Structured3D: A Large Photo-realistic Dataset for Structured 3D Modeling

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https://structured3d-dataset.org

Abstract

Recently, there has been growing interest in developing learning-based methods to detect and utilize salient semi-global or global structures, such as junctions, lines, planes, cuboids, smooth surfaces, and all types of symmetries, for 3D scene modeling and understanding. However, the ground truth annotations are often obtained via human labor, which is particularly challenging and inefficient for such tasks due to the large number of 3D structure instances (e.g., line segments) and other factors such as viewpoints and occlusions. In this paper, we present a new synthetic dataset, Structured3D, with the aim to providing large-scale photo-realistic images with rich 3D structure annotations for a wide spectrum of structured 3D modeling tasks. We take advantage of the availability of millions of professional interior designs and automatically extract 3D structures from them. We generate high-quality images with an industry-leading rendering engine. We use our synthetic dataset in combination with real images to train deep neural networks for room layout estimation and demonstrate improved performance on benchmark datasets.

1. Introduction

Inferring 3D information from 2D sensory data such as images and videos has long been a central research topic in computer vision. Conventional approach to build 3D models of a scene typically relies on detecting, matching, and triangulating local image features (e.g., patches, superpixels, edges, and SIFT features). Although significant progress has been made over the past decades, these methods still suffer from some fundamental problems. In particular, local feature detection is sensitive to a large number of factors such as scene appearance (e.g., textureless areas and repetitive patterns), lighting conditions, and occlusions. Further, the noisy, point cloud-based 3D model often fails to meet the increasing demand for high-level 3D understanding in real-world applications.

When perceiving 3D scenes, humans are remarkably effective in using salient global structures such as lines, contours, planes, smooth surfaces, symmetries, and repetitive patterns. Thus, if a reconstruction algorithm can take advantage of such global information, it is natural to expect the algorithm to obtain more accurate results. Traditionally, however, it has been computationally challenging to reliably detect such global structures from noisy local image features. Recently, deep learning-based methods have shown promising results in detecting various forms of structure directly from the images, including lines [9], planes [15, 28, 12, 30], cuboids [7], floorplans [14, 13], room layouts [10, 34, 21].
Table 1: An overview of structured 3D scene datasets. †: The actual numbers are not explicitly given and hard to estimate, because these datasets contain images downloaded from Internet (LSUN Room Layout, PanoContext), or from multiple sources (LayoutNet, Realtor360). ∗: Dataset is unavailable online at the time of submission.

| Datasets                  | #Scenes | #Rooms | #Frames | Annotated structure                   |
|--------------------------|---------|--------|---------|---------------------------------------|
| PlaneRCNN [12]           | -       | -      | 100,000 | planes                                |
| Wireframe [9]            | -       | -      | 5,462   | wireframe (2D)                        |
| SUN Primitive [27]       | -       | -      | 785     | cuboids, other primitives             |
| LSUN Room Layout [33]    | -       | n/a†   | 5,396   | cuboid layout                         |
| PanoContext [31]         | -       | n/a†   | 500 (pano) | cuboid layout                      |
| LayoutNet [34]           | -       | n/a†   | 1,071 (pano) | cuboid layout                    |
| Realtor360* [29]        | -       | n/a†   | 2,573 (pano) | Manhattan layout              |
| Raster-to-Vector [14]    | 870     | -      | -       | floorplan                             |
| Structured3D             | 3,500   | 21,835 | 196,515 | “primitive + relationship”          |

abstraction 3D shapes [22, 25], and smooth surfaces [8].

With the fast development of deep learning methods comes the need for large amounts of accurately annotated data. In order to train the proposed neural networks, most prior work collects their own sets of images and manually labels the structure of interest in them. Such a strategy has several shortcomings. First, due to the tedious process of manually labelling and verifying all the structure instances (e.g., line segments) in each image, existing datasets typically have limited sizes and scene diversity. And the annotations may also contain errors. Second, since each study primarily focuses on one type of structure, none of these datasets has multiple types of structure labeled. As a result, existing methods are unable to exploit relations between different types of structure (e.g., lines and planes) as humans do for effective, efficient, and robust 3D reconstruction.

