

Vivid4D: Improving 4D Reconstruction from Monocular Video by Video Inpainting

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Project Page: <https://xdimlab.github.io/Vivid4D/>

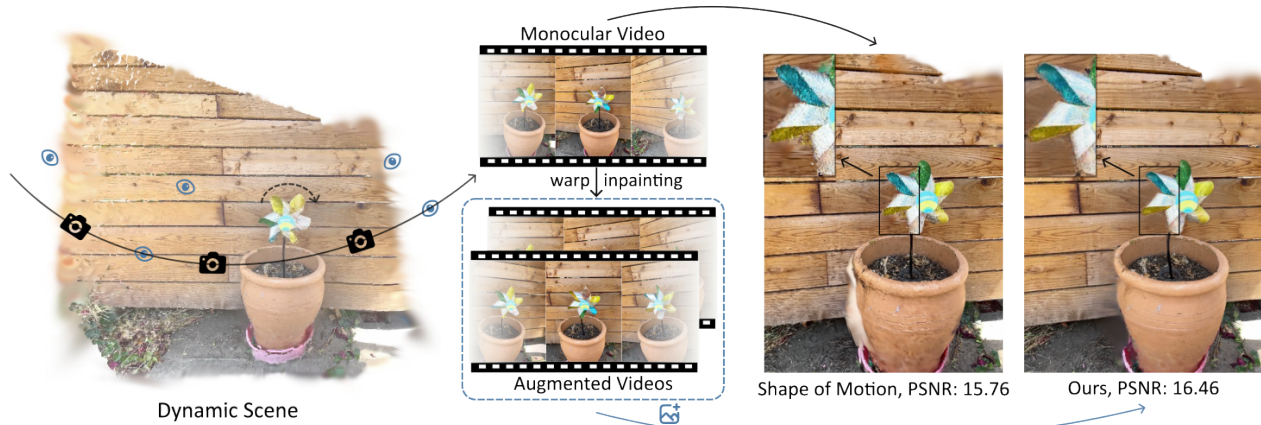


Figure 1. **Vivid4D**. We improve dynamic scene reconstruction from casually captured monocular videos by synthesizing augmented views. Our approach integrates both geometric and generative priors to reformulate the video augmentation as a video inpainting task. This enables our method to effectively complete invisible regions in the scene and enhance reconstruction quality.

Abstract

Reconstructing 4D dynamic scenes from casually captured monocular videos is valuable but highly challenging, as each timestamp is observed from a single viewpoint. We introduce Vivid4D, a novel approach that enhances 4D monocular video synthesis by augmenting observation views — synthesizing multi-view videos from a monocular input. Unlike existing methods that either solely leverage geometric priors for supervision or use generative priors while overlooking geometry, we integrate both. This reformulates view augmentation as a video inpainting task, where observed views are warped into new viewpoints based on monocular depth priors. To achieve this, we train a video inpainting model on unposed web videos with synthetically generated masks that mimic warping occlusions, ensuring spatially and temporally consistent completion of missing regions. To further mitigate inaccuracies in monocular depth priors, we introduce an iterative view augmentation strategy and a robust reconstruction loss. Experiments demonstrate that our method effectively improves monocular 4D scene reconstruction and completion.

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1. Introduction

Reconstructing dynamic 3D scenes from convenient monocular video captures is a highly valuable task in computer vision and graphics, yet remains a profound challenge. Recent advances in 4D reconstruction [9, 17, 21, 23, 44, 50, 61, 83, 96] have made significant progress in modeling dynamic scenes, but they typically rely on synchronized multi-view cameras.

Given the sparse observations of monocular videos where each timestamp is observed from a single viewpoint, existing methods attempt to address this challenging task by incorporating additional priors. One line of studies has explored various geometric priors for monocular 4D reconstruction, including geometric constraints [57, 58], optical flow [41, 42, 81], depth estimation [24, 47], and tracking [38, 69, 78]. However, existing methods yield suboptimal results for two main reasons. First, these auxiliary supervisions are not consistently reliable and may not correlate linearly with rendering performance; for example, a small depth error may lead to significant color shifts in regions with texture changes. Second, these priors, which are derived solely from input views, provide limited guidance for regions occluded or unobserved in the input views. More recently, video diffusion models have emerged as an-

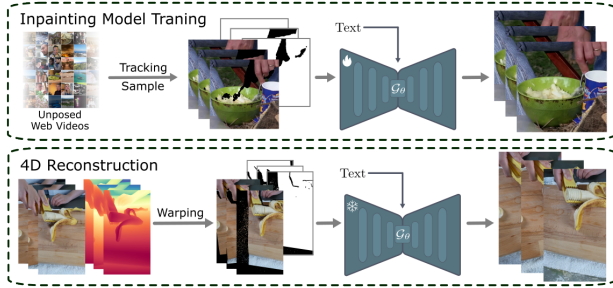


Figure 2. **Video Inpainting for 4D Reconstruction.** To train the video inpainting model, we use 2D tracking to generate masked training pairs from *unposed* web videos. During 4D reconstruction, we warp the monocular video to novel viewpoints, creating masked videos that our inpainting diffusion model then completes.

other type of prior for such tasks, owing to their impressive ability to generate realistic videos [7, 36, 48, 97]. These models can generate plausible RGB images for unknown viewpoints, overcoming the disadvantages of using geometry priors alone. However, existing methods are either limited to static scenes [46, 52, 85, 101, 103], or require a large amount of posed images for training [84, 109], while collecting such training data is highly challenging as dynamic scenes’ camera poses are difficult to obtain.

