Title:
Parametric VR: Leveraging Parametric Modeling and AI-Generated Panoramas for Rapid Ideation for Interior Design

Authors:
Chieh-Jen Lin, t60011@mail.tut.edu.tw, Tainan University of Technology

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Introduction:
Virtual reality (VR), celebrated for its immersive capabilities, allows designers to visualize spatial compositions at a 1:1 scale, fostering a deeper understanding of design concepts. However, traditional VR workflows often fall short in early-phase design due to the high level of detail required for 3D models and the labor-intensive nature of rendering materials, textures, and lighting. This limitation reduces its use to final presentations rather than as an iterative tool for ideation and collaborative feedback. To address the complexity of 3D modeling for interior design, previous research introduced a generative modeling approach based on the Level of Development (LOD) concept, utilizing Grasshopper to convert bubble diagrams of a single-story house into orthogonal floor plans using Voronoi diagrams [4]. This method facilitates the rapid creation of conceptual interior partition models that can be previewed and modified in VR, making it more effective for educational and professional interior design applications compared to cardboard models. However, while this approach enables the rapid creation of VR-ready 3D prototypes as environmental backdrops, the modeling of core interior design elements, such as furniture layout and cabinet configuration, remains a time-consuming and technically challenging task.

Generative AI tools, such as Stable Diffusion [7] and Midjourney offer the capability to generate high-quality panoramic images from simple text prompts, effectively addressing challenges related to lighting, materials, and decorative details in panoramic visualization. However, these tools still face significant issues, particularly in ensuring consistency across different stages of image generation. The alignment of object placement, spatial proportions, and continuity remains difficult to control, which limits their effectiveness in maintaining consistency across multiple perspectives in a virtual space. To address these challenges, previous research has proposed the use of low-Level of Development (LOD) 3D models, manually created, as a foundation for generating semantic segmentation control maps in Grasshopper to guide the AI image generation process[5]. By utilizing ControlNet models[8], which process semantic segmentation and other geometric information, this approach helps ensure that the generated images maintain spatial consistency and accurate object proportions without detailed modeling. These manually modeling low-LOD models serve as reference frames for generating consistent panoramic images that align with the designer's intended layout and style. This method mitigates inconsistencies across different views and provides greater control over object placement and scale, enabling the reliable generation of VR-compatible scenes.

When AI can rapidly generate panoramas based on low-LOD models, the process of creating and modifying these low-LOD models becomes a bottleneck in the creative ideation process. Therefore, this study proposes integrating previous research and utilizing a parametric design to swiftly generate low-LOD 3D models that align with designers' concepts, thereby enhancing the usability of AI-generated panoramas in supporting creative ideation for interior design.

<u>Main Ideas:</u>

Due to the powerful capabilities of ControlNet in guiding the composition and content of AI-generated images, many 3D modeling and BIM software such as SketchUp, ArchiCAD, and Revit have introduced plugins or extensions based on ControlNet and Stable Diffusion, serving as alternatives to traditional real-time rendering tools. However, beyond relying on text prompts, these tools often require higher LOD models to provide sufficient geometric features to influence the composition and content of generated images. But creating these detailed models is time-consuming, and their geometric characteristics can constrain the design styles of the images. For example, modernist architecture, characterized by orthogonal straight-line geometries, can achieve satisfactory results with low-LOD models comprising orthogonal lines. Conversely, other styles such as Art Nouveau or free-form style, which feature prominent curvilinear elements, face more challenges when using low-LOD models. Similarly for interior design, low-LOD models often lack enough geometric clues, causing AI to misidentify objects and produce erroneous results, such as misinterpreting chairs, tables, sofas, and cabinets.

Previous research addressed these challenges by manually assigning semantic colors to low-LOD models for generating semantic segmentation maps that help AI correctly identify object types by applying ControlNet and retain design flexibility in terms of objects' details [5]. This approach allows AI to generate accurate panoramas based on low-LOD models without requiring extensive geometric detail, supporting efficient visual exploration in early-stage design ideation and maintaining the flexibility to experiment with various styles, materials, and other ideas by text prompts. Although low-LOD models can reduce the time required to model individual objects, such as standalone buildings, interior design often involves complex arrangements of multiple objects within a single space. Therefore, the efficiency bottleneck in creating low-LOD models for interior design lies not only in assigning essential geometric attributes to individual objects but also in categorizing and configuring the relationships between them.

