FaceCraft4D: Animated 3D Facial Avatar Generation from a Single Image

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Abstract

We present a novel framework for generating high-quality, animatable 4D avatar from a single image. While recent advances have shown promising results in 4D avatar creation, existing methods either require extensive multi-view data or struggle with shape accuracy and identity consistency. To address these limitations, we propose a comprehensive system that leverages shape, image, and video priors to create full-view, animatable avatars. Our approach first obtains initial coarse shape through 3D-GAN inversion. Then, it enhances multiview textures using depth-guided warping signals for cross-view consistency with the help of the image diffusion model. To handle expression animation, we incorporate a video prior with synchronized driving signals across viewpoints. We further introduce a Consistent-Inconsistent training to effectively handle data inconsistencies during 4D reconstruction. Experimental results demonstrate that our method achieves superior quality compared to the prior art, while maintaining consistency across different viewpoints and expressions.

1. Introduction

4D Avatar generation aims to create animatable 3D head avatars, enabling the generation of consistent identities with custom viewpoints and expressions. High-quality 4D heads have significant applications in gaming, education, and film industries. However, existing 4D avatar building methods [18, 23, 27, 36] often require extensive inputs, such as multiview video with camera pose estimation, which is impractical for widespread use. Furthermore, these methods struggle to produce realistic results for extreme viewpoints and expression changes due to data scarcity, for instance the back view of the head.

The goal of this work is to create a 4D facial avatar from just a single image. This task is challenging because a single image provides limited information, missing essential details like depth and multiple viewpoints that are crucial for constructing a complete 3D model. A single image cannot provide information about the unseen parts of a person's head or capture dynamic aspects like facial expressions. It is also impractical to train an end-to-end model due to the lack of multiview full-head animation datasets. To address these challenges, the system needs to rely on prior knowledge, like shape and expression.

Figure 1. Given a single image input, our method is capable of generating 4D avatars, producing photorealistic textures and consistent expressions across multiple views. Our approach also demonstrates robust performance on challenging inputs, including cartoon characters or old photographs.

Existing single-image avatar generation methods come with many shortcomings, which we summarize in Tab. 1. The works that rely on a single image of novel identity at test time, typically utilize large-scale, unstructured 2D images [1] and videos [7, 39] during training to account for multiview and temporal aspects. Due to the practical challenges in collecting multiview full-head animation datasets, most single-image methods, including recent work [35], cannot reconstruct a complete 360-degree view of the head. While some approaches can generate full views [1, 40], they typically lack the ability to model facial expressions. Among methods that can animate, some methods rely solely on 2D representation [39], which makes these methods multi-view inconsistent by design. To overcome the above limitation, some methods rely on a hybrid representation

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*No biometric data was used to train, validate, or evaluate the model described in this work.

Table 1. Comparison of methods for avatar generation and animation. The first two methods focus on general object generation, while the remaining methods are specifically designed for avatar applications.

Methods	Goal	Dimension	Input	360° view	Animation	3D Consistency	Quality
LDM [32]	Image Generation	2D	Single Image			-	High
DreamFusion [26], SV3D [37]	Image-to-3D	3D	Single Image	✓		Low	Low
LivePortrait [10], AniPortrait [39]	Video Generation	2D	Single Image		✓	Low	High
PanoHead [1], SPI [44]	3D GAN Inversion	3D	Single Image	✓		Medium	Medium
Portrait4D [7], CAP4D [35]	3D Talking Head	3D	Single Image		✓	Medium	High
FaceCraft4D	4D Avatar Generation	3D	Single Image	✓	✓	High	High
HQ3D [36], GA [27]	4D Avatar Generation	3D	Multi-view Videos	✓	✓	High	High

that combines 2D and 3D [7, 34]. However, such methods cannot handle extreme camera angles, as they rely on 2D components for high-resolution synthesis. In contrast, we aim to build our model that has pure 3D representation, and, therefore, is multiview-consistent by design.

We propose FaceCraft4D, which takes a single image as input and creates a 3D Facial Avatar that can be animated and rendered in 360-degree view, as shown in Fig. 1. To tackle such an under-constrained problem, we make use of 3 different types of priors: a geometry prior, an image prior, and a video prior. We use these priors to synthesize personalized multiview images of the given identity, which are then used to train an explicit 3D model of an avatar that can be animated (see Fig. 2). We will refer to such a model as a 4D avatar.

