

Taming Stable Diffusion for Text to 360° Panorama Image Generation

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Figure 1. Our PanFusion can generate realistic and consistent 360° horizontal by 180° vertical FOV panoramas from a single text prompt, compared to the limited FOV of current state-of-the-art method MVDiffusion [47]. Left: PanFusion addresses the problem of repetitive elements (duplicated “ceiling fans”) and inconsistency (the ceiling and wall in the center) of MVDiffusion. Right: While trained mostly on indoor scenes, PanFusion can generalize well to out-of-domain outdoor prompts with more reasonable layout.

Abstract

Generative models, e.g., Stable Diffusion, have enabled the creation of photorealistic images from text prompts. Yet, the generation of 360-degree panorama images from text remains a challenge, particularly due to the dearth of paired text-panorama data and the domain gap between panorama and perspective images. In this paper, we introduce a novel dual-branch diffusion model named PanFusion to generate a 360-degree image from a text prompt. We leverage the stable diffusion model as one branch to provide prior knowledge in natural image generation and register it to another panorama branch for holistic image generation. We propose a unique cross-attention mechanism with projection awareness to minimize distortion during the collaborative denoising process. Our experiments validate that PanFusion surpasses existing methods and, thanks to its dual-branch structure, can integrate additional constraints like room layout for customized panorama outputs.

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1. Introduction

Creating a 360° panorama image from textual prompts is a nascent yet pivotal frontier in computer vision, with profound implications for applications that require extensive environmental representation, such as environmental lighting [1, 4, 51], VR/AR [60, 61], autonomous driving [59], and visual navigation [17]. Despite recent significant strides in text-to-image synthesis, the leap to generating full 360° horizontal by 180° vertical field-of-view (FOV) panorama remains challenging.

There are two major hurdles for achieving this goal. The first hurdle is data scarcity. The availability of text-to-panorama image pairs [20, 47] is significantly less compared with the abundance of text-to-common image pairs [38, 39]. The dearth of data complicates the training and finetuning of generative models. The second hurdle lies in the geometric and domain variations. Panorama images are distinct not only in their aspect ratio (2 : 1) but

also in the underlying equirectangular projection (ERP) geometry [58]. This differs significantly from typical square images of the perspective projection that are used in most generative model training [38, 39].

To mitigate the scarcity of panorama-specific training data, the previous solutions follow a common principle that *leverages the prior knowledge of the pre-trained generative model* [17, 20, 47]. However, taming powerful models like stable diffusion [31, 34] to generate high-fidelity panorama images remains a non-trivial task. Early attempts turn to formulate the 360-degree generation as an iterative image inpainting or warping process [17, 20]. Such solutions suffer from error accumulation and fail to handle loop closure [47]. To address this, MVDiffusion [47] proposes to produce multiple perspective images simultaneously by introducing a correspondence-aware attention module to facilitate multiview consistency, and then stitch together the perspective images to form a complete panorama. Despite the improved performance, the pixel-level consistency between neighboring perspectives in MVDiffusion cannot ensure global consistency, often resulting in repetitive elements or semantic inconsistency, as illustrated in Fig. 1.

Therefore, in this paper, we propose a novel dual-branch diffusion model called *PanFusion* that is tailored to address the limitations of prior models for high-quality text to 360° panorama image generation. Specifically, PanFusion is designed to operate in both panorama and perspective domains, employing a global branch for creating a coherent panoramic “canvas” and a local branch that focuses on rendering detail-rich multiview perspectives. The local-global synergy of PanFusion significantly improves the resulting panoramas against the prevalent issues of error propagation and visual inconsistency that prior models have struggled with. To enhance the synergy between the two branches, we further propose an Equirectangular-Perspective Projection Attention (EPPA) mechanism, which respects the equirectangular projection for maintaining geometric integrity throughout the generation process. In addition, our adoption of parametric mapping for positional encoding is another leap forward, enhancing the model’s spatial awareness and further ensuring the consistency of the generated panorama. Moreover, the panorama branch of PanFusion can be easily leveraged to accommodate supplementary control inputs at the panorama level, such as room layout, allowing for the creation of images that adhere to precise spatial conditions. We summarize our primary contributions as follows.

- We pioneer a dual-branch diffusion model PanFusion, harnessing both the global panorama and local perspective latent domains, to generate high-quality, consistent 360° panoramas from text prompts.
- To enhance the interaction between the two branches, we introduce an “equirectangular-perspective projection at-

ention” mechanism that establishes a novel correspondence between global panorama and local perspective branches, addressing the unique projection challenges of panorama synthesis.

- Our PanFusion not only surpasses prior models in quality and consistency but also supports extended control over the generation process with the inclusion of room layout. Extensive experimental results demonstrate the superiority of our proposed framework.

