BIPS: Bi-modal Indoor Panorama Synthesis via Residual Depth-aided Adversarial Learning

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Abstract

Providing omnidirectional depth along with RGB information is important for numerous applications, e.g., VR/AR. However, as omnidirectional RGB-D data is not always available, synthesizing RGB-D panorama data from limited information of a scene can be useful. Therefore, some prior works tried to synthesize RGB panorama images from perspective RGB images; however, they suffer from limited image quality and can not be directly extended for RGB-D panorama synthesis. In this paper, we study a new problem: RGB-D panorama synthesis under the arbitrary configurations of cameras and depth sensors. Accordingly, we propose a novel bi-modal (RGB-D) panorama synthesis (BIPS) framework. Especially, we focus on indoor environments where the RGB-D panorama can provide a complete 3D model for many applications. We design a generator that fuses the bi-modal information and train it with residual-aided adversarial learning (RDAL). RDAL allows to synthesize realistic indoor layout structures and interiors by jointly inferring RGB panorama, layout depth, and residual depth. In addition, as there is no tailored evaluation metric for RGB-D panorama synthesis, we propose a novel metric to effectively evaluate its perceptual quality. Extensive experiments show that our method synthesizes high-quality indoor RGB-D panoramas and provides realistic 3D indoor models than prior methods. Code will be released upon acceptance.

1. Introduction

Providing omnidirectional depth along with RGB information is important for numerous applications, e.g., VR/AR. However, as the omnidirectional RGB-D data is not always available, synthesizing RGB-D panorama data from the limited information of the scene can be useful. Even though prior works have tried to synthesize RGB panorama images from perspective RGB images [21, 61], these methods show limited performance on synthesizing

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can provide the complete 3D model for many applications. We thus design a generator that fuses the bi-modal (RGB and depth) features. Through the generator, multiple latent features from one branch can help the other by providing the relevant information of different modality.

For synthesizing the depth of indoor scenes, we rely on the fact that the overall layout usually made of flat surfaces, while interior components have various structures. Thus, we propose to separate the depth of a scene into two components: layout depth and residual depth. Here, layout depth corresponds to the depth of planar surfaces, and residual depth corresponds to the depth of other objects, e.g., furniture. With this relation, we propose a joint learning scheme called Residual Depth-aide Adversarial Learning (RDAL). RDAL jointly trains RGB panorama, layout depth and residual depth to synthesize more realistic RGB-D panoramas and 3D indoor models.

Previously, some metrics [23, 57] have been proposed to evaluate the outputs of generative models using latent feature distribution of a pre-trained classification network [63]. However, the input modality of utilizing off-the-shelf network is only limited to perspective RGB images. Therefore, a new tailored evaluation metric for RGB-D panoramas is needed. For this reason, we propose a novel metric, called Fréchet Auto-Encoder Distance (FAED), to evaluate the perceptual quality for RGB-D panorama synthesis. FAED adopts an auto-encoder to reconstruct the inputs from latent features with unlabeled dataset. Then, the latent feature distribution of the trained auto-encoder is used to calculate the Fréchet distance between the synthesized and real RGB-D data.

Extensive experimental results demonstrate that our RGB-D panorama synthesis method significantly outperforms the extensions of the prior image inpainting [47, 62, 89], image outpainting [33, 61], and image-guided depth synthesis methods [12, 25, 38, 52] modified to synthesize RGB-D panoramas from partial arbitrary RGB-D inputs. Moreover, we show the validity of the proposed FAED for evaluating the quality of synthesized RGB-D panorama by showing how well it captures the disturbance level [23].

In summary, our main contributions are three-fold: (I) We introduce a new problem of generating RGB-D panoramas from partial and arbitrary RGB-D inputs. (II) We propose a BIPS framework that allows to synthesize RGB-D panoramas via residual depth-aide adversarial learning. (III) We introduce a novel evaluation metric, FAED, for RGB-D panorama synthesis and demonstrate its validity.