We start with a geometry prior from pretrained 3D-GAN [1]. Since, 3D-GAN is trained with large-scale images that comprises of all the views of the head, it has information about the complete head shape. Through 3D-GAN inversion [31], we obtain personalized shape along with an approximate texture. The resulting 3D representation lacks personalized high-quality multiview consistent texture and can not be used for creating novel expressions or animations (see Tab. 1). To improve the quality of the textures, we use of a 2D image prior. To ensure multi-view consistency and preservation of identity across the views, we employ epipolar constraints and cross-view mutual attention. The resulting multi-view images can be used to build a high-quality static 3D head model, which, however, lacks control over expressions and articulations. To animate the avatar, we utilize a 2D video prior [10], which generates training data for facial animation across different viewpoints.

Finally, for real-time rendering performance, we train a 3D Gaussian representation [16] that is rigged to a FLAME parametric face model [20, 27] using the multi-view videos obtained in the previous steps. To further improve the training consistency across the views and to avoid blur, we propose a COnsistent-INconsistent (COIN) training, which can capture cross-view inconsistencies in an MLP.

In summary, the contributions of our work are as follows:

- We present a novel framework for generating high-quality 4D head models from a single image of a face. We compare our framework with previous methods and summarize the differences in Tab. 1.
- We introduce novel warping-based control generation signals to improve quality and consistency across different views and expressions.
- We introduce COIN training, which enables a 3D Gaussian model to learn from inconsistent data while preserving high-quality, consistent features.

2. Related Work

3D Head generation. Numerous studies have explored the reconstruction of 3D head models. To obtain sufficient information, most approaches [9, 27, 48, 48] utilize monocular video sequences, which provide multiple viewpoints of the subject's head. However, a significant limitation of these methods is their reliance on multiple viewpoints and lengthy video inputs. They also struggle to accurately reproduce less prominent features in videos, such as the back of the head.

Another approach is to train a 3D generator on a large head image dataset. EG3D [3] proposed a hybrid tri-plane representation that can quickly and efficiently render high-quality facial images. Panohead [1] and Portrait3D [40] expanded on EG3D by increasing the number of planes, enabling the generation of 3D heads from limited angles to full 360-degree views. However, most methods in this category rely on hybrid representation having a 2D super-resolution network. This impacts their generalization to extreme camera poses and suffer identity inconsistency across views.

Recently, the rise of text-to-image models has spurred the development of novel approaches for text-to-3D generation tasks. One such approach is Score Distillation Sampling (SDS) [26, 29], which leverages the score function to distill diffusion priors into 3D representations, enabling the generation of 3D content from text or image inputs. Headsculpt [11, 49] incorporates facial keypoint information into the text-to-3D generation method, effectively constraining the facial layout. However, the texture generated by these methods can be oversaturated, making it challenging to achieve photo-realistic head models.

Head animation. Head animation techniques can be

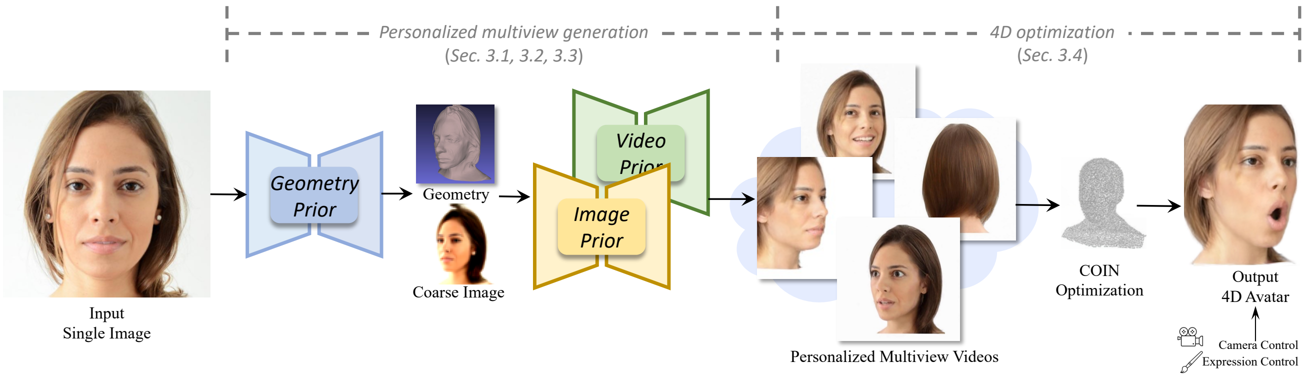


Figure 2. **Overview of FaceCraft4D**: Our approach begins with estimating the geometry of a single input image using a Geometry Prior. This geometry guides the synthesis of personalized multiview images, providing 360° views and varied expressions, with support from both 2D image and video priors. Since the synthesized data often exhibit inconsistency across views, we propose COIN optimization for robust 4D optimization. By fitting the model to the multiview data, we achieve our final 4D avatar. All faces in this manuscript come from the public FFHQ dataset [15].