2. Related Work

Diffusion models. In recent years, diffusion models [6, 12, 41, 42, 44, 62] have taken the world of image generation by storm, as they have become faster [15, 19, 42] and more capable in terms of image quality and resolution [28, 31, 36]. This success has prompted the development of various applications for diffusion models, such as text-to-image [25, 28, 31, 36], image-conditioned generation [24, 64], in-painting [21, 35] and subject-driven generation [10, 33]. Most of these applications try to exploit the prior knowledge of a pre-trained diffusion model to mitigate the scarcity of task-specific data, by either finetuning with techniques like LoRA [14], or introducing auxiliary modules to distill the knowledge. We also adopt the same principle to harness the power of a pre-trained latent diffusion model [31] for panorama image generation.

Panorama generation. Panorama image generation encompasses different settings, including panorama outpainting and text-to-panorama generation. Panorama outpainting [1, 5, 26, 51, 54, 56] focus on generating a 360-degree panorama from a partial input image. Various methods, such as StyleLight [51] and BIPS [26], have addressed specific use cases, focusing on HDR environment lighting and robotic guidance scenarios. Recent works [54, 56] have improved realism with diffusion models, but often lack the exploitation of rich prior information from pre-trained models, limiting generalization. On the other hand, recent developments in generative models have opened new frontiers in synthesizing immersive visual content from textual input [8, 13, 43, 52, 53, 55, 56, 61, 63]. As an image-based representation, generating panorama from text has gained much attention. Text2Light [4] adopt the VQGAN [7] structure to synthesize an HDR panorama image from text. To generate in arbitrary resolution with pre-trained diffusion models, DiffCollage [65], MultiDiffusion [2] and SyncDiffusion [16] propose to fuse the diffusion paths, while PanoGen [17] solves by iteratively inpainting. However, they failed to model the equirectangular projection of 360-degree panoramas. Lu et al. [20] adopts an autoregressive framework, but suffers from inefficient issues. MVDiffusion [47] designs a correspondence-aware attention module to produce multi-view images simultaneously that can be stitched together but results in repetitive elements and in-

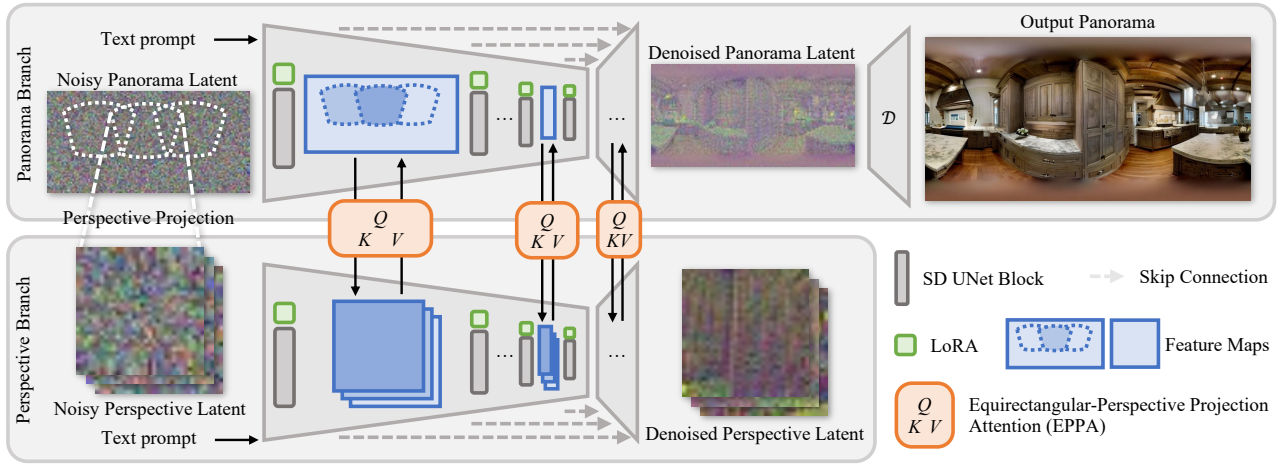


Figure 2. Our proposed dual-branch PanFusion pipeline. The panorama branch (upper) provides global layout guidance and registers the perspective information to get seamless panorama output. The perspective branch (lower) harnesses the rich prior knowledge of Stable Diffusion (SD) and provides guidance to alleviate distortion under perspective projection. Both branches employ the same UNet backbone with shared weights, while finetuned with separate LoRA layers. Equirectangular-Perspective Projection Attention (EPPA) modules are plugged into different layers of the UNet to pass information between the two branches.

consistency. In contrast, our proposed PanFusion, a dual-branch framework, addresses the limitations of existing methods by considering both global panorama views and local perspective views, providing a comprehensive solution for text-driven 360-degree panorama image generation.