In this paper, we present a large synthetic dataset with rich annotations of 3D structure and photo-realistic 2D renderings of indoor man-made environments (Figure 1). At the core of our dataset design is a unified representation of 3D structure which enables us to efficiently capture multiple types of 3D structure in the scene. Specifically, the proposed representation considers any structure as a relationship among geometric primitives. For example, a “wireframe” structure encodes the incidence and intersection relationship between line segments, whereas a “cuboid” structure encodes the rotational and reflective symmetry relationship among its planar faces. With our “primitive + relationship” representation, one can easily derive the ground truth annotations for a wide variety of semi-global and global 3D structures, as well as their mutual relationships.

To create a large-scale dataset with the aim to facilitate research on data-driven methods for structured 3D scene understanding, we leverage the availability of millions of professional interior designs and millions of production-level 3D object models – all coming with fine geometric details and high-resolution texture (Figure 1(a)). We first use computer programs to automatically extract information about 3D structure from the original house design files. As shown in Figure 1(b), our dataset contains rich annotations of 3D room structure including a variety of geometric primitives and relationships. To further generate photo-realistic 2D images (Figure 1(c)), we utilize industry-leading rendering engines to model the lighting conditions. Currently, our dataset consists of more than 196k images of 21,835 rooms in 3,500 scenes (i.e., houses).

To showcase the usefulness and uniqueness of the proposed Structured3D dataset, we train deep networks for room layout estimation on a subset of the dataset. We show that the models first trained on our synthetic data and then fine-tuned on real data outperform the models trained on real data only. We also show good generalizability of the models trained on our synthetic data by directly applying them to real world images.

In summary, the main contributions of this paper are:

- We introduce a unified “primitive + relationship” representation for 3D structure. This representation enables us to efficiently capture a wide variety of semi-global and global 3D structures, as well as their mutual relationships.
- We create the Structured3D dataset, which contains rich ground truth 3D structure annotations of 21,835 rooms in 3,500 scenes, and more than 196k photo-realistic 2D renderings of the rooms.
- We verify the usefulness of our dataset by using it to train deep networks for room layout estimation and demonstrating improved performance on benchmark datasets.

2. Related Work

Datasets. Table 1 summarizes existing datasets for structured 3D scene modeling. Additionally, [22, 25] provide...
In this paper, we present a unified representation of 3D structure in man-made environments, in order to minimize the redundancy in encoding multiple types of 3D structure, while preserving their mutual relationships. We show how most common types of structure previous studied in the literature (e.g., planes, cuboids, wireframes, room layouts, floorplans) can be derived from our representation.

3. A Unified Representation of 3D Structure

The main goal of our dataset is to provide rich annotations of ground truth 3D structure. A naive way to do so is generating and storing different types of 3D annotations in the same format as existing works, like wireframes as in [9], planes as in [12], floorplans as in [14], and so on. But this leads to a lot of redundancy. For example, planar surfaces in man-made environments are often bounded by a number of line segments, which are part of the wireframe. Even worse, by representing wireframes and planes separately, the relationships between them is also lost.

In this paper, we present a unified representation of 3D structure in man-made environments, in order to minimize the redundancy in encoding multiple types of 3D structure, while preserving their mutual relationships. We show how most common types of structure previous studied in the literature (e.g., planes, cuboids, wireframes, room layouts, and floorplans) can be derived from our representation.
Figure 3: The ground truth 3D structure annotations in our dataset are represented by primitives and relationships. (a): Junctions and lines. (b): Planes. We highlight the planes in a single room. (c): Plane-line and line-junction relationships. We highlight a junction, the three lines intersecting at the junction, and the planes intersecting at each of the lines. (d): Cuboids. We highlight one cuboid instance. (e): Manhattan world. We use different colors to denote planes aligned with different directions. (f): Semantic objects. We highlight a “room”, a “balcony”, and the “door” connecting them.

