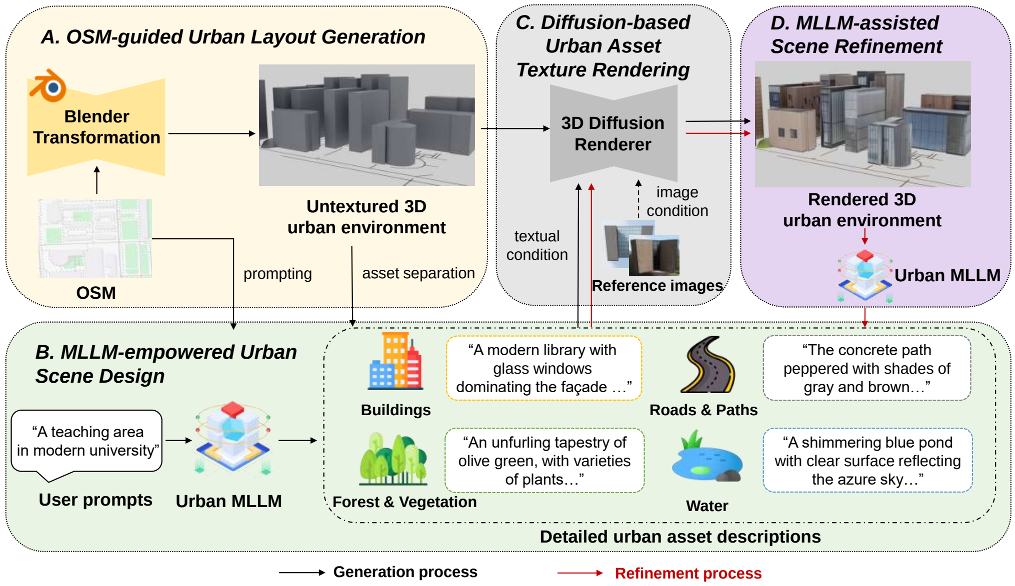

Figure 1: Illustration of the whole framework of UrbanWorld, including four key components: (A) OSM-guided urban layout generation; (B) MLLM-empowered urban scene design; (C) Diffusion-based urban asset texture rendering; (D) MLLM-assisted scene refinement.

3 Methodology

There are three main challenges to solve for building an "urban world model": efficient embodied environment construction, professional urban scene planning and high-quality texture generation. Towards these objectives, UrbanWorld introduces four key components: (1) OSM-guided urban layout generation, an automatic 2D-to-3D transformation module based on globally open-accessible OSM data, which can address the first challenge. (2) MLLM-empowered urban scene design, which exploits the superior urban scene understanding ability of the trained urban MLLM to draft reasonable urban scenes like human designers towards the second challenge. (3) Controllable diffusion-based urban asset texture renderer, a flexible urban asset rendering based on 3D diffusion following customized prompts. (4) MLLM-assisted urban scene refinement, a final reflection module to further improve the scene design, inspired by the iterative revision in the standard operation process of human designers. The last two components contribute to high-fidelity textures of 3D assets, effectively tackling the third challenge. The overview of UrbanWorld is illustrated in Figure 1.

3.1 OSM-guided Urban Layout Generation

Considering the easy accessibility and global coverage of OSM data, UrbanWorld is mainly developed based on OSM to generate 3D urban layouts. OSM data contains a wealth of information, mainly including the geographic locations and attributes of roads, buildings, vegetation, forests, water, and other infrastructure elements. The contained urban assets such as buildings, forest, vegetation, water and roads are then separated as independent objects for subsequent element-wise rendering. In this step, UrbanWorld also records the object center location for further reorganization of assets, making it match the real urban layout.

3.2 MLLM-empowered Urban Scene Design

Aiming to effectively craft customized urban environments, UrbanWorld integrates an advanced urban MLLM trained on extensive urban street-view imagery data. Specifically, we first collected urban street-view images globally and labeled the corresponding textual descriptions with GPT-4 and then conducted a manual check and filtered the low-quality data. Then we fine-tune an open-source MLLM, LLaVA-1.5 (Liu et al., 2024) on around 100K image-text pairs from the collected dataset. We have validated that the obtained urban MLLM possesses outstanding performance on