3. Method

3.1. Preliminary

First introduced in [41], Diffusion models [12, 42, 44] aim to generate images from a noise distribution by iterative denoising with a learned prior distribution. However, the early diffusion models operate in the image space, which is of high dimension and complex. We have recently witnessed the huge success of latent diffusion models [31] that first transform an image x to a latent representation z with a learned encoder \mathcal{E} and then train a UNet [32] model ϵ_θ parameterized by θ for the reverse process in the latent space, formulating the training objective as:

$$\mathcal{L} = \mathbb{E}_{\mathcal{E}(x), t, \epsilon, y} [\|\epsilon - \epsilon_\theta(z_t, t, \tau(y))\|_2], \quad (1)$$

where $\tau(y)$ is an encoding of input condition y (e.g., text prompt or image), z_t is the latent map at time step t , and ϵ is sampled from a Gaussian noise. To sample from the model, z_t is first initialized from standard Gaussian distribution, then the reverse process is applied iteratively to generate z_0 , which is finally decoded into image space with a decoder \mathcal{D} .

3.2. Dual-Branch Diffusion Model

Directly employing pre-trained latent diffusion models [31], e.g., Stable Diffusion (SD) [34], to generate panorama from multiple perspective images, either in an iterative manner [9, 13, 17] or in a synchronized way [2, 47], would

fail to handle loop closure [47] or produce repetitive elements (Fig. 1) due to lack of global understanding. To address this issue, we propose a dual-branch diffusion model, which consists of a panorama branch and a perspective branch both based on the UNet of SD as shown in Fig. 2. The panorama branch is designed to provide global layout guidance and to register the perspective information to get the final panorama without stitching, while the perspective branch is designed to exploit the rich perspective image-generation capabilities of SD and to provide guidance to alleviate distortion under perspective projection. The two branches work together during the diffusion process to generate a denoised panorama latent map. Finally, this latent map runs through the pre-trained decoder \mathcal{D} of SD to produce the final panorama image.

Panorama Branch. Given a text prompt y , our goal is to generate a panorama $x \in \mathbb{R}^{3 \times H \times W}$, where $W = 2H$, $H = 512$. To account for the difference between the target resolution and the one that SD is trained on, we introduce LoRA [14] layers to adapt the model to the new resolution. SD with LoRA can already serve as a strong baseline for panorama generation, but the results are not loop-consistent. Previous works [8, 56] have attempted to overcome this problem using 90 degree rotations of the latent map at each diffusion step. However, the seams are still obvious [56]. On close inspection of the SD model we have observed that the loop inconsistency is mainly caused by the convolutional layers in the UNet backbone, due to the lack of a mechanism to pass information between the two ends of the panorama image. Therefore, we introduce an adaptation to the UNet by adding additional circular padding [40, 54, 66] before each convolutional layer, and then cropping the output feature maps to the original size. In addition, we also add circular padding to the latent map before decoding to

mitigate the less apparent loop inconsistency caused by the decoder. The combination of the techniques outlined above – latent rotation and circular padding – enable the generation of loop-consistent results with negligible computational cost, and can thus serve as another strong baseline. However, these alone do not make full use of the perspective generation capabilities that SD possess.

Perspective Branch. The perspective branch aims to exploit the outstanding capabilities that SD has shown in the generation perspective images. Since it does not generate panoramas directly, it can operate at a lower resolution. Specifically, we set its resolution to $H/2 \times H/2$ and add LoRA layers to adapt to the new resolution. To evenly distribute perspective cameras and fully cover the panorama image, we sample $N = 20$ cameras with poses $R^i \in SO(3), i \in 1, \dots, N$ on an icosahedron, similar to [27, 30], and set the FOV = 90° . We input the same prompt y to both branches, and leave it to the model to decide how to exploit the prompt.

Joint Latent Map Initialization. Previous work [22] has shown that the latent map initialization can affect the layout of the generated image, *i.e.*, the initial noise can be modified to manipulate the layout of the generated image. We find this is particularly important for multi-image generation with correspondence, as the overlapping regions in different views tend to generate different elements if noise is sampled independently. Under this observation, we propose to jointly sample noise for the panorama and perspective latent maps by projecting noise from the panorama to the perspective. To be more specific, we first initialize panorama latent map $z_T^* \in \mathbb{R}^{4 \times H/f \times W/f}$ as Gaussian noise, then initialize perspective latent maps with $z_T^i = P(z_T^*, R^i, \text{FOV}, (H/2f, H/2f)), z_T^i \in \mathbb{R}^{4 \times H/2f \times H/2f}$, where $P(\cdot)$ is the function that projects z_T^* to a perspective view, and f is the down-sampling factor the encoder \mathcal{E} used in SD. We use nearest interpolation for projection as it introduces fewer artifacts than bilinear interpolation.