broadly categorized into 2D-based and 3D-aware approaches, distinguished by their utilization of explicit camera models for rendering. Recent methods [8, 13, 30, 43] have predominantly adopted warping-based strategies, applying deformation fields to intermediate appearance features to capture facial motion characteristics. While effective for frontal and moderate poses, these approaches struggle to maintain geometric consistency during large pose variations due to their inherent lack of 3D modeling.

To enable free-viewpoint rendering with stronger 3D consistency guarantees, researchers integrated explicit 3D representations into the head synthesis pipeline. Early approaches [17, 41] relied on 3D morphable models for representing head geometry and texture. Subsequent works [5, 14, 21, 42, 45] leveraged more sophisticated representations such as Neural Radiance Fields (NeRFs) [25] to better capture complex structures like hair and accessories. Recent advances like GAGAvatar [4, 22], which employs 3D Gaussian splatting [16], have demonstrated impressive performance in both rendering quality and speed. However, these methods are typically limited in their ability to generate full 360-degree views. Our approach enables true 360-degree view synthesis while maintaining real-time rendering capabilities and achieving superior animation quality.

3. Method

In this work, we propose a novel framework for generating high-fidelity 4D avatars from a single portrait image I_R . Reconstructing a 3D dynamic model from a single 2D image is an inherently ill-posed problem, as critical 3D and temporal information is missing. To address this challenge, we leverage several 2D and 3D priors to compensate for the missing data.

The overall pipeline, shown in Fig. 2, consists of two stages: personalized multiview generation and 4D representation optimization. In the Personalized Multiview Generation stage, we utilize geometry priors to estimate the 3D geometry (Sec. 3.1), use image priors to enhance the texture (Sec. 3.2), and video priors to synthesize high-quality, consistent multi-view videos with dynamic expressions (Sec. 3.3). We then leverage this synthetically-generated personalized image set to optimize a robust 4D representation model (Sec. 3.4). The trained 4D model can be animated by the control parameters of a morphable model, enabling the generation of high-fidelity 4D avatars from a single portrait image.

3.1. Geometry Prior

The initialization is crucial for 3D generation. A good initialization should follow the approximate geometry of the head shown in the input image, I_R. For that, we use the prior provided by a 3D-aware generator, PanoHead [1, 40], which was trained on a large 360° head dataset. We obtain a coarse 3D reconstruction for a given input image I_R through GAN inversion. Specifically, we first optimize the latent code z within the generator's domain by minimizing a combination of pixel-wise $\mathcal{L}_2$ loss and image-level LPIPS loss [47]. Subsequently, following [31], we keep the optimized latent code z fixed while fine-tuning the 3D generator's parameters. During this fine-tuning stage, we maintain the same loss functions used in the latent optimization phase to ensure the rendered views closely match the input image. This process gives us an initial 3D head representation, though one that cannot be animated. The optimized generator is then used to synthesize a set of approximate multiview images $\{I_i\}$ and their corresponding depth maps $\{D_i\}$, where i is the view index.

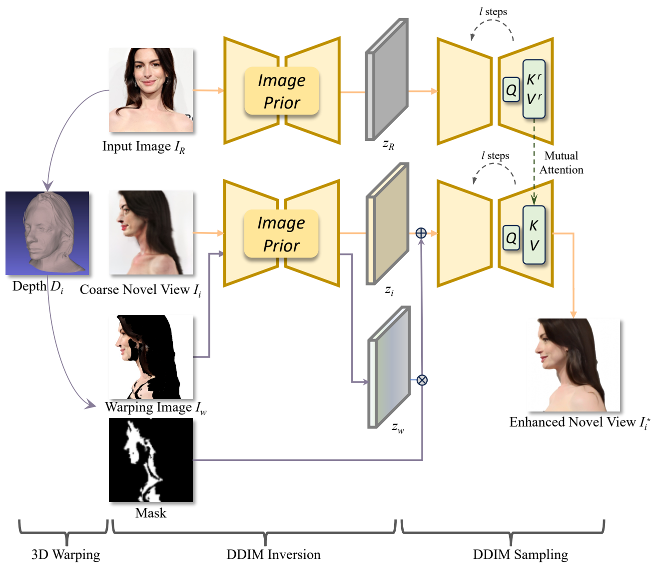


Figure 3. **Image Prior**: We introduce a cross-view mutual attention mechanism and epipolar constraints to enhance consistency in generated novel views. Our approach aligns reference and target images, maintaining visual coherence across viewpoints.

