ELITE: Efficient Gaussian Head Avatar from a Monocular Video via Learned Initialization and TEst-time Generative Adaptation

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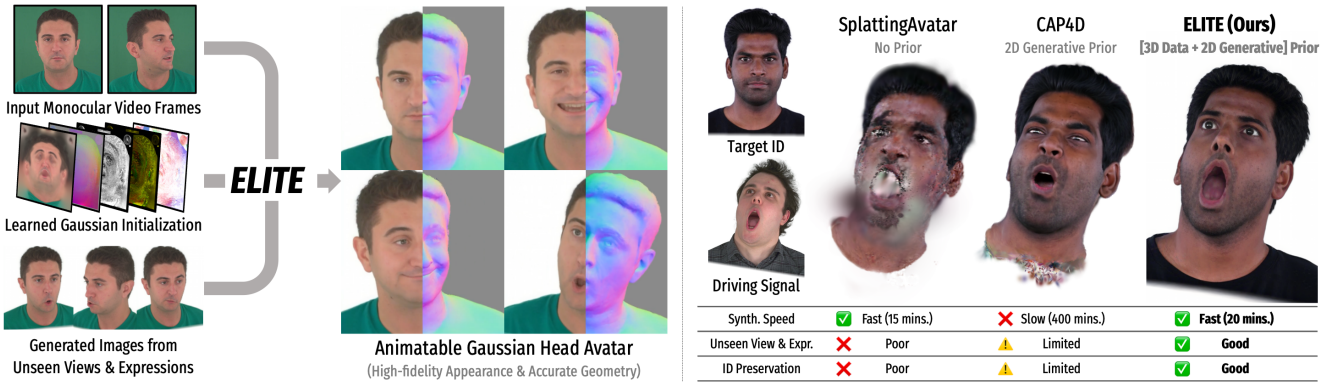


Figure 1. **ELITE** synthesizes an animatable photorealistic Gaussian head avatar from a casual monocular video. To compensate for missing views and expressions from the input video, ELITE leverages two complementary priors: (1) 3D data prior for feed-forward Gaussian initialization, and (2) 2D generative prior for augmenting unseen views and expressions for test-time adaptation. Compared to existing methods [37, 41] that utilize no priors or only a 2D generative prior, ELITE achieves superior generalization across unseen views and expressions in the wild. Please refer to the supplementary video for dynamic avatar animation results.

Abstract

*We introduce **ELITE**, an **E**fficient Gaussian head avatar synthesis from a monocular video via **L**earned **I**nitialization and **TE**st-time generative adaptation. Prior works rely either on a 3D data prior or a 2D generative prior to compensate for missing visual cues in monocular videos. However, 3D data prior methods often struggle to generalize in-the-wild, while 2D generative prior methods are computationally heavy and prone to identity hallucination. We identify a complementary synergy between these two priors and design an efficient system that achieves high-fidelity animatable avatar synthesis with strong in-the-wild generalization. Specifically, we introduce a feed-forward Mesh2Gaussian Prior Model (MGPM) that enables fast initialization of a Gaussian avatar. To further bridge the domain gap at test time, we design a test-time generative adaptation stage, leveraging both real and synthetic images as supervision. Unlike previous full diffusion denoising strategies that are slow and hallucination-prone, we propose a rendering-guided single-step diffusion enhancer that restores missing visual details, grounded on Gaussian avatar renderings. Our experiments demonstrate that ELITE produces visually superior avatars to prior works, even for challenging expressions, while achieving 60× faster synthesis than the 2D generative prior methods. Project page: https://kim-youwang.github.io/elite.*

1. Introduction

Photorealistic human head avatars have become an essential building block for modern immersive applications, including telepresence in virtual and augmented reality [4, 10, 15, 20–22] as well as virtual film production [7]. Advances in neural rendering [9, 12, 24, 25] and 3D human face modeling [13, 30, 35] have greatly improved visual fidelity. However, these approaches still rely on accurately calibrated multi-view video inputs and time-consuming optimization procedures, limiting the popularization of such promising technologies to novice users in reality.