3.3. EPP Attention

To pass the guidance between the perspective and panorama branches, a naive solution is to project the feature maps in different layers from one branch to the other, similar to [47]. However, this will introduce information loss during interpolation and will restrict the receptive field to a small region around corresponding pixels. Instead, we propose an Equirectangular-Perspective Projection Attention (EPPA) module to implicitly pass the guidance in a cross-attention way as shown in Fig. 2. The EPPA operates on feature maps in different layers of two UNet branches, denoted as $F^* \in \mathbb{R}^{c \times h \times w}$ and $F^i \in \mathbb{R}^{c \times h/2 \times h/2}$, where c is the channel dimension, h and w are the height and width of the feature maps, respectively. In addition, while cross-attention bypasses interpolation and provides benefits from

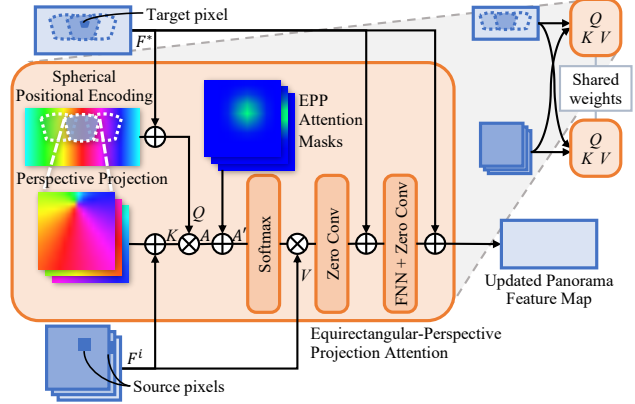


Figure 3. Equirectangular-Perspective Projection (EPP) Attention. As EPP attention module is designed to be bijective to pass information in both directions, we only illustrated the direction of registering perspective information to panorama.

the global receptive field of the attention mechanism, it is unaware of the projection between different formats. To address this issue, as shown in Fig. 3, we introduce two key components: EPP spherical positional encoding and EPP attention mask.

EPP Spherical Positional Encoding. Since the EPPA module tries to associate two different formats, it is important to add positional information in the same space so that the attention mechanism can learn the correspondence. We achieve this by introducing Spherical Positional Encoding (SPE) [4, 23] to the EPPA module. The $\text{SPE}(\theta, \phi) = (\gamma(\theta), \gamma(\phi))$ function maps polar coordinates (θ, ϕ) to a higher dimensional space \mathbb{R}^{4L} with Fourier positional encoding:

$$\gamma(\theta) = \left[\sin(2^0 \pi \theta), \cos(2^0 \pi \theta), \dots, \sin(2^{L-1} \pi \theta), \cos(2^{L-1} \pi \theta) \right]. \quad (2)$$

Here we set $L = c/4$ so that $\text{SPE}(\theta, \phi) \in \mathbb{R}^c$. In the EPPA module, we apply SPE by first computing an SPE map for the panorama feature map, then project it to each perspective feature map with projection function $P(\cdot)$, so that corresponding pixels in different formats share the same SPE vector. Finally, the SPE maps are added to the feature maps accordingly and go through a linear layer to get the query Q and key K , following a matrix product to get the affinity matrix A . Take the perspective-to-panorama direction as an example as shown in Fig. 3, where $Q \in \mathbb{R}^{c \times h \times w}$ and $K \in \mathbb{R}^{N \times c \times h/2 \times h/2}$ are reshaped and multiplied to get the affinity matrix $A \in \mathbb{R}^{hw \times N h^2/4}$.

EPP Attention Mask. In addition to the SPE, we also propose an EPP attention mask to encourage the attention mechanism to focus around the corresponding pixels, inspired by [48]. For example, for a target pixel in the panorama feature map as in Fig. 3, we would like to focus on registering the information from corresponding source pixels in the perspective feature maps. We achieve

this by enhancing the affinity matrix A with a soft mask $M \in \mathbb{R}^{hw \times Nh^2/4}$ highlighting the corresponding pixels. To generate M , we first use $P(\cdot)$ to project a binary mask $M_{j,k}$ for each pixel (j, k) in panorama feature map to each perspective view i . Then we apply a Gaussian kernel to smooth the masks and normalized them to $[-1, 1]$. The masks are stacked and reshaped into M , which is then added to A to get the enhanced affinity matrix A' . The rest goes the same as the vanilla attention mechanism, where a softmax function is applied to A' to get the attention weights, which are finally multiplied with the value V to get the output.

Inspired by [47, 64], we add zero-initialized 1×1 convolutional layers to the output of cross-attention and add it as a residual to the target feature map. This ensures the UNet stays unmodified at the beginning of training and can be gradually adapted to the EPPA modules. We add independent EPPA modules after each down-sampling layer and before each up-sampling layer of UNet to connect two branches, detailed in Sec. A of the supplementary material. Considering that the guidance is passed in both directions following the same equirectangular-perspective projection rule, which is bijective in nature, we share the weights of the EPPA modules in the two directions.