In traditional interior design workflows, the process typically begins with spatial partitioning and furniture layout on a floor plan. Once the spatial configuration and object arrangements have been finalized on the floor plan, the workflow proceeds to 3D modeling for visualizing the design concept for evaluating material selections and lighting ideas. Although modern 3D modeling and BIM software offer highly streamlined modeling processes, they usually do not focus on how to establish and maintain certain relationships between interior spaces and the objects within them. As a result, research and tools for automating floor plan layouts have emerged, such as Finch3D [2] and PlanFinder [6], which use algorithms to generate apartment layouts fitted to specified areas. However, due to differences in lifestyle, equipment standards, and building codes, the layouts produced by these tools often fail to meet the specific needs of Taiwan. On the other hand, the generated results are no different from traditional software when they can be readjusted according to design concepts.

To accelerate the creation of low-LOD models for guiding AI-generated panoramic images that align with local design needs in Taiwan and support design exploration, this study proposes a method using Rhino and Grasshopper to rapidly generate low-LOD models for interior object arrangements. The approach involves developing generative components to produce object layouts that correspond to Taiwan's lifestyle patterns and furniture standard. The American Institute of Architects (AIA) makes a clear distinction between two concepts of LOD: Level of Development [1] and Level of Detail. Therefore, the "Low-LOD model" referred to in this study is basically a mixture of the above two definitions. It not only refers to the basic 3D geometric features of interior elements, and it also refers to the most basic design information required in the early design stages, such as the semantics of object types. This type of model is different from the traditional LOD model in computer graphics, which emphasizes the gradual increase of mesh complexity for real-time rendering; on the contrary, our low LOD model emphasizes semantic clarity rather than geometric accuracy. These models are composed of basic geometric volumes, such as rectangular blocks representing furniture and walls, combined with semantic color annotations for guiding AI through ControlNet's segmentation models. Their primary function is to serve as a semantic scaffold rather than a visual rendering base. By leveraging parametric design techniques and combining different configuration modules, the method ensures flexibility and variability in interior layouts, allowing designers to explore various configuration ideas rather than aiming for an optimized spatial arrangement. The details of the parametric approaches are described below.

Parametric Modules for Residential Interior Layouts
Previous research applied Voronoi diagrams to convert spatial bubble diagrams into orthogonal interior partitions, enabling rapid adjustments to the relative position and size of interior spaces by manipulating individual nodes. This approach allows the creation of orthogonal partitions or segmented open spaces within a defined interior area. However, the previous studies identified spaces using text labels without automatically placing essential interior objects such as cabinets, dining tables, chairs, or sofas. This study therefore develops three additional furniture arrangement modules which were: (1) Cabinet, (2) Dining Set, and (3) Sofa Set Module:

- Cabinet Module: This allows the placement of tall cabinets, countertops, or wall-mounted cabinets along selected or all walls of a space. When applied in kitchen layouts, it also supports the option to include an island countertop (Fig.1a).
- Dining Set Module: This module can automatically generate a rectangular dining set for multiple users based on the available space (Fig.1b).
- Sofa Module: It generates multi-seater sofa configurations according to the space dimensions, following Taiwanese preferences for living room layouts (Fig.1c).

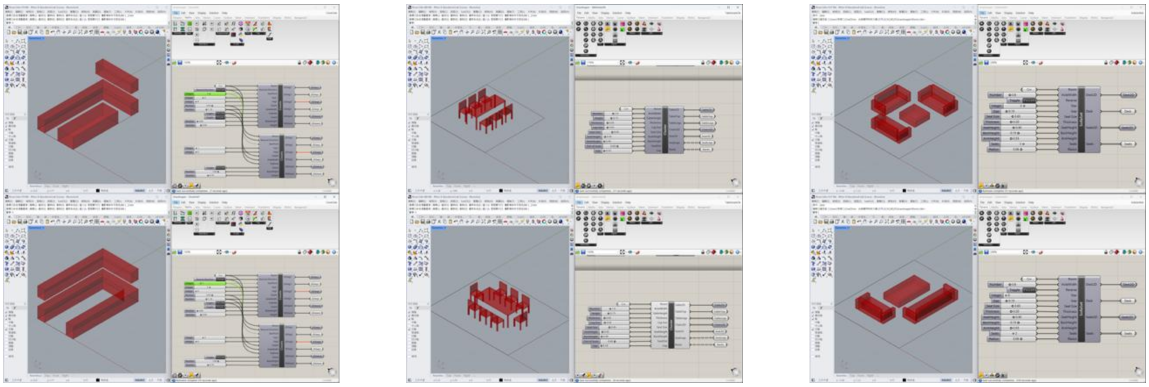

Fig. 1: Parametric furniture arrangement modules: (a) cabinet modules, (b) dining set module, and (c) sofa set module.

These modules automatically combine multiple objects within a space based on their size and predefined rules. To streamline the design process, each module allows designers to flexibly adjust key parameters such as corridor widths or cabinet dimensions, while the relative positions and quantities of objects are generated automatically to minimize complex parameter settings. By integrating spatial configuration and furniture arrangement modules, designers can quickly adjust the interior spaces and easily modify or replace essential furniture pieces. This approach ensures that the early-stage ideation process remains efficient and free from disruptions caused by overly detailed parameter adjustments.