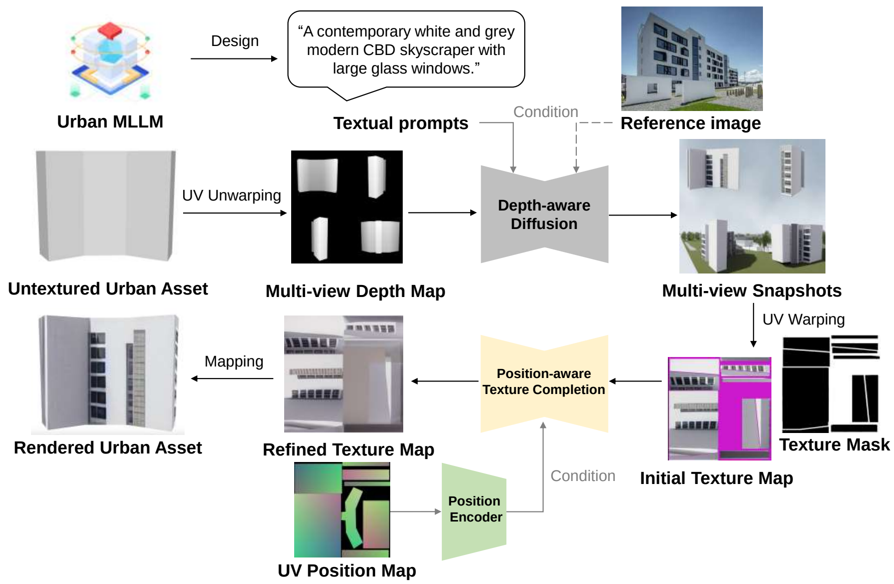

Figure 2: Illustration of the urban asset rendering method in UrbanWorld, mainly including two stages: Depth-aware UV texture generation with flexible control under textual and visual prompts and UV position-aware texture refinement.

urban scene understanding tasks such as image captioning and scene classification thus can benefit the urban scene analysis and design. In UrbanWorld, the urban MLLM is introduced to act as a human-like designer, which automatically drafts high-quality and detailed urban scene descriptions, ensuring the urban scenes are visually coherent. Specifically, taking a simple textual instruction (e.g., a teaching area in the university) from users and the selected OSM layout image as input, UrbanWorld calls the urban MLLM with carefully designed prompts and returns diverse detailed descriptions about visual appearance and materials for each asset. The produced asset descriptions will be used as the condition controlling the later rendering process.

3.3 Controllable diffusion-based urban asset texture rendering

Rendering a large-scale urban scene is challenging due to the existence of complex elements and relations, whereby the scene-level rendering will inevitably result in mismatching and low-resolution texture. Therefore, we follow the element-wise rendering principle to ensure the rendering quality. Simultaneously to speed up the rendering process, we merge some urban element types and finally define four main categories: buildings, roads and paths, forest and vegetation, and water. We implement the rendering with a controllable diffusion-based method consisting of two stages: UV texture generation and texture refinement detailed as shown in Figure 2.

Following the previous procedures, we have obtained the untextured 3D mesh of the whole urban scene S and each asset S_i. For each type of element, we now have corresponding textual descriptions t_i from the MLLM. here the model also supports taking reference image r_i as prompts to control the generation. The UV map of the i-th asset S_i is denoted as U_i.

We first set a series of camera views $v_i = \{v_k\}_{k=1}^{N}$ to capture the multi-view appearance of the object. Next, we utilize the depth-aware ControlNet (Zhang et al., 2023) to control a 2D diffusion model F to generate an image I_i showing the visual appearance on different views, together with the condition $c_i \in \{t_i, r_i, (t_i, r_i)\}$:

$$I_i = F(c_i; d_i; z), \tag{1}$$

where z is the latent embedding for the diffusion process, the depth map from different views d_i is obtained from the rendering process $d_i = P(S_i, v_i)$. Then we conduct a reverse process P^{-1} of rendering to back-project I_i into the UV texture space from each view:

$$U_i = P^{-1}(v_i; I_i; S_i), \tag{2}$$

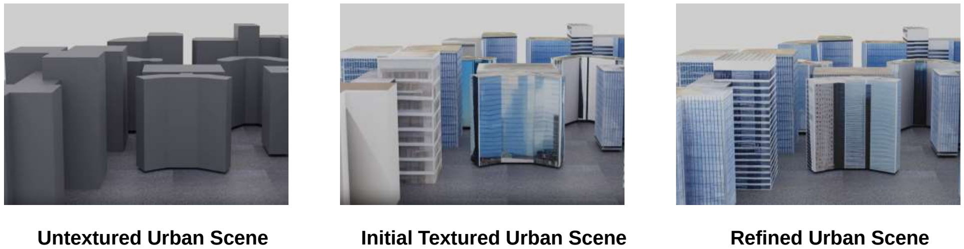

Figure 3: Illustration of the evolution of created urban environments, including the untextured urban scene, initial textured urban scene and refined urban scene.