In this work, we propose Vivid4D, a novel approach for 4D monocular reconstruction that integrates geometric priors from input videos with the generative capabilities of video diffusion models. Instead of directly generating novel views, we reformulate view augmentation as a video inpainting task: first, observed views are warped to unseen viewpoints based on geometric priors; then, a video diffusion model inpaints missing regions to ensure spatial-temporal consistency. This allows us to train the video inpainting model using *unposed* web videos by mimicking warping occlusions based on 2D trackings. Specifically, our method includes two key steps as shown in Fig. 2. First, we train a video inpainting model tailored for our view augmentation task that learns to in-paint occluded regions in a spatial-temporally coherent manner (Fig. 2 top). This model is trained on unposed web videos, using 2D trackings to synthesize occlusion masks. Next, we use the trained video inpainting model for view augmentation in monocular-video-based 4D reconstruction, leveraging monocular depth priors to warp the video to unseen viewpoints, which our inpainting model then completes (Fig. 2 bottom). To maximize scene coverage while compensating for inaccurate monocular depth priors, we propose a progressive view expansion strategy that iteratively generates augmented views, effectively accumulating comprehensive multi-view observations. When further combined with a robust reconstruction loss, the augmented views enables Vivid4D to improve 4D reconstruction while maintaining geometric consistency and temporal coherence.

The main contributions of our work can be summarized as follows: 1) We propose Vivid4D, a novel method for monocular 4D scene reconstruction that leverages multi-view supervision from both video diffusion models and depth-guided warping. 2) We reformulate view augmentation as a video inpainting task, enabling efficient training on unposed web videos through synthesized occlusion masks based on 2D tracking. 3) We design an iterative view augmentation strategy to progressively expand the observation viewpoint of the scene, enabling robust reconstruction and novel view synthesis. 4) We conduct extensive experiments across various dynamic scenes and show that our method improves the quality of novel view synthesis compared to existing approaches on different types of motion and scene complexity.

2. Related Work

3D Novel View Synthesis. Recent advances in neural rendering, from NeRF [3–5, 53, 54, 77] to 3D GS [10, 28, 32, 34, 49, 89, 102, 110], have revolutionized static scene reconstruction and novel view synthesis. To improve reconstruction quality, especially in challenging scenarios such as sparse inputs, researchers have explored two main directions: integrating traditional geometric reconstruction techniques [14, 20, 105] and applying geometric regularizations [35, 39, 56, 61, 75, 92]. Recently, generative models have been leveraged for additional visual supervision. For instance, several methods [12, 88, 112] employ score distillation sampling (SDS) [60] to distill knowledge from pre-trained diffusion models, optimizing the 3D representation to align with learned priors. Another line of work [46, 52, 59, 67, 85, 99, 101, 103] projects dense scene representations [34, 54, 67, 80] and projects them into novel viewpoints, guiding reconstruction with geometrically consistent views generated by diffusion models. Meanwhile, [45] incorporates 3D structure conditioning into video diffusion for 3D-consistent video generation, and [26] generates multi-view images conditioned on input views and target camera poses to provide additional supervision. While these methods achieve impressive results, they are typically limited to static scenes and struggle with dynamic objects and temporal consistency.

4D Monocular Novel View Synthesis. Many methods have extended neural rendering to dynamic scenes, typically based on canonical space modeling with time-dependent deformation fields [21, 44, 47, 50, 61, 83] or 4D time-varying representations [9, 17, 23, 62, 86, 96]. However, these methods typically require multi-view synchronized and calibrated videos, making them ill-posed when multi-view data is limited.

For monocular video reconstruction, some methods leverage data-driven priors like depth [68, 90, 93],

tracks [91], and geometric constraints [38, 42, 47, 58, 69, 78, 81] for initialization or supervision, but these priors may not be fully accurate and do not always correlate linearly with RGB performance. More recently, diffusion models have been introduced for 4D reconstruction. For example, [15] utilizes pre-trained diffusion models [64] for scene completion, though the visual quality still requires improvement. Concurrent work [113] uses LGM [71] to generate pseudo novel views as additional supervision, but it is primarily applied at object level. Other methods [70, 84, 109] generate spatial-temporally consistent frames to optimize 4D scenes, but they require temporally and spatially decoupled data to learn disentangled control over camera motion and time. Additionally, [84, 109] rely on camera motion as input for training, which can be challenging to obtain for dynamic video datasets. In contrast, our approach only requires unposed web videos with simulated warping occlusion masks, enabling training on a wider range of casual video datasets without camera pose information. Moreover, [70] lacks precise camera control during inference, while our method implicitly incorporates precise pose information through warping.

Video Diffusion Models. Video diffusion models have shown remarkable capabilities in video generation tasks. Recent works focused on video inpainting [27, 37, 40, 95, 107, 111, 114] and out-painting [11, 19, 74] have demonstrated the effectiveness of diffusion models in generating temporally consistent content for incomplete videos. However, these methods mainly deal with a single video without perspective changes. Other generative methods [1, 73] take camera poses as input to generate synchronized videos from novel viewpoints, but their quality needs improvement, and they are constrained by static input-output camera viewpoints.