To enable practical and efficient avatar synthesis, we tackle the problem of high-fidelity, animatable head avatar synthesis from more accessible capture setups, such as monocular selfie videos. The core challenge here is the trade-off between the abundance of visual observations and

the burdens caused by the capture setup. High-fidelity 3D/4D avatar reconstruction typically relies on dense visual observations from accurately calibrated multi-view human performance capture systems [7, 11, 14, 20, 44, 45], which require substantial computing resources and complex processing pipelines. On the contrary, accessible and casual capture methods, *e.g.*, monocular phone videos, simplify the acquisition process but require strong prior knowledge to compensate for the lack of visual evidence.

Several works [1, 2, 48, 51] have tried to learn facial appearance, geometry, and expression priors from 3D datasets, to initialize 3D avatars from these priors, and to adapt them to monocular input frames at test time. However, due to practical challenges in scaling the capture dataset and limited observations at test time, this 3D data prior adaptation strategy often struggles to handle in-the-wild edge cases, *e.g.*, long hair and rare facial expressions [2]. More recently, as another line of research, 2D generative prior approaches [40, 41] employ diffusion models to generate facial images from unseen views and expressions, providing additional supervision to complete missing views and expressions during 3D reconstruction. While yielding improved generalization, these methods suffer from severe identity hallucinations, a slow sampling process of diffusion models, and the costly optimization of 3D primitives from scratch.

We observe that existing works have relied either on a 3D data prior or a 2D generative prior, and identify a potential complementary synergy between the two. Our key idea is that (1) the limitations of 3D data prior methods, *i.e.*, hard to generalize in-the-wild, can be alleviated if supervised by synthetic images from a generative model, and (2) slow sampling and hallucinations of 2D generative prior methods can be mitigated if grounded on 3D avatar renderings. Building upon these, we propose **ELITE**, an **E**fficient Gaussian head avatar synthesis by leveraging **L**earned **I**nitialization and **TE**st-time generative adaptation (Fig. 1). We build a 3D data prior model, the Mesh2Gaussian Prior Model (MGPM), that provides an efficient, identity-preserving Gaussian avatar initialization. To bridge the domain gap between the MGPM's training dataset (studio capture) and in-the-wild scenarios, we design a test-time generative adaptation stage that uses both real video frames and synthetic images as test-time supervision. Unlike conventional 2D generative prior approaches [40, 41], which are slow and hallucination-prone because they rely on full-diffusion denoising from pure noise, we leverage Gaussian avatar renderings as strong initializations for image generation. Specifically, we propose a rendering-guided single-step diffusion enhancer that fixes visual artifacts and completes missing visual details, grounded on 3D renderings. We evaluate the quality of ELITE-generated avatars on unseen, diverse identities and expressions and show that ELITE outperforms recent competing methods both visually and quantitatively. We also investigate the effects of the core design choices.

We summarize our main contributions as follows:

- We introduce **ELITE**, an efficient Gaussian head avatar synthesis method that synergizes a 3D data prior with a 2D generative prior, complementing each prior's drawbacks.
- Our feed-forward 3D data prior model initializes Gaussian avatars in a feed-forward manner, enabling fast, stable test-time adaptation via better initialization.
- Our test-time generative adaptation integrates a single-step diffusion enhancement guided by 3D avatar renderings for efficient synthesis and improved identity preservation.

2. Related Work

We aim to build an efficient system that creates an authentic Gaussian head avatar from a monocular video. We categorize related approaches into: {Overfitting, 3D data prior, and 2D generative prior} approaches (see Fig. 2).