Our representation of structure is largely inspired by the early work of Witkin and Tenenbaum [24], which characterizes structure as "a shape, pattern, or configuration that replicates or continues with little or no change over an interval of space and time". Accordingly, to describe any structure, we need to specify: (i) what pattern is continuing or replicating (e.g., a patch, an edge, or a texture descriptor), and (ii) the domain of its replication or continuation. In this paper, we call the former primitives and the latter relationships.

3.1. The “Primitive + Relationship” Representation

We now show how to describe a man-made environment using the “primitive + relationship” representation. For ease of exposition, we assume all objects in the scene can be modeled by piece-wise planar surfaces. But our representation can be easily extended to more general surfaces. An illustration of our representation is shown in Figure 3.

3.1.1 Primitives

Generally, a man-made environment consists of the following geometric primitives:

- **Planes** $\mathbf{P}$: We model the scene as a collection of planar surfaces $\mathbf{P} = \{p_1, p_2, \ldots\}$ where each plane is described by its parameters $p = \{\mathbf{n}, d\}$.

- **Lines** $\mathbf{L}$: When two planes intersect in the 3D space, a line is created. We use $\mathbf{L} = \{l_1, l_2, \ldots\}$ to represent the set of all 3D lines in the scene.

- **Junction points** $\mathbf{X}$: When two lines meet in the 3D space, a junction point is formed. We use $\mathbf{X} = \{x_1, x_2, \ldots\}$ to represent the set of all junction points.

3.1.2 Relationships

Next, we define some common types of relationships between the geometric primitives:

- **Plane-line relationships** ($R_1$): We use a matrix $W_1$ to record all incidence and intersection relationships between planes in $\mathbf{P}$ and lines in $\mathbf{L}$. Specifically, the $ij$-th entry of $W_1$ is 1 if $l_i$ is on $p_j$, and 0 otherwise. Note that two planes are intersected at some line if and only if the corresponding entry in $W_1^T W_1$ is nonzero.

- **Line-point relationships** ($R_2$): Similarly, we use a matrix $W_2$ to record all incidence and intersection relationships between lines in $\mathbf{L}$ and points in $\mathbf{X}$. Specifically, the $mn$-th entry of $W_2$ is 1 if $x_m$ is on $l_n$, and 0 otherwise. Note that two lines are intersected at some junction if and only if the corresponding entry in $W_2^T W_2$ is nonzero.
• **Cuboids** \((R_3)\): A cuboid is a special arrangement of plane primitives with rotational and reflection symmetry along x-, y- and z-axes. The corresponding symmetry group is the dihedral group \(D_{2h}\).

• **Manhattan world** \((R_4)\): This is a special type of 3D structure commonly used for indoor and outdoor scene modeling. It can be viewed as a grouping relationship, in which all the plane primitives can be grouped into three classes, \(P_1, P_2,\) and \(P_3\), \(P = \bigcup_{i=1}^{3} P_i\). Further, each class is represented by a single normal vector \(n_i\), such that \(n_i^T n_j = 0, i \neq j\).

• **Semantic objects** \((R_5)\): Semantic information is critical for many 3D computer vision tasks. It can be regarded as another type of grouping relationship, in which each semantic object instance corresponds to one or more primitives defined above. For example, each “wall”, “ceiling”, or “floor” instance is associated with one plane primitive; each “chair” instance is associated with a set of multiple plane primitives. Further, such a grouping is hierarchical. For example, we can further group one floor, one ceiling, and multiple walls to form a “living room” instance. And a “door” or a “window” is an opening which connects two rooms (or one room and the outer space).

Note that the relationships are not mutually exclusive, in the sense that a primitive can belong to multiple relationship instances of same type or different types. For example, a plane primitive can be shared by two cuboids, and at the same time belong to one of the three classes in the Manhattan world model.

**3.1.3 Discussion**

The primitives and relationships we discussed above are just a few most common examples. They are by no means exhaustive. For example, our representation can be easily extended to included other primitives such as parametric surfaces. And besides cuboids, there are many other types of regular or symmetric shapes in man-made environments, where type corresponds to a different symmetry group.