Then we crop U_i into texture maps from each view $\{U_i^k\}_{k=1}^N$, each containing unique textual information from different views. Subsequently, we merge these texture maps into a single texture map U_i:

$$U_i = \sum_{k=1}^{n} M_i^k \odot U_i^k, \tag{3}$$

where M_i^k denotes the corresponding mask in the UV space from the view v_i.

Up to now, we have obtained the preliminary texture map for the asset S_i, while practically we have found that there are still some untextured areas on the object due to the discrete sampling of views, especially for buildings with many faces. Inspired by the inpainting capability of diffusion models, we introduce an additional UV texture inpainting process to get complete and natural textures. However, such inpainting can not be directly achieved with general diffusion-based inpainting considering there are strict position mapping requirements for UV texture maps. Therefore, we follow the UV inpainting process of general 3D objects (Zeng et al., 2024), and introduce a position map-guided building UV inpainting process.

To be specific, we add a UV position map encoder E_V to encode the position map $V_i \in \mathbb{R}^{H\times W\times 3}$, indicating the adjacency relation of the UV texture fragments, where E_V shares the same architecture of the image encoder in the diffusion model. Then we curate a set of paired UV position maps and UV texture maps for urban assets with complex surfaces and train the position encoder following the pipeline of ControlNet (Zhang et al., 2023). With the control of UV position maps, it's expected to achieve accurate and reasonable inpainting for UV texture maps. The UV inpainting process is formulated as follows:

$$U_i^{refine} = F(c_i; U_i; E_V(V_i)). \tag{4}$$

With the above texture generation and completion steps, UrbanWorld can produce coherent and high-fidelity textures for various urban elements.

For a better visual aesthetic of the rendering, we conduct image upscaling with ControlNet-tile to further enhance the structure sharpness and realism of the texture map, producing more detailed and realistic appearances for urban assets.

3.4 MLLM-ASSISTED URBAN SCENE REFINEMENT

After urban asset rendering, UrbanWorld automatically reorganizes the assets guided by the location information extracted from the real OSM data, effectively recovering the original urban layout. Inspired by the standard operation process of human designing, where experts will take an overview of the scene and make minor adjustments. To mimic such effort, UrbanWorld activates urban MLLM again to scrutinize the crafted 3D urban scenes and texture details. We prompt the MLLM to identify inconsistencies between the scene imagery and previous design prompts and examine whether the texture is as realistic as in the real world. Finally, the urban MLLM will provide sophisticated suggestions for further refinement, including elements to be modified and refined design prompts. Then the rendering module will be activated and the involved elements will be rendered under the refined text prompts and updated in the scene. With such a refinement process, UrbanWorld can further align the generated urban environment to the real cities. We provide a visualization example

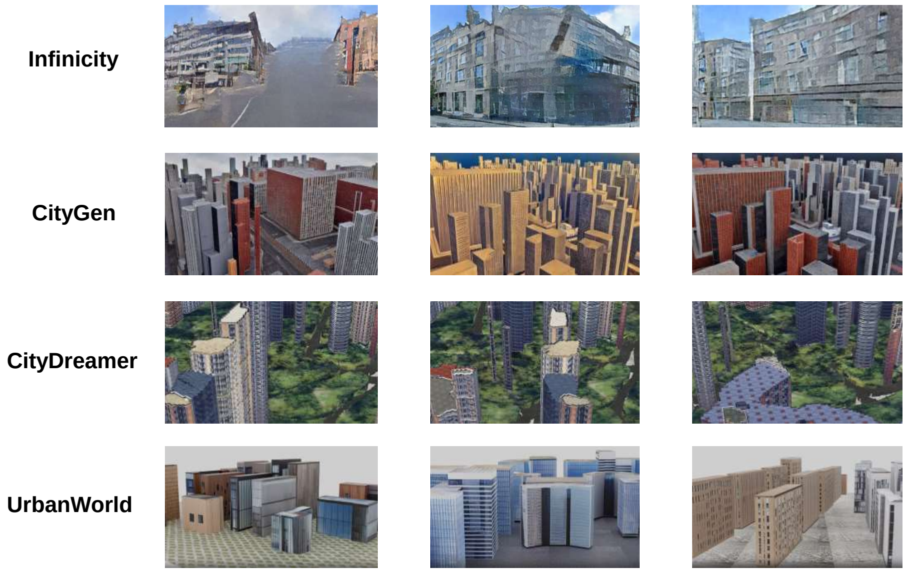

Figure 4: Qualitative comparisons of generated 3D urban environments from Infinicity, CityGen (results from the original paper since the code is not open-source), CityDreamer and UrbanWorld. By comparison, our method can craft more diverse 3D urban scenes with high-fidelity textures following user instructions.

showing the evolution of the created urban environments in Figure 3. It can be seen that UrbanWorld works in an iterative refinement manner to create high-fidelity urban environments, where the low-quality textures will be automatically identified and refined with the powerful urban MLLM.