Overfitting approaches. Early methods proposed to overfit a 3D representation against the input video sequence *from scratch* [5, 6, 49, 50]. Typically, a set of 3D primitives, *e.g.*, a deformable mesh [6], Neural Radiance Fields (NeRF) [5, 24], Signed Distance Fields (SDF) [49], are optimized to minimize photometric losses against the captured frames. Recently, methods leveraging 3D Gaussian Splatting (3DGS) [12] have shown improved fidelity [37, 43]. Although these overfitting approaches are capable of producing plausible results for the training views, they require separate optimization for every new identity, without identity-specific initialization (Fig. 2a). Such per-identity overfitting *from scratch* is inefficient and limits animated avatars' ability to generalize to complex viewpoints or unseen expressions.

3D data prior approaches. To facilitate efficient avatar synthesis, 3D data prior approaches [1, 2, 17, 48, 51] have proposed training a generalizable data-driven prior model for animatable 3D head avatars. Such prior, trained on multi-view performance capture [2, 14, 23] or synthetic 3D head assets [1, 51], encodes strong shape and appearance information. Cao et al. [2] proposed a VAE-style prior model that translates tracked face mesh UV maps into UV-aligned volumetric primitives [21]. Recently, HeadGAP [48] and SynShot [51] proposed 3D prior models that translate the tracked face meshes into a set of 3D Gaussians. At test time, they initialize a 3D avatar from the learned 3D data prior model, and test-time adaptation is applied to reduce domain gaps in in-the-wild setups. Such test-time adaptation from the avatar initialization significantly speeds up avatar synthesis, compared to fitting 3D primitives from scratch. However, test-time supervision still relies on few-shot images with limited viewpoints and expressions; the resulting avatars often overfit to constrained observations or distort the learned expression space of the prior model [2]. Furthermore, they cannot model the torso and shoulder regions and

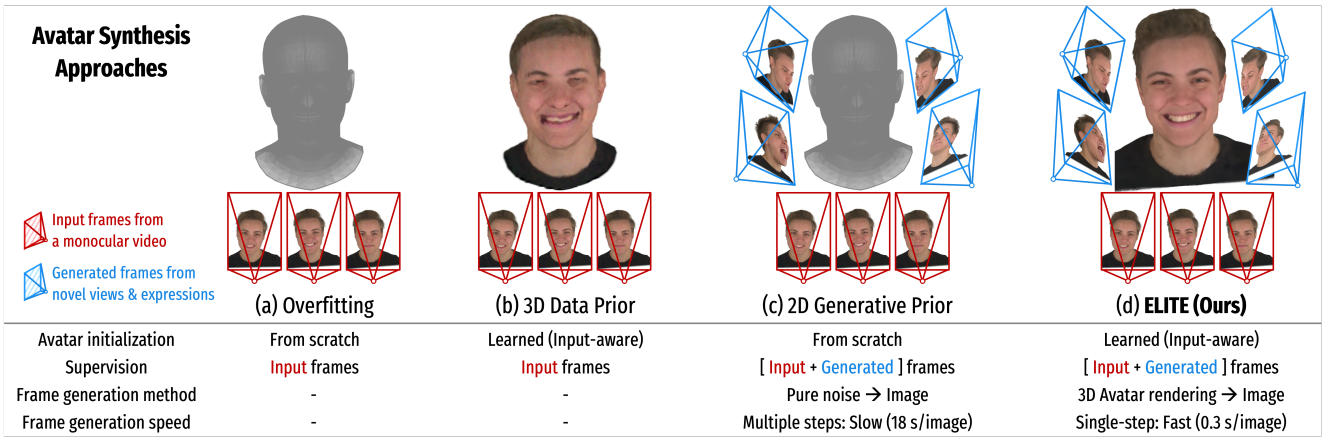


Figure 2. **Comparison of existing avatar synthesis approaches.** (a) Overfitting methods [37, 50] optimize avatars from scratch, starting from 3D primitives anchored on a template mesh, and use only the input video frames as supervision. (b) 3D data prior methods [1, 51] use learned avatar initialization, but use only the input video frames as supervision. (c) 2D generative prior methods [40, 41] use diffusion-generated (full denoising, *i.e.*, slow) images as test-time supervision, but optimize avatars from scratch. (d) Our ELITE enjoys the benefits of (b) and (c), *i.e.*, we use **learned avatar initialization** and **generated images as test-time supervision**. We also generate images using a single-step diffusion that enhances Gaussian avatar renderings, significantly faster than full denoising methods [40, 41].

are closed-source, limiting their practical applicability.