2. Related Works

Image Inpainting Conventional approaches explore diffusion or patch matching [5, 6, 8, 9, 14, 15, 17]. However, they require visible regions sufficiently enough to inpaint the missing regions, thus limiting their ability to synthesize novel textures or structures. The learning-based methods often use generative adversarial networks (GANs) to synthesize texture or structures [27, 39, 80, 90], optimized by the minimax loss [28]. Some works explored different convolution layers, e.g., partial convolution [41] and gated convolution [51, 81], to better handle invalid pixels in the input data to the convolution kernel. Moreover, attention mechanism [66, 67] has also been applied to better capture the contextual information and handle missing contents [40, 42, 71, 76, 80]. Recently, research has been made to synthesize high-resolution outputs [53, 60, 73] or semantically diverse outputs [43, 88]. Although endeavors have been made to tackle this large completion problem [47, 62, 89], they often fail to synthesize visually pleasing panoramas due to only using perspective RGB inputs.

Image Outpainting Conventional methods extend an input image to a larger seamless one; however, they require manual guidance [4, 7, 87] or image sets of the same scene category [30, 59, 70]. By contrast, learning-based methods synthesize large images with novel textures that do not exist in the input perspective image [19, 20, 31, 32, 35, 36, 48, 56, 75, 83]. Some approaches focus on driving scenes [74, 85] or synthesize panorama-like landscapes with iterative extension or multiple perspective images [21, 33, 61, 79]. Although performance has been greatly improved so far, the existing methods are still afflicted by the limited quality from the perspective images.

Image-guided Depth Synthesis One line of research attempts to fuse the bi-modal information, i.e., the RGB image and sparse depth. Some methods, e.g., [45], fuse the sparse depth and RGB image via early fusion while others [18, 26, 29, 37, 44, 64] utilize a late fusion scheme, or jointly utilize both the early and late fusion [36, 65, 68]. Another line of research focuses on utilizing affinity or geometric information of the scene via surface normal, occlusion boundaries, and the geometric convolutional layer [11, 12, 25, 34, 52, 54, 77, 86]. However, these works only generate dense depth maps that has the same FoV as the input perspective RGB images.

Evaluation of Generative Models Image quality assessment can be classified into three groups: full-reference (FR), reduced-reference (RR), and no-reference (NR). There exist many conventional FR metrics, e.g., PSNR, MSE, and SSIM, and deep learning (DL)-based FR metrics, e.g., LPIPS [84]. These metrics typically calculate either pixel-wise, or patch-wise similarity to the ground truth images. By contrast, NR methods, e.g., BRISQUE [49] and NIQE [50] assess image quality without any reference image. Among the DL-based NR metrics, Inception Score (IS) [57] and Fréchet Inception Distance (FID) [23] are two popular approaches [2]. IS and FID scores are calculated based on pretrained classification models, e.g., Inception model [63], aiming to capture the high-level fea-
depth sensors are used, we choose whether to use cameras or depth sensors, and randomly sample the parameters to create the parameters of cameras, horizontal FoV as δ, vertical FoV as ψ, and number of viewpoints as n. When n > 1, we arrange the viewpoints in a circle having the sampled pitch angle from the equator and at the same intervals. We do not consider roll and yaw, as they do not affect the results (i.e., the output is equiradial to the horizontal shift of input) thanks to using circular padding. Practically, we sample the parameters from δH ∼ U[60°, 90°], δV ∼ U[60°, 90°], ψ ∼ U[−90°, 90°], and n ∼ U[1, 2, 3, 4], where U[·] represents uniform distribution.

Parameters of Depth Sensors $I_d^n$ can be obtained from mechanical LiDARs or perspective depth sensors, thus we should generate arbitrary depth input masks for both. For
the LiDARs, we denote the parameters as lower FoV $\delta_L$, upper FoV $\delta_U$, pitch angle $\psi$, yaw angle $\omega$, and the number of channels $\eta$. The yaw angle is needed here to consider the relative yaw motion to the camera arrangement. For the perspective depth sensors providing dense depth, there are many similar parameters and viewpoints with those of the RGB-D cameras. Therefore, we use the same sampled parameters with the cameras (i.e., $(\delta_H, \delta_V, \psi, \omega, \eta)$). In practice, we first sample the parameters from $\psi \sim U[-90^\circ, 90^\circ]$, $\omega \sim U[0, 360^\circ]$, and $\eta \sim U\{2, 4, 8, 16\}$. Then, we sample $\delta_L$ and $\delta_U$ from $U(\eta, 2\eta, 3\eta)$. Finally, our problem is formulated as:

$$(r_{gb}^{\text{rgb}}, r_{g}^{d}) = \left(\text{ERP}r_{gb}^{\text{rgb}}, \text{ERP}r_{g}^{d} \right) = G(I_{\text{in}}^{\text{rgb}}(\delta_H, \delta_V, \psi, \omega, \eta, \delta_H, \delta_V, \omega, \eta))$$