3.4. Layout-Conditioned Generation

One of the most important applications for panorama generation is to generate panorama according to a given room layout. This is particularly useful for panorama novel view synthesis [57] and can potentially benefit indoor 3D scene generation [8, 13]. However, this problem is not well researched for diffusion-based panorama generation, largely due to the difficulty of introducing layout constraints while exploiting the rich prior knowledge of SD in perspective format at the same time. For panorama generation from multi-view [17, 47], one naive solution is to project layout condition into different views to locally condition the generation of perspective images. Instead, for our dual-branch diffusion model, we can naturally exploit the global nature of the panorama branch to enforce a much stronger layout constraint. Specifically, we render the layout condition as a distance map, then use it as the input of a ControlNet [64] to condition the panorama branch.

3.5. Training

During training, we employ the same technique for latent map initialization to jointly sample noise for the panorama and perspective view, which we denote as ϵ^* and ϵ^i , respectively. Given a GT panorama x^* , we apply supervision on the panorama branch with the loss in Eq. (1):

$$\mathcal{L}^* = \mathbb{E}_{\mathcal{E}(x^*), t, \epsilon^*, y} [\|\epsilon^* - \epsilon_\theta^*(z_t^*, t, \tau(y))\|_2], \quad (3)$$

where ϵ_θ^* is the predicted noise from the panorama branch. To encourage the synchronization between the

two branches, we also apply supervision on the perspective branch with the following loss:

$$\mathcal{L}^i = \mathbb{E}_{\mathcal{E}(x^i), t, \epsilon^i, y} [\|\epsilon^i - \epsilon_\theta^i(z_t^i, t, \tau(y))\|_2], \quad (4)$$

where x^i is a perspective image projected from x^* and ϵ_θ^i is the predicted noise from the perspective branch. We joint train the EPPA modules and the LoRA layers in the two branches by combining the above two losses as $\mathcal{L} = \mathcal{L}^* + \frac{1}{N} \sum_{i=1}^N \mathcal{L}^i$. Note that the SD UNet blocks remain frozen.

4. Experiment

4.1. Experimental Setup

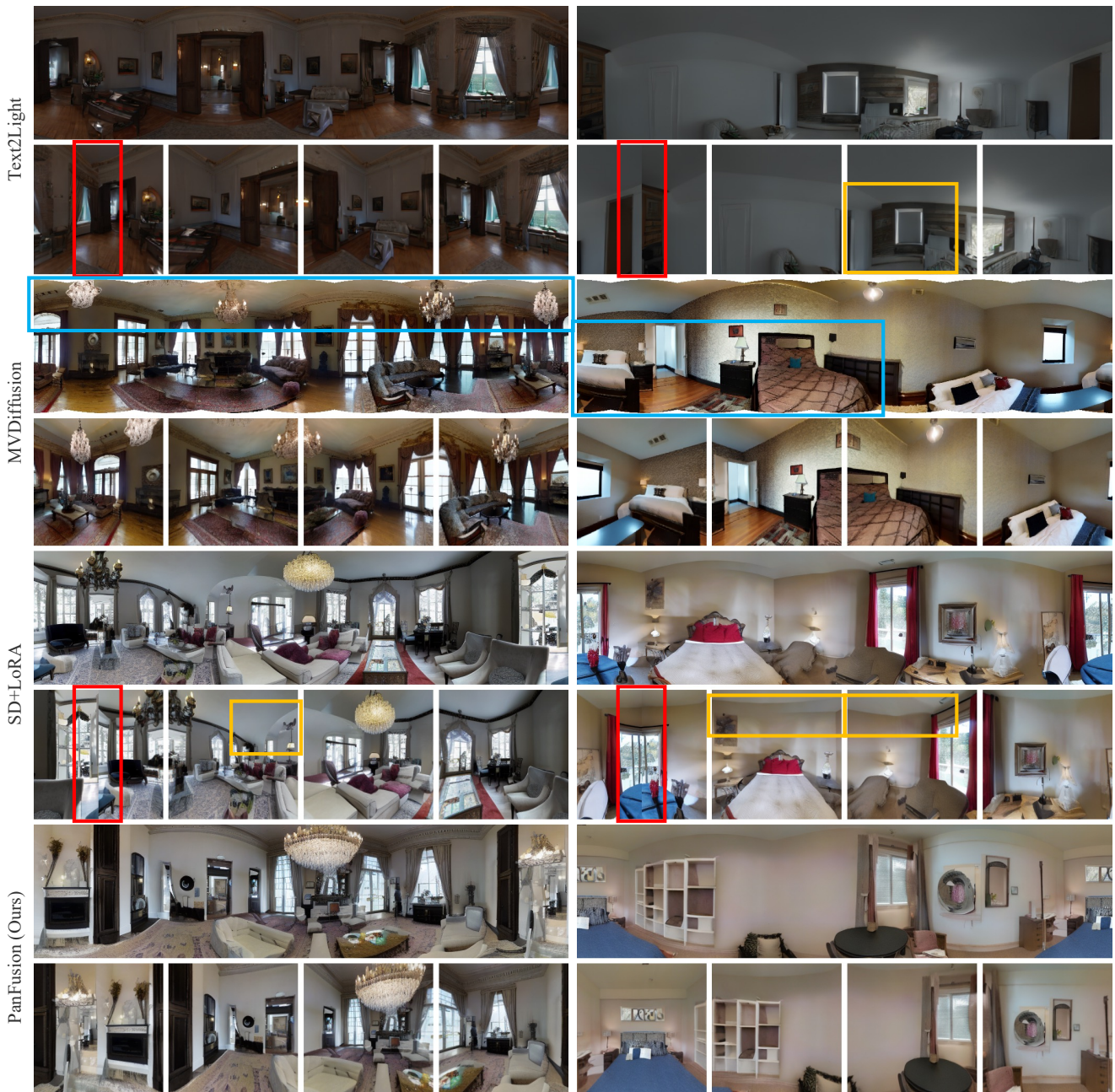
Dataset. We follow the MVDiffusion [47] to use the Matterport3D dataset [3], which has 10,800 panoramic images with 2,295 room layout annotations. We employ BLIP-2 [18] to generate a short description for each image.