Some works [6, 108] attempt to overcome viewpoint constraints by inpainting videos after perspective changes. These methods utilize geometric constraints [63, 100, 108] or pseudo 4D Gaussian fields [6] to obtain masked videos after warping, and fine-tune video diffusion models [7, 30, 97] for multi-view synthesis. While these approaches show the potential of diffusion models in generating consistent content for partially observed videos, they rely on expensive training data from video warping or 4D Gaussian field creation. Moreover, they focus primarily on camera-controlled video generation [2, 29] rather than 4D reconstruction, which does not guarantee consistency or efficiency for novel view playback like Gaussian Splatting. In contrast, our method simply uses a pre-trained tracking model [33] to generate masked training data and fine-tunes the model to provide additional supervision for 4D monocular reconstruction through iterative view expansion. Note that [52, 101] also employ diffusion models to inpaint

warped videos, but they are limited to static scenes.

3. Method

We present a novel approach for improving monocular 4D scene reconstruction through view augmentation using monocular depth priors and video diffusion models. The key to enhancing the 4D monocular video synthesis is to warp the monocular video to augmented views based on the depth prior, followed by a video inpainting model to fill occluded regions. Our key components include a video inpainting model tailored for the task of view augmentation from a single monocular video (Sec. 3.1), and an iterative augmented view generation strategy (Sec. 3.2). The original and the augmented videos are then used for 4D reconstruction (Sec. 3.3). Fig. 3 illustrates our 4D reconstruction based on view augmentation.

3.1. Video Inpainting Diffusion Model

We aim to learn a video inpainting diffusion model to inpaint the occluded or invisible areas in a masked video while ensuring spatial-temporal consistency. To align with our core objective of 4D reconstruction, it is essential to provide training data in which the regions requiring inpainting primarily result from camera motion. Unlike previous methods, which require known camera poses [84, 101], or apply random mask to input videos [52], our method leverages a pre-trained 2D tracking model [33] for generating the training data for the video inpainting model, allowing us to leverage casual, unposed videos for training.

Training Data Preparation: Given an unposed input video sequence $\mathcal{V} = \{I_t\}_{t=1}^T$ with T frames, we first employ a pre-trained 2D tracking model [33] to establish point correspondences across frames. Let $\mathcal{P}_1 = \{p_1^i\}_{i=1}^N$ denote the set of N pixel points sampled from the first frame I_1 . The tracking model generates trajectories $\mathcal{T} = \{(p_t^i)_{t=1}^T\}_{i=1}^N$ that record the positions of these initial points throughout the video sequence. For each subsequent frame I_t ($t > 1$), we identify pixels that are not associated with any tracked point from $\mathcal{P}_1$. These untracked pixels form our mask region $\mathcal{M}_t$, as they likely correspond to areas that were previously occluded or newly revealed in the scene. Formally, we define the mask for frame t as:

$$\mathcal{M}_t = \{q \in I_t \mid q \notin \{p_t^i\}_{i=1}^N\}$$

where $\{p_t^i\}_{i=1}^N$ represents the set of tracked points in frame t . The masked frame can be obtained as:

$$\mathcal{V}^m = \{I_t^m\}_{t=1}^T, \quad I_t^m = I_t \odot \mathcal{M}_t$$

where $\odot$ indicates element-wise multiplication. This approach naturally captures regions that become visible due to object motion or camera movement, providing ideal training data for our video inpainting task.

Anchor-Conditioned Video Inpainting Diffusion Model:

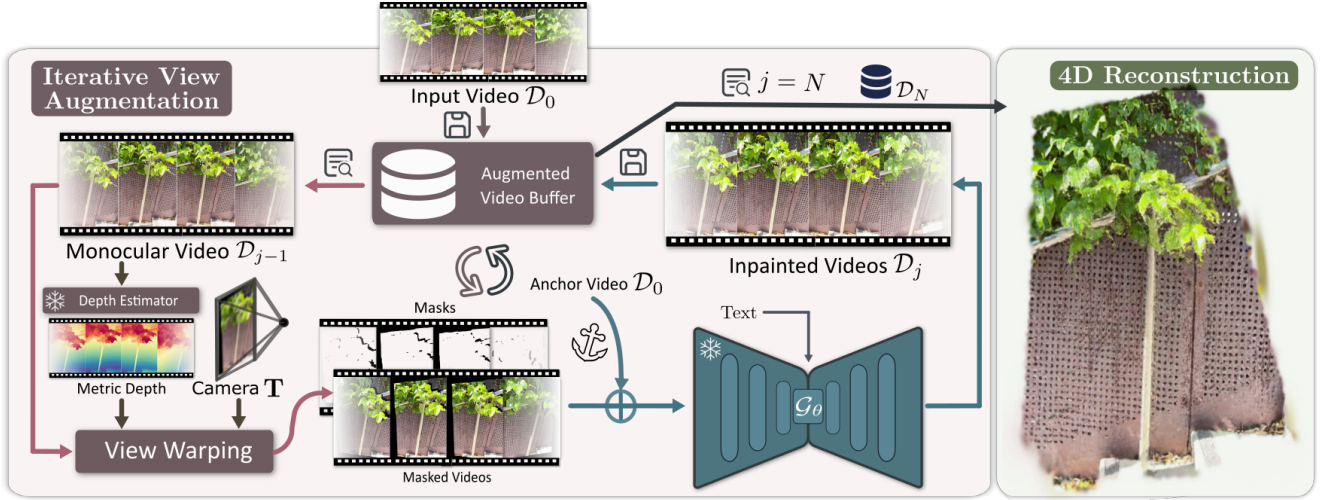


Figure 3. **4D reconstruction based on view augmentation.** Given an input monocular video, we first perform sparse reconstruction to obtain camera poses and align monocular depth to metric scale, forming an initial data buffer $\mathcal{D}_0$. In each iterative view augmentation step, we select frames at each timestamp from the previous buffer $\mathcal{D}_{j-1}$ and warp them to novel viewpoints using pre-defined camera poses $\mathbf{T}$, creating new perspective videos with continuous invisible region masks. These masked videos, along with binary masks and an anchor video, are fed into our pre-trained anchor-conditioned video inpainting diffusion model to produce completed novel-view videos. We update the buffer $\mathcal{D}_j$ with these enhanced videos, their metric depths and poses. Finally, both the original monocular video and all synthesized multi-view videos are used to supervise 4D scene reconstruction.