(1)

3.2. RGB-D Panorama Synthesis Framework

Overview An overview of the proposed BIPS framework is depicted in Fig. 2. BIPS consists of a generator $G$ (Sec.3.2.1) and a discriminator $D$ (Sec.3.2.2). G takes the perspective RGB image $I_{\text{rgb}}^{\text{rgb}}$ and depth $I_{\text{d}}^{\text{d}}$ as inputs. We notice that the quality of the RGB-D panorama depends on both the overall (mostly rectangular) layout and how the furniture are arranged in the indoor scene. Inspired by [82], we separate the depth data $I_{g}^{d}$ into layout depth $I_{g}^{d,\text{lay}}$, and residual depth (the interior components) $I_{g}^{d,\text{res}}$ which is defined as $(I_{g}^{d} - I_{g}^{d,\text{lay}})$. The generator $G$ outputs the RGB panorama image $I_{\text{out}}^{gb}$, the layout depth $I_{\text{out}}^{d,\text{lay}}$ and residual depth $I_{\text{out}}^{d,\text{res}}$ simultaneously. As these are jointly trained with adversarial loss, we call this learning scheme as Residual Depth-aided Adversarial Learning (RDAL).

3.2.1 Generator

Input Branch $G_{\text{in}}$ consists of two encoding branches, $G_{\text{rgb}}^{\text{rgb}}$ and $G_{\text{depth}}^{\text{in}}$ which takes $I_{\text{rgb}}^{\text{rgb}}$ and $I_{\text{in}}^{d}$ respectively. These branches independently process $G_{\text{rgb}}^{\text{rgb}}$ and $G_{\text{depth}}^{\text{in}}$ with six conv layers before fusing them. As the inputs have a resolution of $512 \times 1024$, the filter size of the first conv layer is set as 7 and then reduced to 3 and 4 gradually.

Bi-modal Feature Fusion (BFF) Branch BFF branch $G_{\text{BFF}}$ takes $G_{\text{rgb}}^{\text{rgb}}(I_{\text{rgb}}^{gb})$ and $G_{\text{in}}^{d}(I_{\text{in}})$ as inputs, as shown in Fig. 4. Although $I_{\text{rgb}}^{gb}$ and depth $I_{\text{d}}^{d}$ are in two different modalities, we assume that the cameras and depth sensors are well calibrated and synchronized. Then, to utilize this highly correlated bi-modal information in its two branches, $G_{\text{BFF}}$ consists of two-stream encoder-decoder networks fusing the bi-modal features. These two encoder-decoder networks have an identical structure (see Fig. 4).

Moreover, the bi-modal features are fused in between the layers of $G_{\text{BFF}}$. In particular, the features from both branches are concatenated and fed back to each other. Overall, the fusion is done after the features pass two ‘DownBlocks’ and before passing two ‘UpBlocks’. In addition, multi-scale residual connections are used to vitalize transfer of information between the layers and branches. As multiple latent features from one branch help the other by sharing the information apart in both ways, $G_{\text{BFF}}$ can generate features by fully exploiting the information of the 3D scene.

The Output Branch Realistic indoor space comes from precise layout structure and high perceptual interior. Therefore, to enable RDAL to jointly train the layout and residual depth of the indoor scene, we design $G_{\text{out}}$ to have three decoding branches. Each of them generates RGB panorama $I_{\text{out}}^{gb}$, layout depth panorama $I_{\text{out}}^{d,\text{lay}}$, and residual depth panorama $I_{\text{out}}^{d,\text{res}}$ respectively, as shown in Fig. 4. Intuitively, $I_{\text{out}}^{d,\text{lay}}$ determines the layout structure and $I_{\text{out}}^{d,\text{res}}$ determines the interior objects. Then, element-wise addition of $I_{\text{out}}^{d,\text{lay}}$ and $I_{\text{out}}^{d,\text{res}}$ gives the output total depth map panorama.