4 Experiments

In this section, we first introduce the experimental setup and implementation details (see Section 4.1), and then we present the generation results of UrbanWorld for qualitative estimation (see Section 4.2). Finally, we provide some quantitative evaluations of the created urban environments to demonstrate the superiority of UrbanWorld (see Section 4.3).

4.1 Implementation Details

UrbanWorld incorporates three key techniques: Blender as the professional 3D modeling software, diffusion-based rendering and MLLM-empowered scene design and refinement. Specifically, we use Blender-3.2.2 for Linux systems and the compatible Blosm addon to handle the OSM transformation. In terms of diffusion-based rendering, we utilize Stable Diffusion-1.5 (Rombach et al., 2022) as the fundamental diffusion backbone, together with ControlNet-Depth (Zhang et al., 2023) in the generation of multi-view images. We also introduce IP-Adapter (Ye et al., 2023) to support taking reference images as the additional generation condition. We use ControlNet-inpainting (Zhang et al., 2023) as the diffusion controller in the UV texture refinement and ContrlNet-tile (Zhang et al., 2023) in the realness enhancement stage. For the hyper-parameter settings in the diffusion-based rendering, we set the number of camera views $N = 4$, which can basically satisfy the rendering needs of most urban assets. The number of inference steps in all diffusion processes is set as 30 by default. The UV maps of 3D assets are unwrapped in the "smart projection" mode operated in Blender. As for the urban MLLM, we fine-tune LLaVA-1.5 on a curated dataset with 100K streetview image-text data pairs. All experiments are conducted on a single NVIDIA Tesla A100 GPU.

4.2 Qualitative Results

We present some generation results of UrbanWorld in Figure 4, including various representative urban scenes, including educational places, commercial blocks and residential areas. For intuitive

Table 2: Quantitative evaluation of existing works for 3D urban scene generation and UrbanWorld on depth error, homogeneity index and realistic score.

Method	Depth Error (↓)	Homogeneity Index (↓)	Realistic Score (↑)
SceneDreamer (Chen et al., 2023)	0.152	0.746	5.6
CityDreamer (Xie et al., 2024)	0.147	0.745	6.0
UrbanWorld	**0.089**	**0.683**	**6.8**

comparison, we also provide some generation samples from Infinicity (Lin et al., 2023), CityGen (Deng et al., 2023) and CityDreamer (Xie et al., 2024). The results of Infinicity and CityGen are taken from the original paper because the codes are not open-source. It can be seen that scenes from Infinicity are short of clear textures and well-maintained building structures. Scenes from CityGen feature homogeneous styles without clear characteristics of urban functions. Similarly, the visual appearance of urban elements (especially buildings) in the environments from CityDreamer lacks diversity and is hard to distinguish. Besides, there are also clear geometric distortions of the building boundaries in CityDreamer. These issues will pose great challenges for the real interactions between subjects and urban environments. For example, embodied agents are hard to be trained to conduct urban navigation because the surrounding elements are too similar to recognize. By comparison, the urban elements created by UrbanWorld possess distinct functional characteristics, benefiting from the high controllability with text and reference image prompts. Besides, the overall scene is more authentic and visually harmonious, demonstrating the effectiveness of intelligent scene planning and design of the MLLM.

4.3 Quantitative Evaluations

To better demonstrate the superior generation performance of UrbanWorld, in this section, we provide quantitative results from the following three aspects:

Depth error. Depth error (DE) is utilized to evaluate the 3D geometry accuracy, following the implementation of EG3D (Chan et al., 2022) and CityDreamer (Xie et al., 2024). Specifically, we use the pre-trained depth estimation model (Ranftl et al., 2020) to obtain the "ground truth" of depth maps via density accumulation. DE is then calculated as the L2 distance between the normalized predicted depth maps and the "ground truth". The final result is averaged on the result from 100 captured frames of generated urban scenes.