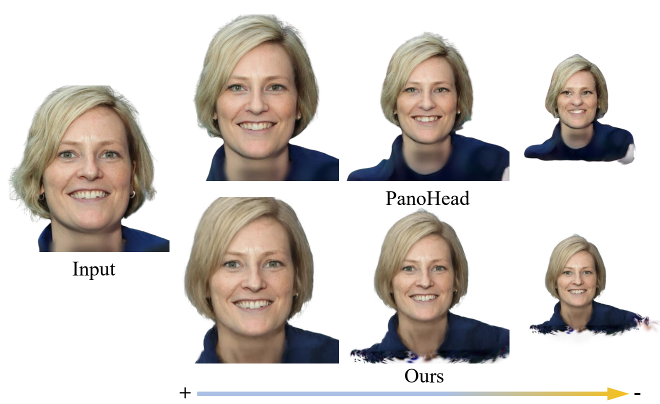


Figure 4. Triplane-based methods (*e.g.* PanoHead) are sensitive to focal length (scale) and exhibit significant degradation of quality as focal length decreases. In contrast, our Gaussian-based methods maintain robust performance across varying focal lengths.

3.2. Image Prior

The textures synthesized from the geometry prior may lack visual quality, and the identity of the individual may not be well preserved across the views. In particular, when rendering with different focal lengths, triplane-based methods [1] exhibit substantial degradation in image quality, as illustrated in Fig. 4. We enhance the generated multiview images using 2D diffusion models [32], which have demonstrated powerful generative capabilities. Although direct image-to-image translation [24] appears to be a straightforward solution, this approach poses significant risks: the denoising process may introduce cross-view inconsistencies and also modify the original semantic content. To address these risks, we propose two strategies that constrain the generation process, which we describe next and illustrate in Fig. 3.

Cross-view mutual attention. Inspired by MasaCtrl [2], we introduce a cross-view attention mechanism to replace the standard self-attention during the generation process. This modification allows us to inject information from the reference image into the novel view. Specifically, we first perform DDIM inversion [33] to introduce noise to both the reference frame I_R and the coarse image I_i of the target novel view. This step preserves the overall face structure and contour. Then, the diffusion model is used to gradually denoise two images to enhance the texture. In this process, we replace the key K and value V matrices (calculated in self-attention) of the novel view with those derived from the reference image. Different from [2], we adopt a batch-processing strategy in which multiple images I_i representing different viewpoints are treated as a single batch, with the reference image I_R serving as the consistent source for all subsequent calculations. This not only streamlines the generation process but also ensures uniformity in feature injection across novel viewpoints.

The rationale behind this approach lies in the observation that, despite variations in viewpoint, the underlying textures (represented by the attention values) should maintain consistency across the views. The cross-view attention mechanism enables the transfer of information from the reference to the novel views, enhancing both the fidelity and coherence of the generated novel views.

Warping-based control generation. The consistency across the views is further enforced by epipolar constraints, which enforce geometric relationships between novel views and the input view. We first use cross-view mutual attention to generate the view of the back of the head. The generated back view along with the reference image are set as anchors. Then, we propagate the texture information to novel views through depth-based warping. Specifically, we lift the anchor image into 3D space and then project it to the adjacent view with depth guidance $\{D_i\}$. During the projection, we form a mask to indicate the visibility of pixels to filter invisible areas using the rendered depth values. The projected image is then used to guide the texture enhancement process. The intermediate latent of the enhanced image in the diffusion model is blended with the latent of the projected image via a simple mask copy-pasting operation. By combining the latent, the resulting images benefit from both the improved consistency provided by the epipolar constraints and the enhanced quality achieved through the denoising process. We repeat this process for various azimuth angles, creating a comprehensive set of viewpoints.