Given the masked video $\mathcal{V}^m$ and corresponding binary mask $\mathcal{M}$, we introduce a video diffusion model that inpaints occluded or invisible regions with spatial-temporal consistency while incorporating priors from unwarped videos. To leverage pre-trained video diffusion models effectively, we fine-tune an existing model [51, 76] and adapt its architecture for video inpainting in view augmentation. Our modifications include processing the masked input and conditioning the model on unwarped videos to utilize full observed frames for context.

Specifically, we modify the standard video diffusion model in two ways. First, we extend the input processing to handle masked videos by encoding the incomplete video sequence through a VAE encoder, producing a 4-channel latent representation $\mathbf{z}_m \in \mathbb{R}^{T \times H \times W \times 4}$ that is concatenated with the corresponding resized binary mask $\mathcal{M}' \in \mathbb{R}^{T \times H \times W \times 1}$ [64] and the noisy latent $\mathbf{z}_t \in \mathbb{R}^{T \times H \times W \times 4}$. Second, we introduce an anchor video mechanism, where frames sampled from the same video clip but at different timestamps serve as additional spatial-temporal context. Note that in our later 4D reconstruction stage, we use the original, unwarped monocular video as the anchor video. The anchor video is similarly encoded through the VAE into latent space $\mathbf{z}_a \in \mathbb{R}^{T \times H \times W \times 4}$. During training, our modified U-Net receives a latent input $\mathbf{z} = [\mathbf{z}_t; \mathbf{z}_m; \mathcal{M}'; \mathbf{z}_a]$, where these maps are concatenated along the channel dimension. While $\mathbf{z}_a$ are not spatially aligned with other maps using this simple concatenation, our 3D U-Net can effectively learn spatio-temporal contexts by fusing local struc-

tures via spatio-temporal convolutions and identifying related regions through attention operations. The model is trained with the following objective:

$$\mathcal{L} = \mathbb{E}_{\mathbf{x}, t, \epsilon \sim \mathcal{N}(0, 1)} \|\epsilon - \epsilon_\theta(\mathbf{z}_t, t, \mathbf{z}_m, \mathcal{M}', \mathbf{z}_a)\|_2^2$$

where $\mathbf{z}_t = \alpha_t \mathbf{x} + \sigma_t \epsilon$ is the noised latent of the ground truth video $\mathbf{x}$, and t is the diffusion timestep.

3.2. Diffusion-based View Augmentation

Given the trained video inpainting model, we augment the monocular input used for 4D reconstruction to generate multi-view supervision, as illustrated in Fig. 3.

Depth Estimation and Scale Alignment: Given a monocular video $\mathcal{V} = \{I_t\}_{t=1}^T$ with T frames, we first utilize COLMAP [65, 66] to obtain its camera intrinsics $\mathbf{K}$, camera poses $\{\mathbf{T}_t\}_{t=1}^T$, and a sparse point cloud $\{X_i\}_{i=1}^M$, where each point $X_i \in \mathbb{R}^3$ denotes the 3D coordinates reconstructed in the world coordinate system.

For depth estimation, we adopt a two-step approach that combines learning-based prediction with geometric refinement, as presented in Fig. 3 (left). We first employ an off-the-shelf monocular depth estimation model (e.g., [94]) to obtain initial depth maps $\{\hat{D}_t\}_{t=1}^T$. Next, we align them with the metric scale using the sparse point cloud $\{X_i\}_{i=1}^M$ from COLMAP via Least Square and RANSAC [22], obtaining the metric depth maps $\{D_t\}_{t=1}^T$. Please refer to supplementary (Sec. 6.3) for details.

Iterative View Augmentation: Using the scale-aligned metric depth, we can warp the observed frames $\mathcal{V} =$

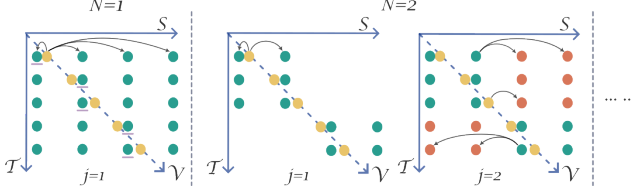


Figure 4. **Difference between Direct Warping and Iterative Warping.** $\mathcal{S}$ and $\mathcal{T}$ denote spatial and temporal dimensions, with $\mathcal{V}$ being the input monocular video (yellow dots indicating camera poses in 4D space). Left: With $N = 1$, we directly warp the input video to new perspectives (green dots) in a single iteration. Warped frames are ranked by warping distance per timestamp and organized into a video (purple underline). Right: With $N = 2$, the video is first warped the closest pre-defined poses (green dots, $j = 1$), then additional perspectives (red dots, $j = 2$) are generated by selecting frames with minimal warping angles from existing frames. This iterative approach minimizes distortion and floaters caused by depth inaccuracies in large-angle warping, enhancing reconstruction quality.