Homogeneity index. Realistic cities are featured by complex elements with diverse visual appearances, indicating various functional uses of different urban areas. In order to capture this key character, we propose to evaluate the homogeneity of generated scenes, mainly measuring the variance of different urban scenes. To be specific, we first extract the visual feature of each generated scene image with ResNet (He et al., 2016). The homogeneity index is then calculated as the averaged cosine similarity of each pair of scenes in the feature space. The smaller value of the homogeneity index means a higher diversity of generated urban environments.

Realistic score. Another important aspect to evaluate is the realness of generated urban environments, which is challenging even for human designers. Here we introduce an off-the-shelf MLLM (GPT-4o) as the evaluator to score the realistic level and quality of generated urban elements (ranging from 1 to 10). A higher realistic score indicates better realness and fidelity of generated textures of urban assets.

We compare our model with some existing methods for urban scene generation, mainly including SceneDreamer (Deng et al., 2023) and Citydreamer Xie et al. (2024), representing the most advanced performance of automatic 3D urban environment generation. We don't provide results from other methods such as CityGen (Deng et al., 2023), CityCraft (Deng et al., 2024) and SceneCraft (Hu et al., 2024) because the source codes are not open when this work was done.

From the results presented in Table 2, it can be seen that UrbanWorld outperforms on each quantitative metric compared with baselines. Statistically, UrbanWorld achieves 39.5% on depth error compared with the most competitive baseline, demonstrating the geometry-preserving ability of UrbanWorld. By comparison, rendering methods such as SceneDreamer and CityDreamer can produce

Table 3: Study of the effectiveness of three key designs in UrbanWorld: MLLM-empowered urban scene design, texture enhancement and MLLM-assisted scene refinement.

Method	Depth Error (↓)	Homogeneity Index (↓)	Realistic Score (↑)
UrbanWorld	**0.089**	**0.683**	**6.8**
w/o scene design	0.104	0.701	6.1
w/o texture enhancement	0.125	0.687	6.5
w/o scene refinement	0.096	0.690	6.4

visually appealing urban scenes, but commonly lose geometry consistency. In terms of the homogeneity index, UrbanWorld has 8.3% improvement compared with baselines. Consistent with the observation on the qualitative results in Section 4.2, the generated scenes from existing methods exhibit high homogeneity, limited to the style of training data. By comparison, UrbanWorld can produce more diverse urban environments according to user instruction, effectively achieving customized creation. This makes it real for crafting any type of 3D urban environment adapting to the needs of different scenes. Lastly, the created urban environments from UrbanWorld show outstanding realness and high texture fidelity, increasing 11.8% realistic score compared with baselines. The overall impression of scenes crafted by SceneDreamer and CityDreamer is harmonious, however, the texture quality with a closer look is unsatisfying. Differently, UrbanWorld conducts element-wise texture rendering based on the specific 3D mesh, ensuring the geometric matching and fidelity of generated textures.

4.4 Ablation study

To further validate the effectiveness of key designs in UrbanWorld, we conduct ablation studies and show the results in Table 3. We explore the influence of three designs on the performance, including MLLM-empowered urban scene design, texture enhancement and MLLM-assisted scene refinement. The results indicate that all these techniques contribute to the final generation performance. Specifically, the scene design from the MLLM contributes most to the realness of generated urban environments, benefiting from the powerful knowledge understanding and reasoning ability of MLLMs. The texture completion and enhancement operation has the most notable effect on the estimated depth error because better texture fidelity can help with geometric perception. Besides, the final scene refinement process leads to a gain in all evaluation metrics, further promoting the whole performance.

5 Conclusion

We propose UrbanWorld, the first generative urban world model to create realistic, customized and interactive 3D urban environments with flexible control conditions in a fully automatic manner. Integrating the powerful urban scene understanding ability of urban MLLM and the controllable generation ability of diffusion models, UrbanWorld can effectively craft high-fidelity and diverse urban environments outperforming existing urban scene generation methods. More importantly, the created urban environments can provide realistic and high-fidelity information feedback, ensuring embodied agents interact with and learn from the richly detailed, realistic urban world. We are contributing UrbanWorld as an open-source tool to benefit broad research communities, including but not limited to AI agents and embodied intelligence. We believe this work can pave a new way to efficiently establish the 3D virtual urban environment, accelerating the development of AGI.

For future work, we will continue to enhance the current version of UrbanWorld and there are mainly three directions. Firstly, we will supplement more elements into urban environment creation, such as persons and vehicles, further improving the richness and realness of crafted environments. Secondly, we will conduct experiments on interactive tasks such as visual recognition and navigation for embodied agents to validate the real usability of created 3D environments. Lastly, we are organizing the codes and the generated 3D urban environment assets for release. We expect to make UrbanWorld an open-source toolkit for convenient use in various real applications.

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