Implementation Details. For text-conditioned generation, the training and inference schedules are kept the same as MVDiffusion [47] to make a fair comparison. For text-layout conditioned generation, we train the additional ControlNet with other parameters fixed.

Evaluation Metrics. Following previous works, we evaluate image quality in panorama [4] and perspective [47] domain. For layout-conditioned generation, we propose a new metric to evaluate how well the generated panorama follows input layout. Specifically, we use the following metrics:

- *Panorama.* We follow Text2Light [4] to report Fréchet Inception Distance (FID) [11] and Inception Score (IS) [37] on panoramas to measure realism and diversity. Additionally, CLIP Score (CS) [29] is used to evaluate the text-image consistency. While FID is widely used for image generation, it relies on an Inception network [46] trained on perspective images, thus less applicable for panorama images. Therefore, a variant of FID customized for panorama, Fréchet Auto-Encoder Distance (FAED) [26], is used to better compare the realism.
- *Perspective.* To simulate the real-world scenario where the user can freely navigate a panorama by viewing from different perspective views, we also report FID and IS for 20 randomly sampled views to compare with methods that generate 180° vertical FOV. We also follow MVDiffusion [47] to report FID, IS and CS scores on 8 horizontally sampled views. It is worth noting that this group of metrics favors MVDiffusion by measuring its direct outputs, while ours involve interpolation for perspective views.
- *Layout Consistency.* We propose a layout consistency metric, which employs a layout estimation network HorizonNet [45] to estimate the room layout from the generated panorama and then compute its 2D IoU and 3D IoU [45] with the input layout condition.

See Supplementary Sec. B for more details of the above.



“A living room with a chandelier.”

“A bedroom with a bed and a table.”

Figure 4. Qualitative comparisons of text-conditioned panorama generation. We show panoramas cropped to the vertical FoV of MVDiffusion [47]. Below each panorama, we show 4 evenly spaced perspective projections, with the first view crossing the left and right boundaries. We highlight the **loop inconsistency**, **distorted lines** and **repetitive objects and unreasonable furniture layout** of baseline methods with corresponding colors of boxes, which are addressed by our method. More results can be found in Sec. E of the supplementary.

4.2. Comparisons with Previous Methods

Baselines. We compare our PanFusion with the following baselines (see Supplementary Sec. B for details).

- *MVDiffusion* [47] utilizes a multi-view diffusion model to generate 8 horizontal views that can be stitched into a panorama with vertical FOV of 90° . It requires separate prompts for training while providing an option to generate

from a single prompt.

- *Text2Light* [4] generates a 180° vertical FOV panorama from a text prompt in a two-stage auto-regressive manner.
- *SD+LoRA* is our baseline model that uses LoRA [14] to finetune a Stable Diffusion [31] on panorama images.
- *Pano Branch* is SD+LoRA with additional modifications as described in Sec. 3.2 to ensure loop consistency.

Method	Panorama				20 Views		Horizontal 8 Views [47]		
	FAED ↓	FID ↓	IS ↑	CS ↑	FID ↓	IS ↑	FID ↓	IS ↑	CS ↑
Text2Light [4]	97.24	76.5	3.60	27.48	36.25	5.67	43.66	4.92	<u>25.88</u>
MVDiffusion [47]	-	-	-	-	-	-	25.27	6.90	26.34
SD+LoRA [14, 31]	<u>7.19</u>	51.69	<u>4.40</u>	28.83	<u>19.32</u>	<u>6.90</u>	20.68	6.48	24.77
Pano Branch	7.90	<u>50.40</u>	4.54	<u>28.67</u>	20.10	7.06	<u>20.56</u>	6.37	24.85
PanFusion (Ours)	6.04	46.47	4.36	28.58	17.04	6.85	19.88	<u>6.50</u>	24.98

Table 1. Comparison with SoTA methods. We evaluate the panorama image quality with Fréchet Auto-Encoder Distance (FAED), Fréchet Inception Distance (FID), Inception Score (IS), and CLIP Score (CS). In addition, we evaluate the perspective image quality in two settings. We first randomly sample 20 views, which is the closest to the real-world scenario where the user can freely navigate the panorama to view the scene from different perspectives. We then follow MVDiffusion [47] to horizontally sample 8 evenly spaced views.