With the aforementioned guidance and epipolar constraints, we can ensure coherence across the entire view

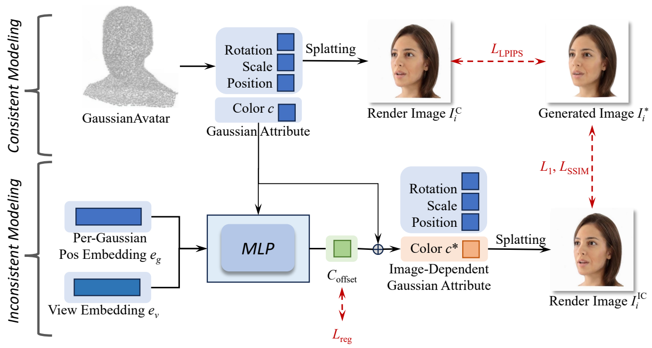


Figure 5. **COIN-Training**: To address geometric and color inconsistencies between the views, we train two 3D representations: a view-consistent base model (GaussianAvatar) and an MLP, encoding inconsistencies between the views. The MLP with inconsistencies lets us robustly reconstruct the high-quality 3D base model.

space and generate high-fidelity view-consistent images $\{I_i^*\}$ for further reconstruction.

3.3. Video Prior

The view-consistent data created in the previous step has a static expression similar to that of reference image I_R . This may not be enough to create diverse expressions as the images do not contain some of the expression-dependent information. For example, if the reference image has the mouth closed, the synthesized dataset would not have details inside the mouth region. To incorporate expression-dependent textures and geometry that may not be available in the multiview image generation stage (Sec. 3.2), we need to create multi-view facial expression data. We use LivePortrait [10] as a video prior, which can help generate multi-view expressive videos. LivePortrait uses a single source image and a driving video to generate new videos where the source identity mimics the expressions and poses from the target video. Instead of directly copying the driving video's motion, one has the option of capturing the changes in relative expression but maintain the pose of the input image. Given that we have the reference and multiview-consistent enhanced images $\{I_i^*\}$ from the previous step, we provide these to LivePortrait as the source images together with driving videos with diverse poses and expressions (details in Sec. 4), and obtain target videos. Because the identity is consistent across the input views, the resulting videos also maintain the identity. Using identical driving videos ensures synchronized expressions.

3.4. Robust 4D optimization with COIN training

The synthesized multi-view videos have high-quality textures and good cross-view consistency, but small misalignment of features and colors is unavoidable. Learning 4D representation directly on such data leads to blurry textures for the rendered objects. Here, we address this problem by proposing a robust training paradigm. At a high level, we learn a base representation that is common to all views, and a delta representation that is specific to each view during training. This helps in cornering inconsistencies concerning each view to separate representation. The base model will have a coarse but consistent representation learned, while the high-frequency details end up in the delta-space representation. At test time, we choose one of the views as our reference view and use its delta representation as the common high-frequency details for all the views.

In specific, we achieve this by jointly training two 4D representations: a consistent GaussianAvatar [27], which represents the 3D structure using Gaussians bound to a FLAME-tracked [20] mesh, and a NeRF-style MLP, tasked with encoding inconsistencies between the views. As shown in Fig. 5, we design the losses that prioritize structure reconstruction in the consistent GaussianAvatar (LPIPS), and high-frequency detail reconstruction in the MLP with the view-dependent inconsistencies (L1 and SSIM). By isolating view-dependent variations in a separate model, this strategy prevents these inconsistencies from corrupting the base representation. The approach can be considered a form of robust regression, with the key difference that the view-dependent MLP ensures that inconsistencies (outliers) are spatially localized. This cannot be achieved with robust norms (*e.g.*, L1), which do not maintain the information about the spatial position of outliers.

We choose GaussianAvatar as our consistent representation because it lets us animate the avatar with controllable FLAME expression and pose parameters, providing a solid foundation for modeling consistent geometric and appearance features. The details of FLAME tracking and controlling are explained in Sec. 1.3 of the supplementary. To model the view-dependent variations, we design a lightweight MLP-based architecture that introduces minimal computational overhead while effectively capturing view-specific details. The network encodes the offset in the color of each Gaussian (see Fig. 5), which can be formulated as:

$$c_{\text{offset}} = \text{MLP}(e_{\text{view}}, c, e_g; \theta), \tag{1}$$

where $e_{\text{view}} \in \mathbb{R}^d$ is a learnable view-specific embedding that encodes view-representation, c represents the initial Gaussian color attributes from the GaussianAvatar, e_g is a position embedding for each Gaussian, accounting for location-specific color variation ranges (e.g., eyes vs. mouth regions), and θ is a vector of the trainable parameters. The final view-dependent color is computed as the sum of the base GaussianAvatar color and the offset: $c^* = c + c_{\text{offset}}$. The MLP consists of only two layers to maintain computational efficiency and preserve the real-time rendering capabilities of the Gaussian-based representation.