$\{I_t\}_{t=1}^T$ to unseen viewpoints for synthesizing multi-view observations, where each warped frame $I'_t \in \mathbb{R}^{H \times W \times 3}$ is accompanied by a binary mask $\mathcal{M}'_t \in \{0, 1\}^{H \times W}$. However, due to inaccuracies in the depth priors (e.g., bleeding edges), directly warping the videos by a large angle introduces noticeable artifacts, which degrade the performance of 4D reconstruction. To address this, we propose an iterative view augmentation strategy, as illustrated in Fig. 3 (middle), leveraging the fact that artifacts like bleeding edges are less severe when the warping angle is small. Fig. 4 shows the difference between direct warping and iterative warping.

Specifically, we first pre-compute a set of target unseen camera viewpoints and perform iterative view augmentation over N iterations. As presented in Fig. 4, when $N = 1$ (left), we directly warp the original video to all target frames in a single step. In contrast, when $N > 1$ (right), we progressively expand the warped angles over multiple iterations. We start with a data buffer $\mathcal{D}_0$ containing the input monocular video $\mathcal{V}^0$, its aligned depths D^0 and camera poses $\mathbf{T}^0$, formally expressed as $\mathcal{D}_0 = (\mathcal{V}^0, D^0, \mathbf{T}^0)$. At each iteration j ($1 \leq j \leq N$), we select frames with the smallest warping angles from the data buffer $\mathcal{D}_{j-1}$ at each timestamp t and warp them to target poses $\mathbf{T}^j$, generating multiple new videos of T frames. The warped videos and corresponding masks, together with the anchor video, are then fed into our diffusion model to synthesize completed videos $\hat{\mathcal{V}}^j$. Next, we estimate the metric depth D^j using our scale alignment strategy and update the data buffer as follows: $\mathcal{D}_j = \mathcal{D}_{j-1} \cup (\hat{\mathcal{V}}^j, D^j, \mathbf{T}^j)$. This process is repeated until all pre-defined target poses have been covered by each frame. Furthermore, to avoid the inconsistency in 4D reconstruction supervisions caused by repeated inpainting across different iterations, we introduce a supervision

mask $\mathcal{S}_t^j \in \{0, 1\}^{H \times W}$ for each augmented frame, in which pixel value 1 indicates valid for supervision. Please refer to supplementary (Sec. 6.5) for more details.

3.3. 4D Reconstruction

4D Scene Representation: Our method can effectively produce accurate, consistent, and high-fidelity novel view videos from monocular input, offering rich multi-view supervision for 4D scene reconstruction. It is compatible with various 4D reconstruction approaches, including those extending static representations with temporal dimensions [96] and those modeling dynamic scenes via deformation or motion fields [78, 83]. In our experiments, we adopt a motion field-based 3DGS representation [78] to capture both geometric structure and temporal dynamics effectively.

Loss Function: We rely solely on the multi-view constraints from our synthesized novel views to guide reconstruction. To mitigate distortions from depth estimation errors and video diffusion artifacts, we propose to use IV RGB loss, a robust pixel-wise loss inspired by [18], as the supervisory signal for our augmented views. Specifically, we compute the L1 loss between each pixel in the rendered image and the closest 3×3 pixels in the corresponding augmented supervision image, backpropagating only through the pixel with the minimum error. This loss, denoted as $\mathcal{L}_{IV}$, improves reconstruction robustness by reducing sensitivity to slight misalignments. For the original frames, we use standard L1, SSIM and LPIPS loss to supervise the entire image. For our valid augmented frames, we use the loss function as follows:

$$\mathcal{L} = \sum_{j=1}^N \sum_{t=1}^T \left(\lambda_r \mathcal{L}_{IV}^{t,j} + \lambda_s \mathcal{L}_{ssim}^{t,j} + \lambda_l \mathcal{L}_{lpips}^{t,j} \right)$$

where each loss term is computed only in regions where the supervision mask $\mathcal{S}_t^j$ equals 1. Specifically, for time step t in iteration j :

$$\begin{aligned} \mathcal{L}_{IV}^{t,j} &= \sum_p \mathcal{S}_t^j(p) \cdot \text{IV}(\bar{T}_t^j(p), \hat{I}_t^j(p)) \\ \mathcal{L}_{ssim}^{t,j} &= \text{SSIM}(\bar{T}_t^j \odot \mathcal{S}_t^j, \hat{I}_t^j \odot \mathcal{S}_t^j) \\ \mathcal{L}_{lpips}^{t,j} &= \text{LPIPS}(\bar{T}_t^j \odot \mathcal{S}_t^j, \hat{I}_t^j \odot \mathcal{S}_t^j) \end{aligned}$$

Here, p denotes pixel locations, $\bar{T}_t^j$ and $\hat{I}_t^j$ are rendered and our augmented supervisions respectively, and $\odot$ indicates element-wise multiplication. The hyperparameters λ_r , λ_s and λ_l balance the contribution of each loss term.