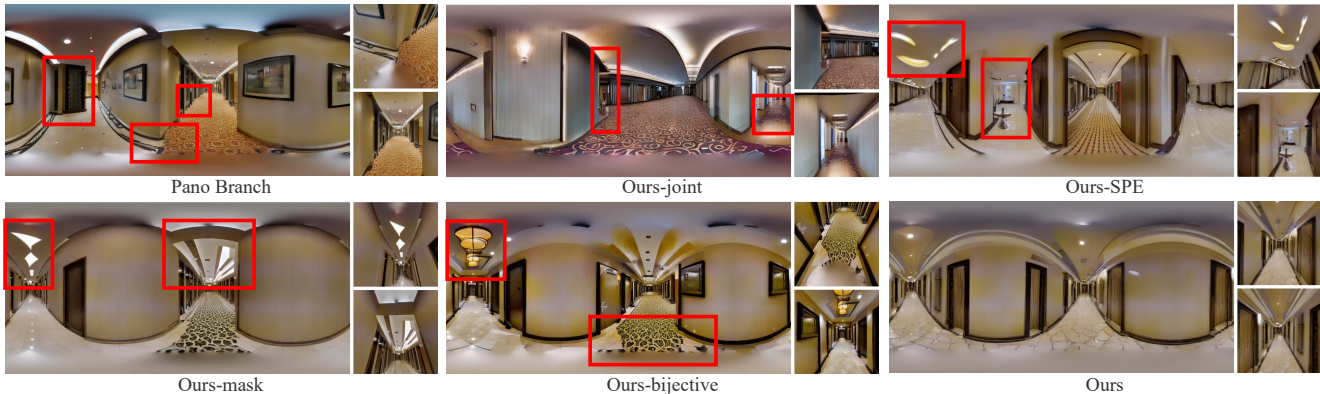


Figure 5. Ablation study. Artifacts are highlighted with red boxes and projected to perspective views. Prompt: “A hallway in a hotel.”

Method	Panorama				20 Views	
	FAED ↓	FID ↓	IS ↑	CS ↑	FID ↓	IS ↑
Pano Branch	7.90	50.40	4.54	28.66	20.10	<u>7.06</u>
Ours-joint	7.75	59.43	4.34	27.94	29.68	6.82
Ours-SPE	<u>6.63</u>	49.55	4.65	28.66	20.82	7.00
Ours-mask	6.77	45.49	4.35	28.66	15.81	6.81
Ours-bijective	7.36	48.35	<u>4.58</u>	28.66	18.78	7.12
Ours	6.04	46.47	4.36	<u>28.58</u>	17.04	6.85

Table 2. Ablation study. We compare the ablated versions of our method on both panorama and perspective domains. Here, “-” indicates removing the subsequent component.

Quantitative Results. Tab. 1 shows the quantitative comparison results. Here, we assign the highest value to realism in image generation, measured in FAED and FID. On these two metrics, our method outperforms baseline methods in both panorama and perspective. For IS, our method’s performance is slightly lower than baselines. This is likely due to the fact that IS evaluates diversity of objects in generated images, using a classifier, and our model, unlike the baselines, tends to not generate unexpected objects. Similarly, it is possible to say that baseline models present slightly higher CS is due to the repetition of objects reinforcing alignment with prompts. Considering SD+LoRA is superior to Pano Branch on FAED and is on par in other metrics, we only qualitatively compare with SD+LoRA below.

Qualitative Results. Fig. 4 shows the qualitative comparison results. **Loop inconsistency** can be observed for

Text2Light and SD+LoRA due to lack of message passing between left-right boundaries. They also suffer from **distorted lines** in perspective views, meaning the generated panorama does not follow the correct equirectangular projection. MVDiffusion on the other hand suffers from **repetitive objects and unreasonable furniture layout**, which is likely due to the lack of global context. Our method generates the most realistic scenes and aligns to text condition the best, also with less distortion in perspective views.

4.3. Ablation Study

In Sec. 4.2 and Tab. 1, we show that our full model outperforms Pano Branch, the baseline model of our method without the perspective branch. Here, as shown in Tab. 2 and Fig. 5, we further conduct an ablation study to validate the effectiveness of each component in our method. For a consistent comparison, we keep the layout similar between different ablated versions by sampling the same noise for latent map initialization, exploiting the observation of [22].