3.2.2 Discriminator

We use the multi-scale discriminator $D$ from [72], but modify it to have five input and output channels (three for $I_{\text{rgb}}^{gb}$, one for $I_{\text{d}}^{\text{lay}}$, one for $I_{\text{d}}^{\text{res}}$). The detailed discriminator structure can be found in the suppl. material.

3.2.3 Loss Function

For training $G$, we use weighted sum of pixel-wise L1 loss and adversarial loss. The pixel-wise L1 loss between the GT and the output panorama, denoted as $L_{\text{pixel}}$, consists of...
three terms as the $G$ has three outputs (RGB, layout depth, residual depth panorama):

$$L_{\text{total}} = L_{\text{rgb}} + L_{\text{lay}} + L_{\text{res}}.$$  (2)

For the adversarial loss $L_{\text{adv}}$, we used LSGAN loss [46]:

$$L_{\text{adv}} = \frac{1}{2} E \left[ (D(t_{\text{out}}) - 1)^2 \right],$$ where $t_{\text{out}}$ is concatenation of generator outputs $r_{\text{out}}, p_{\text{out}}^\prime,$ and $l_{\text{out}}$, and $D$ is a discriminator trained to output one for GT and zero for $t_{\text{out}}$ with MSE loss. By decomposing the total depth loss into $L_{\text{lay}}$ and $L_{\text{res}}$, our RDAL scheme allows the generator $G$ to synthesize RGB-D panorama that generates highly plausible interior. Finally, the total loss for generator is:

$$L_G = \lambda L_{\text{total}} + L_{\text{GAN}}.$$  (3)

where $\lambda$ is a weighting factor. The generator $G$ is trained by minimizing the total loss $L_G$. Detailed loss terms can be found in the suppl. material.

3.3. Fréchet Auto-Encoder Distance (FAED)

3.3.1 Auto-Encoder Network

Similar to the high-level features in a CNN trained with large-scale semantic labels, latent features $f_{\text{latent}}$ in a trained auto-encoder also contain high-level information, as it is forced to reconstruct the input from the latent features. Therefore, we propose to train an auto-encoder, which can be done without any labels in the dataset, and use the latent features in the auto-encoder to extract perceptually meaningful information. In this way, performance evaluation can be performed for any data that lacks a labeled dataset. The auto-encoder $A$ consists of an encoder and decoder: $A_{\text{encoder}}$ and $A_{\text{decoder}}$, as shown in Fig. 5. The detailed structure of $A$ is given in the suppl. material.

3.3.2 Calculation of FAED for RGB-D Panorama

We denote $f_{\text{latent}}$ at $c$-th channel, $h$-th row, and $w$-th column as $f_{\text{latent}}(c,h,w)$. Note that as we use ERP, the $h$ and $w$ has one-to-one relation to latitude and longitude.

Longitudinal Invariance To evaluate the performance of $G$, we extract $f_{\text{latent}}$ from generated samples using $A_{\text{encoder}}$. However, as we generate the upright ERP image, it is expected to have a distance metric that is invariant to the longitudinal shift. This is because an upright ERP panorama represents the same scene when it’s cyclically shifted in the longitudinal direction. Therefore, to make the resulting distance metric invariant to the longitudinal shift, we take the mean for the longitudinal direction of $f_{\text{latent}}$ as:

$$f'_{\text{latent}}(c,h) = \frac{1}{W} \sum_{w} f_{\text{latent}}(c,h,w).$$  (4)

Latitudinal Equivariance As the ERP has varying sampling rates depending on the latitude $\phi$, we apply different weights on $f_{\text{latent}}$ based on the latitude. Specifically, we multiply $\cos(\phi)$ to feature at the latitude $\phi$, because in ERP, each pixel occupies $\cos(\phi)$ area in the spherical surface, compared with the pixels in the equator. Formally, the resulting feature $f''_{\text{latent}}$ is expressed as:

$$f''_{\text{latent}}(c,h) = \cos(\phi) f'_{\text{latent}}(c,h).$$  (5)

Fréchet Distance We treat the resulting $f''_{\text{latent}}$ as a vector and assume that it has a multi-dimensional Gaussian distribution. Then, we get the distribution of ground truths $\mathcal{N}(m,C)$ and that of generated samples $\mathcal{N}(\tilde{m},\tilde{C})$, and calculate the Fréchet distance $d$ between them as given by [16]:

$$d^2(\mathcal{N}(m,C),\mathcal{N}(\tilde{m},\tilde{C})) = ||m - \tilde{m}||_2^2 + Tr(C + \tilde{C} - 2(C\tilde{C})^{1/2}).$$  (6)

We use $d^2$ as a perceptual distance metric where $m$ and $C$ denote mean and covariance, respectively.