4. Experiments

In this section, we begin by comparing our method with SOTA 4D scene reconstruction methods in Sec. 4.1. After that, we conduct ablation studies to evaluate our design choices in Sec. 4.2. We highlight the **best**, **second-best**,

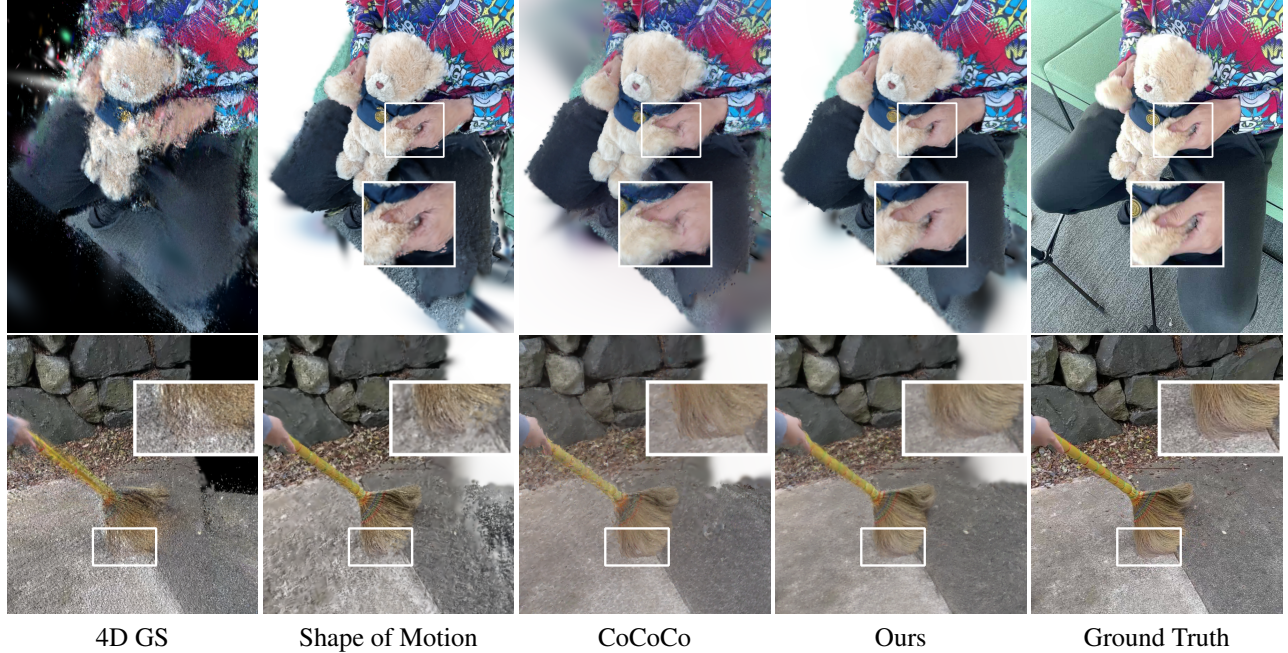


Figure 5. **Qualitative comparison of dynamic scene reconstruction** on iPhone dataset and HyperNeRF dataset. The black holes in 4D GS and the white areas in Shape of Motion indicate regions where the input video lacks visibility. In contrast, our method effectively fills these invisible areas within the scenes, leveraging multi-view constraints and spatiotemporal priors to enhance reconstruction quality.

and **third-best** scores achieved on any metrics. Please refer to supplementary (Sec. 6.2) for more training details.

4.1. Monocular 4D Reconstruction

Dataset and Metrics: We evaluate dynamic scene reconstruction from monocular video using the iPhone [25] and HyperNeRF [58] datasets. Our test sets comprise 5 iPhone and 3 HyperNeRF scenes, each with synchronized static cameras for novel-view synthesis evaluation. From the original video sequences, we select continuous clips with a few dozen frames, chosen for their large perspective differences from the test view to emphasize our method’s efficacy. We assess reconstruction quality using mPSNR, mSSIM, and mLPIPS [25] for dynamic foreground, static background, and the overall scene, employing a co-visible mask to specify visible areas for reconstruction.

Comparison Baselines: We compare our method against 4D GS [96], Shape of Motion [78], CoCoCo [114], StereoCrafter [108], and ViewCrafter [101]. CoCoCo and StereoCrafter are designed for video inpainting, while ViewCrafter focuses on 3D-aware inpainting. We integrate their diffusion models into our pipeline for warped video inpainting to validate the necessity of our anchor-conditioned model. For fairness, we provide CoCoCo with the same text prompt for each scene and use the first frame of our anchor video as the image conditioning input for ViewCrafter. Additionally, we compare against the state-of-the-art monocular reconstruction method Shape of Motion [78] and the

Condition	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	FVD $\downarrow$
w/o anchor	25.34	0.8053	0.1056	18.99
w anchor (ours)	27.22	0.8223	0.0801	14.30

Table 1. **Quantitative ablation study on anchor video condition** on our processed 5K videos from OpenVid-1M.

general 4D reconstruction approach 4D GS [96].

Results: The results are shown in Fig. 5 and Tab. 2. It can be observed that our pipeline significantly improves reconstruction quality over 4D GS and Shape of Motion, which exhibit outliers or over-sharpening artifacts. In contrast, our method not only produces a smoother results but also better preserves dynamic foreground details. Additionally, it fills missing regions invisible in the input video, addressing the inner holes seen in 4D GS and Shape of Motion. Compared to CoCoCo, which also achieves high-quality reconstruction, our method offers greater overall clarity, finer details—especially in dynamic areas—and more contextually consistent inpainting, thanks to our anchor-based video inpainting model. Quantitatively, our approach clearly outperforms all baselines across all metrics, further demonstrating its effectiveness in 4D reconstruction.