During training, we render two types of images: I_i^{C} from

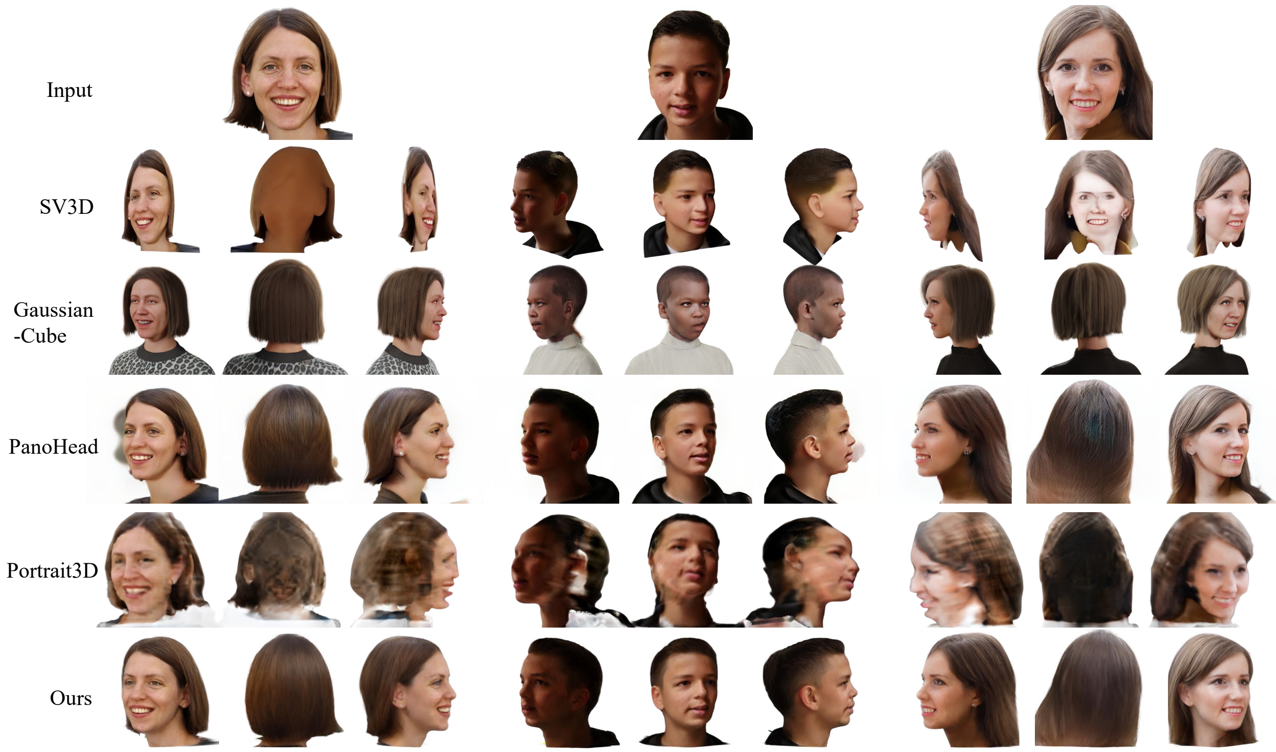


Figure 6. Qualitative comparison on static 3D head generation from a single image.

the consistent component alone, and I_i^{IC} from the combination of both components. To ensure accurate reconstruction of high-frequency details, we supervise I_i^{IC} using pixel-wise losses:

$$\mathcal{L}_{\text{pixel}} = \lambda_1 \mathcal{L}1(I_i^{\text{IC}}, I_i^*) + \lambda_{\text{SSIM}} \text{SSIM}(I_i^{\text{IC}}, I_i^*) \quad (2)$$

To prevent the inconsistent component from dominating the representation and maintain the effectiveness of the consistent component, we introduce a structural supervision loss and a regularization term:

$$\mathcal{L}_{\text{struc}} = \lambda_{\text{LPIPS}} \text{LPIPS}(I_i^{\text{C}}, I_i^*) \quad (3)$$

$$\mathcal{L}_{\text{reg}} = \lambda_{\text{offset}} \mathcal{L}1(c_{\text{offset}}, 0), \quad (4)$$

where LPIPS loss ensures image-level supervision for the consistent component, and the offset regularization encourages minimal view-dependent modifications. The hyper-parameters are set to $\lambda_1 = 0.8$, $\lambda_{\text{SSIM}} = 0.2$, $\lambda_{\text{LPIPS}} = 0.05$ and $\lambda_{\text{offset}} = 1$.