4. Experimental Results

Synthetic Dataset Structured3D dataset [91] provides various textures of indoor scenes with a $512 \times 1024$ resolution. We split the dataset into train, validation, and test set where the numbers of data are 17468, 2183, and 2184, respectively. In addition, with the corner locations provided in the dataset, we manually generated layout depth maps of each 3D scene. The residual depth maps are obtained by subtracting the layout depth from the GT depth map.

Real Dataset We used a combination of two datasets: Matterport3D [10], and 2D-3D-S dataset [3]. Both datasets provide real-world indoor RGB-D panorama. Since this dataset does not provide sufficient number of annotated layout, it can’t be used for training our framework and only used for test purpose. We excluded data with too many of invalid pixels from test dataset, then its number of data is 603.

Implementation Details For the details about our implementation, please refer to the supplementary material.

4.1. Verification of FAED

To show the effectiveness of FAED on measuring the perceptual quality of RGB-D panorama, we corrupt the Structured3D dataset [91] in two ways: corrupting RGB images only and corrupting depth maps only. Following [23],
Table 1. Quantitative results of RGB panorama synthesis on Structured3D dataset. As [61] uses 4 identical perspective RGB masks on horizontal central line, we report our results in same setting. In other cases, we follow designed arbitrary configuration of RGB sensor that uses 14 number of inputs. Zero number of depth input means that depth map is not used for RGB panorama synthesis. For FAED calculation, GT depth is used along with synthesized RGB panorama. **Bold** numbers indicate the best results.

| Category          | Method          | Input no. (n) | RGB metric | Layout metric | Proposed metric |
|-------------------|-----------------|---------------|------------|---------------|-----------------|
|                   |                 |               |            |               |                 |
|                   |                 |               | PSNR(↑)    | SSIM(↑)       | LPIPS(↓)        | 2D Corner error(↓) | FAED(↓) |
| Inpainting        | BRGM [47]       | 1/2/3/4       | 14.00      | 0.5310        | 0.6192          | 72.52          | 442.3  |
|                   | CoModGAN [89]   |               | 14.35      | 0.5837        | 0.4768          | 62.45          | 208.2  |
|                   | LaMa [62]       |               | 13.74      | 0.5207        | 0.5658          | 51.12          | 379.2  |
| Outpainting       | Boundless [33]  |               | 13.74      | 0.5663        | 0.6144          | 74.47          | 429.4  |
|                   | Ours            |               | 16.21      | 0.6161        | 0.4549          | 39.63          | 162.3  |
| Panorama syn.     | Sumantri et. al. [61] | 4             | 18.49      | 0.6680        | 0.4190          | 50.76          | 443.4  |
|                   | Ours            |               | 17.29      | 0.6510        | 0.3975          | 34.68          | 103.1  |

Figure 6. Verification of FAED in Structured3D dataset. It can be seen that FAED correlates well perceptual evaluation of human, as FAED increases as the disturbance level (Gaussian blur) is increased.

Figure 7. Qualitative comparison to Sumantri et. al. [61]. While the result from [61] is blurry, our result is sharp and realistic.

we corrupt the dataset by applying various types of noise: Gaussian blur, Gaussian noise, uniform patches, swirl, and salt and pepper noise. Here, we only show the plots for Gaussian blur in Fig. 6 due to the lack of space. Other results can be found in suppl. material. Note that the evaluation is done for RGB-D panorama, neither for RGB image alone nor for depth map alone. As shown in Fig. 6, the Fréchet distance for both RGB and depth panorama increases as the disturbance level (Gaussian blur) is increased. We show that the same applies to the other four types of noises in the supplementary material. This indicates the perceptual quality of RGB-D panorama becomes poorer as the FAED score increases.

4.2. RGB-D Panorama Synthesis

**RGB Panorama Evaluation** Table 1 shows the quantitative comparison with the inpainting and outpainting methods on the Structured3D dataset. We use PSNR, SSIM and LPIPS to evaluate the quality of RGB panorama. We also measure 2D corner error, where the 2D GT corner points are compared with the estimated 2D corner points using DuLa-Net [78] on the synthesized RGB panorama. We also use the proposed FAED to jointly evaluate the quality of RGB-D information.