Semantic Segmentation Maps of Parametric Modeling
By using semantic color labels for object classification, semantic segmentation models of ControlNet can be applied to guide AI in generating objects corresponding to specific color-coded categories. Previous studies followed ADE20K's 150 object categories [9], assigning each category a unique color and creating 150 display layers in which the models had to be placed for accurate semantic segmentation guidance. However, the large number of layers can overwhelm users and complicate the management of multiple conceptual model versions. To address this issue, this study separates object layers from semantic color representation. With the aid of Grasshopper modules, objects generated by spatial and furniture configuration modules can be "baked" into Rhino with correct semantic colors, simplifying the process of categorizing objects in conceptual models. By using Grasshopper's flexible interface, designers can also modify the default semantic classifications in the parametric modules, enabling the generation of different types of objects and expanding the potential for design exploration. For example,

it is easy to change the parametric models' categories from counters and island to sofa and coffee table for changing a kitchen (Fig.2a) to a living room concept (Fig. 2 b). This approach reduces the complexity of managing object categories while providing more flexibility in experimenting with various design ideas.

Fig. 2: Parametric semantic segmentation maps of the same concept model: (a) an opening kitchen with counters and an island, (b) a living room with a sofa and a coffee table.

Parametric AI-Generated Panoramas

The key parameters of AI-generated images are: (1) the base model, (2) text prompts, (3) generation parameters such as samplers and steps, and (4) additional fine-tuning models like LoRA [3] or ControlNet. Text prompts allow AI to assist in specifying materials, lighting, and decorative details in VR scenes. However, using ControlNet to guide scene composition and content generation still requires higher-LOD models to provide geometric features such as object outlines. Among the ControlNet models, only the semantic segmentation model can generate specified object types based on color-coded display areas without requiring detailed object geometry. This retains spatial relationships between multiple objects while avoiding constraints on object geometric details. Based on prior work, this study developed parametric modules for generating low-LOD conceptual models, accelerating the creation process and simplifying the manipulation of basic object shapes and spatial relationships. Additionally, the study developed parametric modules that rapidly create and modify semantic segmentation maps for guiding AI-generated panoramas (Fig.3). This combination of parametric modeling and AI image generation establishes a streamlined workflow for creating parametric AI-generated panoramas (Fig.4).

Fig. 3: Two semantic segmentation maps of a concept model with different parameters of interior furniture layouts in the same apartment.

Fig. 4: AI-generated panoramas form the two semantic segmentation maps in Fig. 3.

Although bounding boxes can indeed provide basic object positions and are characteristic of low-LOD models, certain ControlNet models (such as depth or canny) require richer geometric cues to infer spatial depth, surface boundaries, and object orientation. High-LOD models, in this context, are not detailed mesh models but slightly enhanced representations that provide distinct outlines or silhouettes sufficient for edge-based AI guidance. When semantic segmentation is used instead (e.g., ADE20K format), such high-level geometry can be replaced by color-coded object categories, making bounding-box-style low-LOD models viable again with appropriate semantic encoding.

Conclusions:

The proposed workflow integrates parametric modeling with AI-assisted panoramas through a multi-stage process. First, low-LOD conceptual models are generated using Grasshopper, which define spatial partitions and furniture arrangements with minimal geometry but embedded semantic tags. Next, these are exported as semantic segmentation maps for ControlNet models to generate panoramas. Although it is possible to add more image features to gain more control over the generated panoramas, such as depth or canny features. However, current study focuses on the semantic segmentation models, and how to use multiple ControlNet models but avoid complicated modeling still needs further study.

Parametric modeling tools address the challenges of creating complex shapes through algorithmic modeling. However, there is still no effective algorithm for quickly generating or adjusting materials, lighting, and other decorative details needed for VR scenes to matching designers' concepts. Generative AI can produce high-quality panoramic images based on text prompts, but it remains difficult to control the composition and content of these images to align with the designer's intention. To address this issue, this study proposes a parametric approach to guide AI in generating panoramic images that correspond to low-LOD conceptual models. Designers can quickly construct interior design conceptual models with simplified object shapes and spatial relationships, thereby reducing the complexity of traditional modeling processes. Semantic segmentation maps generated by parametric modules are used to guide the AI, ensuring that the panoramic images maintain spatial coherence and align with the structure of the conceptual models. With the help of AI-generated panoramas, designers can quickly verify their ideas before further detailed modeling. However, more research is needed on how to quickly incorporate the details in AI-generated panoramas into further refined modeling.

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Chieh-Jen Lin, https://orcid.org/0000-0001-9981-5864

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