Joint latent map initialization. We ablate the joint latent map initialization by initializing the latent maps of the panorama and perspective branches separately (**Ours-joint**). Significant performance drop can be observed in all metrics and qualitative results, demonstrating the importance of joint latent map initialization. Interestingly, Ours-joint is even worse than Pano Branch in FID. It is likely due to that joint latent map initialization helps the corresponding

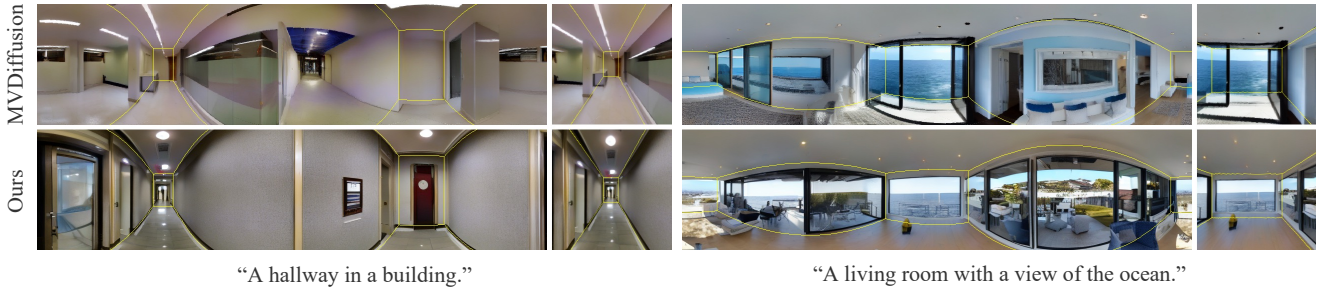


Figure 6. Layout-conditioned generation comparisons. We showcase how layout-conditioned panorama generation can benefit from our dual-branch structure. The input layout is drawn on the generated panorama as yellow lines, while the panorama is cropped to the FoV of MVDiffusion and projected to one view to highlight the layout consistency.

Method	Layout Consistency		Horizontal 8 Views [47]		
	3D IoU \uparrow	2D IoU \uparrow	FID \downarrow	IS \uparrow	CS \uparrow
MVDiffusion [47]	61.06	64.43	28.83	5.60	26.79
PanFusion (Ours)	68.46	71.82	22.58	5.10	26.04
GT image	74.31	77.15	-	-	-

Table 3. Layout-conditioned comparisons. We evaluate layout consistency between the condition and the layout of each generated image extracted by a layout estimator HorizonNet [45]. “GT image” indicates the upper bound of the layout estimator.

pixels to share a similar noise distribution from the beginning of the diffusion process, which is essential for EPPA to align the content of overlapped regions.

EPP SPE and attention mask. We ablate spherical positional encoding (**Ours-SPE**) and attention mask (**Ours-mask**) from EPPA module. From Tab. 2, we can see that missing SPE hurts FAED and FID, which is likely due to that SPE helps the model to learn the relative position of the pixels between the two branches. Missing attention mask gets FID better, but it hurts FAED, which is more accurate in evaluating the panorama quality as it is customized for the target dataset. Both result in clear artifacts around point light sources, inconsistent textures of the floor, and distortions in the highlighted projections, as shown in Fig. 5.

Bijjective EPPA. We ablate the bijjective EPPA (**Ours-bijjective**) by using separate parameters for the two directions in the EPPA module. Both FAED and FID get worse for Ours-bijjective. In addition, the ablated version struggles to generate consistent textures for the floor and ceiling for the two directions of the hallway in Fig. 5. On the contrary, our full model generates floor and ceiling with consistent style, showing a better global understanding of the scene.

4.4. Application: Layout-Conditioned Generation

To showcase the advantage of our method in generating panorama images with additional layout conditions, we build a baseline model by adding a ControlNet to MVDiffusion as described in Sec. 3.4. We render the layout condition into a distance map and then project it to perspective views to condition its generation of multi-view images. The training settings are kept the same as our PanFusion. As shown in Tab. 3, our method outperforms the baseline



Figure 7. Failure case. Our method sometimes generates indoor scenes with no entrance.

model in layout consistency while keeping the realism advantage of perspective projections. We visualize the layout condition as wireframes overlaid on generated panorama images in Fig. 6, where we can see our generated panorama images follow their layout conditions better, especially as highlighted in perspective views. More details can be found in Sec. F of the supplementary material.

5. Conclusion

In this paper, we have proposed PanFusion, a novel text-to-360°-panorama image generation method that can generate high-quality panorama images from a single text prompt. Particularly, a dual-branch diffusion architecture has been introduced to harness prior knowledge of Stable Diffusion in the perspective domain while addressing the repetitive elements and inconsistency issues observed in previous works. An EPPA module has been further introduced to enhance the information passing between the two branches. We have also extended our PanFusion for the application of layout-conditioned panorama generation. Comprehensive experiments have demonstrated that PanFusion can generate high-quality panorama images with better realism and layout consistency than previous methods.

Limitations. Although the dual-branch architecture of PanFusion combines the advantages in both panorama and perspective domains, it comes with a cost of higher computational complexity. Additionally, our method sometimes fails to generate entrance for indoor scenes, as shown in Fig. 7, which is essential for use cases like virtual tour.

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