**3.2. Relation to Existing Models**

Given our representation which contains primitives \(P = \{P, R, X\}\) and relationships \(R = \{R_1, R_2, . . .\}\), we show how several types of 3D structure commonly studied in the literature can be derived from it. We again refer readers to Figure 2 for illustrations of these structures.

**Planes**: A large volume of studies in the literature model the scene as a collection of 3D planes, where each plane is represented by its parameters and boundary. To generate such a model, we simply use the plane primitives \(P\). For each \(p \in P\), we further obtain its boundary by using matrix \(W_1\) in \(R_1\) to find all the lines in \(L\) that form an incidence relationship with \(p\).

**Wireframes**: A wireframe consists of lines \(L\) and junction points \(P\), and their incidence and intersection relationships \((R_2)\).

**Cuboids**: This model is same as \(R_3\).

**Manhattan layouts**: A Manhattan room layout model includes a “room” as defined in \(R_5\) which also satisfies the Manhattan world assumption \((R_4)\).

**Floorplans**: A floorplan is a 2D vector representation which consists of a set of line segments and semantic labels (e.g., room types). To obtain such a vector representation, we can identify all lines in \(L\) and junction points in \(X\) which lie on a “floor” (as defined in \(R_5\)). To further obtain the semantic room labels, we can project all “rooms”, “doors”, and “windows” (as defined in \(R_5\)) to this floor.

**Abstracted 3D shapes**: In addition to room structures, our representation can also be applied to individual 3D object models to create abstractions in the form of wireframes or cuboids, as described above.

**4. The Structured 3D Dataset**

Our general, unified representation enables us to encode a rich set of geometric primitives and relationships for structured 3D modeling. With this representation, our ultimate goal is to build a dataset which can be used to train machines to achieve the human-level understanding of the 3D environment.

As a first step towards this goal, in this section, we describe our ongoing effort to create a large-scale dataset of indoor scenes which include (i) ground truth 3D structure annotations of the scene and (ii) realistic 2D renderings of the scene. Note that in this work we focus on extracting ground truth annotations on the room structure only. We plan to extend our dataset to include 3D structure annotations of individual furniture models in the future.

**4.1. Extraction of Structured 3D Models**

To extract a “primitive + relationship” representation of the 3D scene, we make use of a large database of over one million house designs hand-crafted by professional designers. An example design is shown in Figure 4(a). All information of the design is stored in an industry-standard format in the database so that specifications about the geometry (e.g., the precise length, width, and height of each wall), textures and materials, and functions (e.g., which room the wall belongs to) of all objects can be easily retrieved.

From the database, we have selected 3,500 house designs with about 21,854 rooms. We created a computer program to automatically extract all the geometric primitives associated with the room structure, which consists of the ceiling,
floor, walls, and openings (doors and windows). Given the precise measurements and associated information of these entities in the database, it is straightforward to generate all planes, lines, and junctions, as well as their relationships ($R_1$ and $R_2$).

Since the measurements are highly accurate and noise-free, other types of relationship such a Manhattan world ($R_3$) and cuboids ($R_4$) can also be easily obtained by clustering the primitives, followed by a geometric verification process. Finally, to include semantic information ($R_5$) into our representation, we simply map the relevant labels provided by the professional designers to the geometric primitives in our representation. Figure 3 shows examples of the extracted geometric primitives and relationships.

4.2. Photo-realistic 2D Rendering

We have developed a photo-realistic renderer on top of Embree [23], an open-source collection of ray-tracing kernels for x86 CPUs. Our renderer uses the well-known path tracing [17] method, a Monte Carlo approach to approximating realistic Global Illumination (GI) for rendering.

Each room is manually created by professional designers with over one million CAD models of furniture from world-leading manufacturers. These high-resolution furniture models are measured in real-world dimensions and being used in real production. A default lighting setup is also provided for each room. Figure 4 compares the 3D models in our database with those in the public SUNCG dataset [20], which are created using Planner 5D [1], an online tool for amateur interior design.