During inference, we input a single fixed view-embedding for the inconsistent component. Given that our reference image I_R contains superior quality and identity information compared to the generated multiview images $\{I_i^*\}$, we select its corresponding view embedding for inference. Novel expressions and poses can be easily generated by adjusting the FLAME parameters, leveraging the animation capabilities of our backbone model.

4. Experiments

Implementation details. During the multiview generation stage, we use PanoHead [1] as our geometry prior, Cosmicman [19] as the image prior, and LivePortrait [10] as the video prior model. We render 24 views along the horizon orbit for static reconstruction. For animation, we select I_R and 11 frontal views from these generated images as source images and randomly sample 8 video clips from the NerSemble [18] dataset as driving videos. The source images and driving videos are then input to the video prior model to produce multiview video data. In the 4D optimization stage, we first optimize the GaussianAvatar [27] model with the static data over 30K iterations. Next, we apply COIN-optimization techniques, finetuning the static Gaussian model over 90K iterations. The complete process takes approximately two hours to generate a single 4D avatar.

Evaluation metrics. In the absence of ground truth data, we use commonly adopted non-reference metrics to evaluate the rendered images in terms of image quality and identity similarity. For overall image quality, we use the FID [12] score. To assess multi-view consistency, we employ the CLIP-I [28] score. For identity preservation, we calculate ID scores by measuring the cosine distance of face

Figure 7. Qualitative comparison on animation of different views.

Table 2. Quantitative comparison on static 3D head generation.

Method	CLIP-I ↑	ID ↑	FID ↓
GaussianCube [46]	0.6830	0.4300	258.81
PanoHead [1]	**0.8233**	0.4246	195.28
SV3D [37]	0.7656	0.4331	234.86
Portrait3D [40]	0.7066	0.3719	302.74
Ours	0.8053	**0.5082**	**174.36**

Table 3. Quantitative comparison on 3D head animation.

Method	CLIP-I ↑	ID ↑	FID ↓
AniPortrait [39]	0.4653	0.4171	364.99
Portrait-4D-V2 [7]	0.5236	0.4592	248.36
Ours	**0.5737**	**0.4602**	**201.76**

recognition features [6] between the novel views and the reference images.

Datasets. We conducted our analysis on a subset of facial images from FFHQ [15] dataset, a high-quality, in-the-wild facial dataset. For evaluation, we select 100 images with unoccluded faces to evaluate our model and baselines.

4.1. Static 3D Generation Comparisons

Baselines. We compare our method with existing image-to-3D approaches, including a general object-focused model, SV3D [37], and three head-specific methods: the inference-based GaussianCube [46], the 3D-GAN-based PanoHead [1], and the optimization-based Portrait3D [40].

Qualitative results. Fig. 6 shows visual comparisons where our method achieves the highest visual fidelity and identity coherence compared to other approaches. Notably, it preserves details such as teeth and earrings in side views. In contrast, SV3D, which focuses on general objects, struggles to capture accurate head geometry, often degenerating into a flat plane. GaussianCube tends to "toonify" the input head due to the nature of its training data. While PanoHead achieves good visual quality, it suffers from detail loss and floating artifacts during pose rotation. Portrait3D also falls short in quality, as the SDS [26] optimization introduces variations that lead to blurring artifacts.

Quantitative results. For each generated head model, we render images from five viewpoints: left-frontal, left, right-frontal, right, and frontal. All five rendered images, along with the reference image, are used to compute the CLIP-I, ID, and FID metrics. As shown in Tab. 2, our method outperforms others in both ID and FID scores. This aligns with the observed visual fidelity, as our results appear more realistic and coherent. Our method achieves higher identity similarity and better detail preservation, even in side views. The results for the MEAD multiview dataset [38] can be found in the supplementary material.

4.2. Animation Comparisons

Baselines. We compare our method with one-shot video-based head reenactment approaches, including the 2D-based AniPortrait [39] and the 3D-based Portrait-4D-V2 [7]. For AniPortrait, which uses keypoints as intermediate driving signals, we modify the Euler angles of the expression image to rotate the keypoints and generate novel view videos. In the case of Portrait-4D-V2, novel views can be generated directly by editing the camera parameters.

Qualitative results. As shown in Fig. 7, our method preserves expressions with greater accuracy. Portrait-4D-V2 lacks a back-of-head model, so when rotated to side views, the back appears empty. AniPortrait, as a 2D-based method, can achieve high texture quality. However, with large-angle rotations, AniPortrait struggles to preserve identity details and introduces noticeable artifacts in the hair and background. In contrast, our method maintains accurate geometry and expression, even with camera movement.