2D generative prior approaches. With the advancements in image generative models [26, 32], animatable head avatar synthesis methods using generated images as supervision have emerged [40, 41]. GAF [40] and CAP4D [41] are analogous, where they optimize Gaussian avatar *from scratch* by using a set of synthetic face images with diverse viewpoints and expressions, generated by a multi-view image diffusion model [32, 46] (Fig. 2c). While the direction of using synthetic images to enhance the avatar's generalization to extreme viewpoints and expressions is promising, the multiple diffusion sampling steps are required to ensure high-fidelity generation, making the overall pipeline computationally expensive and time-consuming. Moreover, because such diffusion models generate images from pure noise, the resulting images exhibit severe identity shifts, hindering 3D representation optimization and degrading the fidelity and identity consistency of the avatar.

Our approach. From the previous works, we observe disconnected advancements of a 3D data prior and a 2D generative prior. We identify their potential complementarity and propose a systematic coupling of both priors (Fig. 2d): (1) a learned 3D data prior model can achieve generalization if supervised by synthetic images from a generative model, (2) a 2D generative model can generate identity-preserving images with improved speed if a 3D prior model provides reliable image initialization, *e.g.*, 3D avatar renderings. Unlike the previous works that rely either on a 3D data prior or a 2D generative prior, we show that systematic coupling of both priors enables efficient and high-fidelity avatar synthesis by mitigating the drawbacks of prior works (see Fig. 1).

3. ELITE: Efficient Gaussian Head via Learned Initialization & TEst-time Adaptation

We introduce ELITE: how we train the feed-forward 3D data prior model for avatar initialization (Sec. 3.1), how we perform test-time adaptation by leveraging real images (Sec. 3.2), how we train a single-step diffusion enhancer guided by rendered avatar (Sec. 3.3), and how we design test-time generative adaptation (Sec. 3.4).

3.1. Feed-forward Gaussian Head Avatar Initialization via Learned Mesh2Gaussian Prior Model

The core module of ELITE is the Mesh2Gaussian Prior Model (MGPM). The MGPM is a feed-forward U-Net [33] model that efficiently initializes a 3D avatar given monocular video frames as input. The MGPM is trained to translate 3D mesh surface information, *e.g.*, RGB color and vertex displacement, into a set of 2D Gaussian primitives (see Fig. 3).

MGPM pipeline. The MGPM takes the concatenated canonical FLAME [18] UV texture and geometry maps, $[\mathbf{M}_{\text{tex}}, \mathbf{M}_{\text{geo}}] \in \mathbb{R}^{H\times W\times(3+3)}$, as an input. We obtain both UV maps via photometric FLAME tracking [29] on videos. To control the dynamic expressions and movements of the output Gaussian head avatar, we inject FLAME driving signals, *i.e.*, expression code ψ_{expr}, joint poses $\boldsymbol{\theta}_{\text{jaw}}$, $\boldsymbol{\theta}_{\text{eyes}}$, $\boldsymbol{\theta}_{\text{neck}}$, global head rotation $\boldsymbol{\theta}_{\text{glob}}$, and translation $\mathbf{t}$, as conditioning signals through FiLM [27] layers. The MGPM U-Net, $\mathcal{F}_\phi$, then translates mesh UV maps and driving signals into UV-aligned 2D Gaussians (2DGS) as:

$$\mathbf{M}_{\text{gs}|\boldsymbol{\Theta}} = \mathcal{F}_\phi([\mathbf{M}_{\text{tex}}, \mathbf{M}_{\text{geo}}], \boldsymbol{\Theta}), \tag{1}$$

where $\boldsymbol{\Theta}=[\psi_{\text{expr}}, \boldsymbol{\theta}_{\text{jaw}}, \boldsymbol{\theta}_{\text{eyes}}, \boldsymbol{\theta}_{\text{neck}}, \boldsymbol{\theta}_{\text{glob}}, \mathbf{t}]$. The generated