At the time of rendering, a panorama or pin-hole camera is placed at random locations not occupied by objects in the room. We use $1024 \times 512$ resolution for panoramas and $640 \times 480$ for perspective images. Figure 5 shows example panoramas rendered by our engine. For each room, we generate a few different configurations (full, simple, and empty) by removing some or all the furniture. We also modify the lighting setup to generate images with different tem-
5. Experiments

To demonstrate the benefits of our new dataset, we use it to train deep neural networks for room layout estimation, an important task in structured 3D modeling.

5.1. Experiment Setup

**Real dataset.** We use the same dataset as LayoutNet [34]. The dataset consists of images from PanoContext [31] and 2D-3D-S [2], including 818 training images, 79 validation images, and 166 test images. Note that both datasets only provide cuboid-shape layout annotations (i.e., 4 corners), we choose 12k panoramic images with the cuboid-shape layout in our dataset. We split the images into 10k for training, 1k for validation, and 1k for testing.

**Evaluation metrics.** Following [34, 21], we adopt three standard metrics: i) 3D IoU: intersection over union between predicted 3D layout and the ground truth, ii) Corner Error (CE): Normalized $\ell_2$ distance between predicted corner and ground truth, and iii) Pixel Error (PE): pixel-wise error between predicted plane classes and ground truth.

**Baselines.** We choose two recent CNN-based approaches, LayoutNet [34] and HorizonNet [21], based on their performance and source code availability. LayoutNet uses a CNN to predict a corner probability map and a boundary map from the panorama and vanishing lines, then optimizes the layout parameters based on network predictions. HorizonNet represents room layout as three 1D vectors, i.e., boundary positions of floor-wall, and ceiling wall, and existence of wall-wall boundary. It trains CNNs to directly predict the three 1D vectors. In this paper, we follow the default training setting of the respective methods and stop the training once the loss converges on the validation set.

5.2. Experiment Results

We have conduct several sets of experiments to measure the usefulness of our synthetic dataset.

**Impact of synthetic data.** In this experiment, we train LayoutNet and HorizonNet in three different manners: i) training only on our synthetic dataset (“s”), ii) training only on the real dataset (“r”), and iii) pre-training on our synthetic dataset, then fine-tuning on the real dataset (“s → r”).

**Performance vs. synthetic data size.** We further study the relationship between the number of synthetic images used in pre-training and the accuracy on the real dataset. We sample 2.5k, 5k and 10k synthetic images for pre-training, then fine-tune the model on the real dataset. The results are shown in Table 4. As expected, using more synthetic data generally improves the performance.

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1. Right: real-world decoration.

2. https://github.com/zouchuhang/LayoutNet

3. https://github.com/sunset1995/HorizonNet

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Table 2: Room layout statistics.

| # Corners | 4 | 5 | 6 | 7 | 8 | 9 | 10+ | Total |
|-----------|---|---|---|---|---|---|-----|------|
| Realtor360 | 1246 | 0 | 950 | 0 | 316 | 0 | 61 | 2573 |
| Structured3D | 13743 | 52 | 3727 | 30 | 1575 | 17 | 2691 | 21835 |
Table 3: Quantitative evaluation under different training schemes. The best and the second best results are boldfaced and underlined, respectively. ∗: The results are reported in the original papers of corresponding methods.

| Methods          | Configuration | PanoContext | 2D-3D-S |
|------------------|---------------|-------------|---------|
|                  | 3D IoU (%) ↑  | CE (%) ↓    | PE (%) ↓| 3D IoU (%) ↑  | CE (%) ↓ | PE (%) ↓|
| LayoutNet [34]   | s             | 71.53       | 1.25    | 4.04    | 64.97     | 1.62    | 4.41    |
|                  | r             | 73.78       | 1.09    | 3.50    | 76.64     | 0.90    | 2.90    |
|                  | r*            | 75.12       | 1.02    | 3.18    | 77.51     | 0.92    | 2.42    |
|                  | s → r         | 77.32       | 0.90    | 2.81    | 77.99     | 0.90    | 2.77    |
| HorizonNet [21]  | s             | 76.33       | 1.04    | 3.12    | 72.00     | 1.09    | 3.78    |
|                  | r             | 82.87       | 0.73    | 2.06    | 83.26     | 0.64    | 2.07    |
|                  | r*            | 84.23       | 0.69    | 1.90    | 83.51     | 0.62    | 1.97    |
|                  | s → r         | 84.37       | 0.64    | 1.89    | 86.01     | 0.78    | 2.07    |