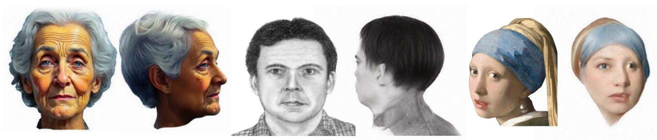
Quantitative results. We test our data on unseen views (especially 60°–180°), to highlight each method's performance under varying viewing angles, as handling extreme rotations is often challenging. The results are presented in Tab. 3. Our method outperforms all baselines, demonstrating robustness across varied views. The performance

Input Warped Image w/o Warping w/o MA Full

Figure 8. Ablation of multiview image generation modules.

Input w/o Video Prior w/o COIN Full

Figure 9. Ablation of animation modules.



Input Novel View Input Novel View Input Novel View

Figure 10. More results with diverse inputs.

of baselines degrades significantly as the viewing angle increases. Additional results and baseline comparisons are provided in the supplementary material.

4.3. Ablation Study

Multiview image generation. We conduct an ablation study on two multi-view generation modules, as shown in Tab. 4 and Fig. 8. Incorporating the warping module allows us to preserve finer details, like tattoos, in novel views. While removing MA may lead to semantic inconsistencies, such as changes in gender. Adding mutual attention (MA) further improves fidelity and enhances identity similarity by injecting features from the reference images.

Animation. Our 3D representation is based on GaussianAvatar [27], which is FLAME-driven, enabling direct animation through FLAME parameters. To evaluate the base performance, we remove our video prior module. As shown in Fig. 9, without the video prior, the final avatar fails to synthesize accurate expressions. For consistency modeling, we compare our model with and without the COIN training. Without COIN, training directly on inconsistent generated images results in blurred textures. With COIN training, regions such as the teeth remain sharp, and finer details, like individual hair strands, are preserved. The quantitative results in Tab. 5 further validate the effectiveness of the COIN optimization across novel views.

Processing times. We analyzed the processing times of each stage. Our method consists of three stages: a) 3D GAN inversion (2 mins); b) Multiview image & video generation

Table 4. Ablation of multiview image generation modules. "Warp" refers to the warping-based control generation (Sec. 3.2) and MA to cross-view mutual attention (Sec. 3.2).

Method	CLIP-I ↑	ID ↑	FID
w/o Warp w/o MA	0.7328	0.4787	182.27
w/o Warp	0.7886	0.4915	171.08
w/o MA	0.8151	0.4951	172.43
Full	**0.8162**	**0.4984**	**166.96**

Table 5. Ablation of animation modules.

Method	CLIP-I ↑	ID ↑	FID ↓
w/o COIN	0.7688	0.4952	144.95
Full	**0.7729**	**0.5010**	**142.80**

Table 6. Time comparison with optimization-based avatar reconstruction methods.

Method	NerFace	IMAvatar	PointAvatar	HeadStudio
Time (hour)	54h	48h	6h	2h
Method	MonoGA	GaussianAvatar	Hq3davatar	Ours
Time (hour)	7h	2h	12h	2.5h

(10 mins), FLAME parameters extraction (10 mins); and c) COIN-training to overfit multiview videos (2 hours). The generation of a single avatar ~2.5 hours, which is comparable to or faster than other optimization-based avatar reconstruction methods, as shown in Tab. 6. At inference, we achieve real time rendering at 156 FPS with a resolution of 512×512.

Diverse inputs. To validate robustness, we conduct experiments on diverse inputs, including cartoon, line drawing, and portraits with extreme camera poses. The results in Fig. 10 demonstrate consistent performance across various domains. Additional video results are available on the webpage in the supplementary materials.

5. Conclusions

In this paper, we present a novel method for generating high-quality 4D portraits from a single image. By leveraging multiple priors, including 3D-GAN for geometry initialization, image prior for texture enhancement, and video prior for animation, our method can generate animated avatars with detailed textures, excellent consistency, and plausible rendition of views missing in the input. The proposed depth-guided warping ensures cross-view consistency during the generation process, while our COIN-training strategy enables high-quality 4D reconstruction from potentially inconsistent multi-view data. Extensive experiments demonstrate that our method outperforms existing approaches in terms of geometry accuracy, texture quality, and identity preservation across different viewpoints and expressions. Our framework makes high-quality 4D portrait generation more accessible by removing the requirement for multi-view data capture, paving the way for broader applications.

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