As shown in Table 1, our method outperforms the image inpainting and outpainting methods: BRGM [47], CoModGAN [89], LaMa [62] and Boundless [33], by a large margin for all metrics. For instance, our method outperforms the best inpainting method, CoModGAN, by an 4.6% decrease of LPIPS score, 36.5% drop of 2D corner error, and 22% decline of FAED score. The effectiveness can also be visually verified in Fig. 8(a). Our method produces clearer RGB panorama images compared with LaMa producing blurry images. Although CoModGAN produces clear RGB outputs, it doesn’t consider the indoor layout and semantic information of the furniture, e.g. electric cooker is combined with bookshelves, as shown in Fig. 8. Therefore, its layout is semantically inconsistent with the input RGB region and its FAED score is higher than ours.

We also compare with the panorama synthesis method, Sumantri et al. [61]. Our method shows slightly lower scores using the conventional metrics, PSNR and SSIM; however, it shows the much better LPIPS score (0.3975 vs 0.4190), 2D corner error (34.68 vs 50.76) and FAED score (103.1 vs 443.4), respectively. We argue that PSNR and SSIM merely measure local photometric similarity, and thus fail to well reflect the perceptual quality. This can be verified from Fig. 7 where we visually compare with [61]. Our method synthesizes better textures and shows much higher visual quality. More results can be found in suppl. material.

**Depth Panorama Evaluation** We compare our method with the image-guided depth synthesis methods on Structured3D dataset. To evaluate the quality, we use AbsREL and RMSE, and the proposed FAED. We also use layout 2D IoU, as was done in [13]. The details of the metrics and results can be found in the supplementary material.

Table 2 shows the quantitative comparison with the
Table 2. Quantitative results of depth panorama synthesis on Structured3D dataset. Depth input type L/P means that we use LiDAR (L) and dense perspective depth sensor (P) in arbitrary configurations for the input. Full RGB image is used along with synthesized depth panorama for FAED calculation. Bold numbers indicate the best results.

| Category | Method           | Input type | Depth metric | Layout metric | Proposed metric |
|----------|------------------|------------|--------------|---------------|-----------------|
|          |                  | RGB        | Depth        | AbsREL↓       | RMSE↓          | 2D IoU↑       | FAED↓          |
| Depth syn. | CSPN [12]         | Full       | L/P          | 0.0855        | 2214           | 0.8062        | 428.9          |
|          | NLSNP [52]        |            |              | 0.1268        | 2807           | 0.7333        | 836.1          |
|          | MSG-CHN [38]      |            |              | 0.1764        | 3296           | 0.6724        | 896.4          |
|          | PENet [25]        |            |              | 0.1740        | 3145           | 0.7033        | 906.0          |
|          | Ours              |            |              | 0.0844        | 1942           | 0.8286        | 131.5          |

Figure 8. (a) Visual results for RGB panorama synthesis on Structured3D dataset. Two methods, LaMa and CoMoGAN, are visualized for comparison. (b) Visual results for depth panorama synthesis on Structured3D dataset. CSPN is also visualized for comparison. More qualitative results can be found in suppl. material.

Table 3. Ablation study results of BIPS framework. The experiments in four rows take RGB-D input.

| Method       | Metric | 2D IoU↑ | FAED↓ |
|--------------|--------|---------|-------|
| IwDS ([89] + [12]) | 0.7561 | 640.9   |
| Ours w/o BFF | 0.7859 | 381.4   |
| Ours w/o RDAL| 0.7164 | 329.0   |
| Ours         | 0.8158 | 198.0   |

depth synthesis methods: CSPN [12], NLSNP [52], MSG-CHN [38] and PENet [25]. In particular, our method outperforms on of the best depth synthesis method, CSPN, with much better AbsREL score (0.0844 vs 0.0855), RMSE (1942 vs 2214), 2D IoU (0.8286 vs 0.8062) and FAED score (131.5 vs 428.9). With the proposed RDAL scheme, our method estimates the best layout depth, which is demonstrated by the highest layout 2D IoU. This in turn, considerably affects the overall depth error in other metrics as well. Figure 8(b) shows the qualitative comparison with CSPN [12]. CSPN synthesizes the interior components, e.g., beds, relatively well; however, the depth of planes (e.g., walls and ceiling) are not clear. Therefore, it cannot synthesize a valid layout, failing to generate a realistic 3D indoor model. By contrast, our synthesized depth panorama shows an undisturbed and clear layout.