Table 4: Quantitative evaluation using varying synthetic data size in pre-training. The best and the second best results are boldfaced and underlined, respectively.

| Methods          | Synthetic Data Size | PanoContext | 2D-3D-S |
|------------------|---------------------|-------------|---------|
|                  | 3D IoU (%) ↑  | CE (%) ↓    | PE (%) ↓| 3D IoU (%) ↑  | CE (%) ↓ | PE (%) ↓|
| LayoutNet [34]   | 2.5k               | 75.80       | 0.94    | 2.95    | 77.17     | 0.82    | 2.64    |
|                  | 5k                 | 76.41       | 0.91    | 2.80    | 76.76     | 0.88    | 2.89    |
|                  | 10k                | 77.32       | 0.90    | 2.81    | 77.99     | 0.90    | 2.77    |
| HorizonNet [21]  | 2.5k               | 84.33       | 0.64    | 1.80    | 83.31     | 0.84    | 2.30    |
|                  | 5k                 | 83.67       | 0.69    | 1.95    | 85.50     | 0.64    | 2.01    |
|                  | 10k                | 84.37       | 0.64    | 1.89    | 86.01     | 0.78    | 2.07    |

Table 5: The generalizability of synthetic and real datasets.

| Methods          | Train Set | 3D IoU (%) ↑  | CE (%) ↓    | PE (%) ↓ |
|------------------|-----------|---------------|-------------|----------|
|                  |           | PanoContext   | 2D-3D-S     |          |
| LayoutNet [34]   | Ours      | 71.53         | 1.25        | 4.04     |
|                  | 2D-3D-S   | 60.28         | 2.82        | 6.96     |
| HorizonNet [21]  | Ours      | 76.33         | 1.04        | 3.12     |
|                  | 2D-3D-S   | 50.40         | 4.59        | 8.81     |

Generalization to different domains. To compare the generalizability of the models trained on the synthetic dataset and the real dataset, we conduct experiments in two different configurations: i) training on our synthetic data, and ii) training on one real dataset. Then we test both models on the other real dataset. Note that the data used in LayoutNet is from two domains, *i.e.* PanoContext (PC) and 2D-3D-S. In this experiment, we use the two datasets separately.

As shown in Table 5, when tested on PanoContext, the model trained on our data significantly outperforms the one trained on 2D-3D-S. When tested on 2D-3D-S, the model trained on our data is competitive with or slightly better than the one trained on PanoContext. Note that our dataset and PanoContext both focus on residential scenes, whereas images in 2D-3D-S are taken from office areas.

Limitation of real datasets. Due to human errors, the annotation in real datasets is not always consistent with the actual room layout. In the left image of Figure 7, the room is a non-cuboid shape layout, but the ground truth layout is labeled as cuboid-shape. In the right image, the front wall is not labeled as ground truth. These examples illustrate the limitation of using real datasets as benchmarks. We avoid such errors in our dataset by automatically generating ground truth from the original design files.

6. Conclusion

In this paper, we present Structured3D, a large synthetic dataset with rich ground truth 3D structure annotations and photo-realistic 2D renderings. We view this work as an important and exciting step towards building intelligent machines which can achieve human-level holistic 3D scene understanding: The unified “primitive+relationship” representation enables us to efficiently capture a wide variety of 3D structures and their relations, whereas the availability of millions of professional interior designs makes it possible to generate virtually unlimited amount of photo-realistic images and videos. In the future, we will continue to add more 3D structure annotations of the scenes and objects to the dataset, and explore novel ways to use the dataset to advance techniques for structured 3D modeling and understanding.
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