4.2. Ablation Study

We ablate various components of our method on the iPhone dataset and HyperNeRF dataset for 4D reconstruction to verify design choices of our approach.

Dataset	Dynamic Part			Static Part			All		
Method	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$
iPhone Dataset									
4D GS	12.28	0.8757	0.5249	14.54	0.4870	0.5594	14.01	0.3877	0.5939
Shape of Motion	11.87	0.8894	0.4778	15.42	0.5744	0.5082	14.56	0.4570	0.5292
CoCoCo	12.20	0.8964	0.4650	15.85	0.5809	0.5130	14.99	0.4701	0.5280
StereoCrafter	12.09	0.8989	0.4811	15.60	0.5989	0.5593	14.85	0.4945	0.5676
ViewCrafter	12.13	0.8985	0.5053	15.82	0.5946	0.5315	14.94	0.4888	0.5772
Ours	12.34	0.8990	0.4516	16.31	0.6088	0.4726	15.20	0.5004	0.4930
HyperNeRF Dataset									
4D GS	17.93	0.9556	0.3819	18.32	0.4737	0.4409	18.24	0.4200	0.4450
Shape of Motion	17.70	0.9609	0.3027	19.12	0.5659	0.4520	18.82	0.5176	0.4589
CoCoCo	18.47	0.9648	0.3048	19.11	0.5599	0.4627	19.00	0.5147	0.4692
StereoCrafter	18.51	0.9660	0.3343	18.98	0.5677	0.5171	18.86	0.5231	0.5181
ViewCrafter	18.53	0.9658	0.3228	18.98	0.5691	0.4860	18.91	0.5259	0.4888
Ours	18.85	0.9666	0.3020	19.57	0.5910	0.4407	19.45	0.5446	0.4449

Table 2. Quantitative comparison of dynamic scene reconstruction on iPhone dataset and HyperNeRF dataset.

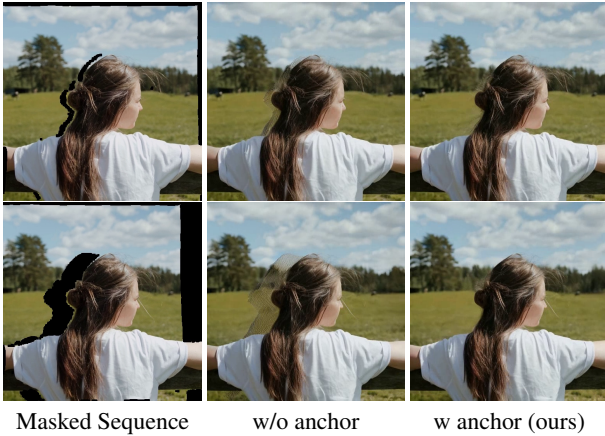


Figure 6. Quantitative ablation study on anchor video condition on our processed 5K videos from OpenVid-1M.

Effect of Anchor condition: We explored the impact of anchor video condition on the video inpaint results of our diffusion model, as presented in Tab. 1 and Fig. 6. Without the anchor condition, the model’s filling capability weakens, resulting in noticeable artifacts. In contrast, after incorporating the anchor video, the filled areas become more consistent with the surrounding content, significantly reducing artifacts. This demonstrates that our model effectively leverages spatiotemporal priors from the anchor video.

Effect of View Warping and Video inpainting: To assess the effectiveness of our view augmentation, which includes view warping and video inpainting, and to compare it with direct depth supervision loss $\mathcal{L}_D$, we compare our full method against: (a) no view augmentation or depth supervision, (b) direct depth supervision without view augmentation, and (c) iterative view warping without video inpainting. For fairness, all experiments use the same Gaussian initialization, and our view augmentation is set to 6 itera-

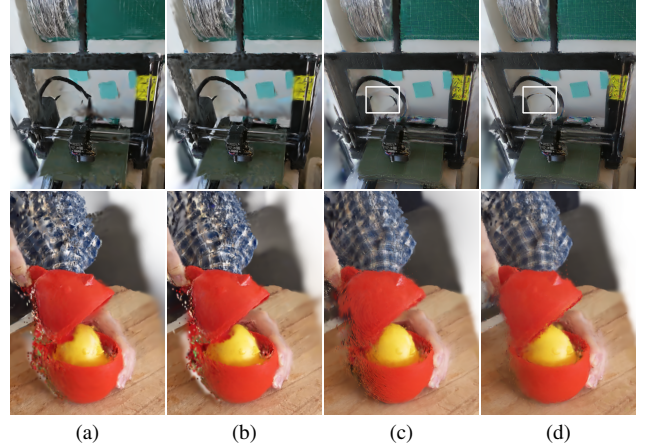


Figure 7. Qualitative ablation study on view warping and video inpainting on HyperNeRF dataset. (a) w/o warping, w/o inpainting, w/o depth; (b) w/o warping, w/o inpainting, w/ depth; (c) w/ warping, w/o inpainting; (d) w/ warping, w/ inpainting (ours).

tions. The results are presented in Tab. 3 and Fig. 7.

It can be observed that directly leveraging the depth for supervision (b) only leads to minor improvement compared with (a). In contrast, using the same depth to synthesize augmented training views leads to larger improvement even without inpainting (c). This verifies that directly adopting geometric priors for supervision may not linearly correlate with the reconstruction performance in the RGB space. Moreover, with our inpainting model to complete the warped views (d), reconstruction further improves, correctly recovering previously invisible areas and reducing flying artifacts. This demonstrates that leveraging depth priors via warping benefits reconstruction, while integrating diffusion priors further enhances completion and quality in 4D reconstruction.