Evaluation on Real Dataset We evaluated our synthesized RGB-D panorama on real indoor scenes in Matterport3D and 2D-3D-S dataset. An output RGB-D panorama and its 3D indoor model are visualized in Fig. 11. Overall, our method synthesizes high-quality RGB-D panorama on real indoor scenes, unseen during training. Our synthesized depth panorama shows precise indoor layout and plausible residuals, generating a realistic 3D indoor model. For quantitative result, our method achieved better FAED score than IwDS (4645 vs 5099). Since the FAED score between synthetic and real dataset is 3517, it demonstrates that there exists distribution shift between the datasets and our result shows realistic RGB-D panorama and 3D indoor models consistently in both synthetic and real indoor scenes. More results can be found in suppl. material.

4.3. Ablation Study and Analysis

Inpainting w/ Depth Synthesis (IwDS) One solution to obtain RGB-D panorama from partial RGB-D inputs is sequentially accomplishing RGB synthesis (inpainting) and depth synthesis. To be specific, a RGB panorama is first synthesized from partial RGB input using the image inpainting method. Then, depth panorama is synthesized by applying the depth synthesis method to the synthesized RGB panorama and partial depth input. We chose CoModGAN [89] and CSPN [12] for RGB and depth synthesis methods, which showed the highest FAED score in Table 1 and Table 2. In Table 3, it can be seen that IwDS leads lower 2D IoU score and a much higher FAED score than our method. This indicates that the two-stage, sequential synthesis of RGB-D panorama is less effective than our BIPS framework that fuses the bi-modal features, trained with one-stage, joint learning scheme. Also, IwDS fails to generate realistic 3D indoor models, with distorted indoor layouts and severe bumpy surfaces as shown in Fig. 10.

Impact of BFF We study the effectiveness of RGB-D panorama synthesis by removing the BFF branch in the
Figure 9. Visualization of our synthesized RGB-D panorama results using RGB-D data in arbitrary configurations. (a) and (b) take both RGB and depth data, (c) takes only RGB and (d) takes only depth data. More results are visualized in suppl. materials.

Figure 10. Visualization of ablation study results on Structured3D dataset. Result without BFF shows artifacts irrelevant to given input and result without RDAL infers distorted room layout while our final model synthesizes perceptual undistorted indoor room.

Figure 11. Visualization of our synthesized RGB-D panorama and 3D indoor model on Matterport3D dataset.

generator. In details, $G_{BFF}$ is replaced with a single branch network taking the concatenation of $G_{rgb}^{in}(I_{rgb}^{in})$ and $G_{depth}^{in}(I_{depth}^{in})$. As shown in Table 3, the 2D IoU drops and FAED score increases without BFF. Fig. 10 shows that texture of the RGB-D output is not consistent with the given arbitrary RGB-D input. This reflects that BFF significantly contributes to well-process the bi-modal information.

Impact of RDAL. We further validate the effectiveness of RDAL by comparing the results without RDAL. The number of output branches are reduced to two, and each are designed to learn RGB and total depth panorama, respectively. As shown in Table 3, the 2D IoU score drops, and FAED score increases without RDAL. It shows that RDAL is critical for estimating precise indoor layout. The impact of RDAL is visually verified in Fig. 10. The result without RDAL shows distorted indoor layout while having fewer artifacts than ours w/o BFF. In summary, dividing the total depth into layout and residual depth helps to synthesize more structural 3D indoor model.

5. Conclusion

In this paper, we tackled a novel problem of synthesizing RGB-D indoor panoramas from arbitrary configurations of RGB and depth inputs. Our method can synthesize high-quality RGB-D panoramas with the proposed BIPS framework by utilizing the bi-modal information and jointly training the layout and residual depth of indoor scenes. Moreover, a novel evaluation metric FAED was proposed and its validity was demonstrated. Extensive experiments show that our method achieves the SoTA RGB-D panorama synthesis performance.

Limitation. We mainly focused on indoor scenes, and proposed RDAL is hardly applicable to outdoor scenes. Future work will extend our method to various environments.
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