Effect of Iterations: We investigated the impact of iter-

Method	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$
(a) w/o warp, w/o inpaint, w/o $\mathcal{L}_D$	16.04	0.4617	0.5249
(b) w/o warp, w/o inpaint, w/ $\mathcal{L}_D$	16.12	0.4699	0.5084
(c) w/ warp, w/o inpaint, w/o $\mathcal{L}_D$	16.44	0.4913	0.4876
(d) w/ warp, w/ inpaint, w/o $\mathcal{L}_D$ (ours)	16.80	0.5170	0.4750

Table 3. **Quantitative ablation study on view warping and video inpainting** on iPhone dataset and HyperNeRF dataset.

Iterations	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$
w/o view aug., w/o depth	16.04	0.4617	0.5249
$N = 1, j = 1$	15.80	0.4711	0.4959
$N = 6, j = 2$	16.41	0.5054	0.4964
$N = 6, j = 4$	16.56	0.5104	0.4868
$N = 6, j = 6$ (ours)	16.80	0.5170	0.4750

Table 4. **Quantitative ablation study on iterations** on iPhone dataset and HyperNeRF dataset.

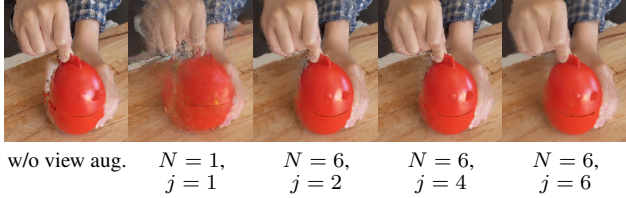


Figure 8. **Qualitative ablation study on iterations** on HyperNeRF dataset.

ation count on reconstruction results, as shown in Tab. 4 and Fig. 8. When no iterations are performed (w/o view aug), meaning only a single monocular video is used for supervision, the rendered image exhibits holes and noticeable artifacts at object edges. After applying view augmentation, we obtain more comprehensive observations of the scene. However, directly warping the initial video into multiple views at once ($N = 1, j = 1$) results in poor reconstruction due to large-angle warping, which introduces severe artifacts when transforming to distant viewpoints (e.g., bleeding artifacts are more noticeable at larger viewing angles). In contrast, our iterative strategy gradually enhances viewpoints, reducing warping angles and minimizing the impact of depth inaccuracies. Even with a small number of iterations (e.g., 2 or 4), the scene is better filled, and multiview supervision helps mitigate floaters. As iterations increase, more comprehensive views of the scene are obtained for each timestamp, leading to more robust reconstruction. Although the overall scene coverage remains the same for $N = 1, j = 1$ and $N = 6, j = 6$, additional iterations reduce warping distortion and improve reconstruction fidelity. Quantitative metrics further confirm that increasing the number of iterations leads to progressively better reconstruction results.

Effect of Depth Estimation Methods: Next, we evaluate various depth estimation methods [8, 13, 31, 68, 94] to assess their impact, as shown in Tab. 5. We observe that dif-

Model	mPSNR $\uparrow$	mSSIM $\uparrow$	mLPIPS $\downarrow$
DepthCrafter	16.76	0.5135	0.4835
ChronoDepth	16.78	0.5133	0.4874
Depth Pro	16.79	0.5121	0.4807
Video Depth Anything	16.79	0.5159	0.4875
Depth Anything V2 (ours)	16.80	0.5170	0.4750

Table 5. **Quantitative ablation study on various depth estimation models** on iPhone dataset.

	L1	IV (ours)
Loss		
mPSNR $\uparrow$	16.50	16.80
mSSIM $\uparrow$	0.5118	0.5170
mLPIPS $\downarrow$	0.5097	0.4750

Figure 9. **Qualitative ablation on loss function** on HyperNeRF dataset.

Table 6. **Quantitative ablation study on loss function** on iPhone dataset and HyperNeRF dataset.

ferent methods yield similar results, indicating our method’s robustness against monocular depth estimation variations. This may be attributed to aligning monocular depth predictions with COLMAP’s scale, along with our interactive view warping and robust RGB loss. By default, we use Depth Anything V2 [94], as it achieves slightly better performance than the others.

Effect of Loss Function: Lastly, we also evaluated the effectiveness of IV RGB loss on the robustness of the results. Instead of using $\mathcal{L}_{IV}$ for RGB supervision, we directly applied the L1 loss. The results, shown in Tab. 6 and Fig. 9 (best viewed zoomed in), reveal that L1 loss leads to blurrier renderings due to misaligned supervision. In contrast, our method backpropagates errors only to the pixel with the minimum difference within adjacent patches, effectively reducing blurring caused by distortion.

5. Conclusion

We introduced Vivid4D, a novel approach for 4D monocular reconstruction that combines geometric priors with video diffusion models. By reformulating view augmentation as a video inpainting task, our method leverages unposed web videos for training and employs an iterative view expansion strategy with a robust loss to minimize artifacts from depth errors. Experiments demonstrate that Vivid4D consistently outperforms existing methods across dynamic scenes, producing more coherent and detailed novel view synthesis results while effectively filling unobserved regions. Our approach bridges geometric-based methods and generative models, enabling high-quality 4D reconstruction from casual monocular videos, with applications in virtual reality and content creation. Future work will focus on enabling plausible scene extrapolation beyond observed regions, and improving robustness to complex camera motions and scene dynamics.

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