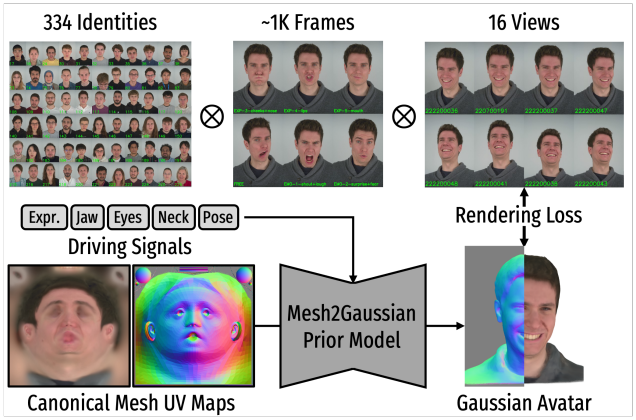


Figure 3. **Training Mesh2Gaussian Prior Model (MGPM).** We train a 3D avatar prior model, MGPM, that takes mesh UV maps and 3D face driving signals, *e.g.*, expression codes, poses (jaw, eyes, neck, head), as inputs and outputs a Gaussian avatar, structured in the form of UV-aligned 2D Gaussian primitives. We supervise the MGPM training using images from the face capture dataset [14] that spans diverse identities across different expressions and viewpoints.

2DGS UV map $\mathbf{M}_{\text{gs}|\mathbf{\Theta}} \in \mathbb{R}^{H\times W\times 13}$ contains channel-separated 2DGS parameters for each UV coordinate (u, v) as: $[\delta\mathbf{x}, \mathbf{c}, \mathbf{q}, \mathbf{s}, \mathbf{o}]^{u,v} \in \mathbb{R}^{(3+3+4+2+1)}$, where $\delta\mathbf{x}$ is the position offset of a 2D Gaussian from the template mesh surface, and $\mathbf{c}$, $\mathbf{q}$, $\mathbf{s}$, and $\mathbf{o}$ denote the color, rotation, scale, and opacity for each 2D Gaussian, respectively. Please refer to the supplementary material for implementation details on the network design and the pipeline.

Training MGPM. To make the MGPM learn to predict 2DGS UV maps, conditioned on identity, expressions, and viewpoints, we train it on a face performance capture dataset [14], which contains multi-view, synchronized videos of diverse identities with diverse facial expressions.

During training, MGPM takes the tracked canonical FLAME UV maps to produce a 2DGS UV map. With randomly sampled frames and viewpoints, the 2DGS avatar is differentiably rasterized into image space using the driving signal $\mathbf{\Theta}$ and camera parameters. Then, we measure the rendering loss between the rendered and ground-truth images, which consists of L1 photometric loss $\mathcal{L}_{\ell 1}$ and perceptual loss $\mathcal{L}_{\text{LPIPS}}$ [47]. We also add the 2DGS geometry regularization losses [9], *i.e.*, the depth distortion loss $\mathcal{L}_{\text{depth}}$, and normal consistency loss $\mathcal{L}_{\text{normal}}$:

$$\mathcal{L}_{\text{MGPM}} = \mathcal{L}_{\ell 1} + \lambda_{\text{lpips}}\mathcal{L}_{\text{LPIPS}} + \lambda_{\text{d}}\mathcal{L}_{\text{depth}} + \lambda_{\text{n}}\mathcal{L}_{\text{normal}}, \quad (2)$$

where $\lambda_{\{\cdot\}}$ denote loss weights. We train MGPM by minimizing the loss function $\mathcal{L}_{\text{MGPM}}$ across all the identities in the multi-view expressive face performance capture data [14].

Feed-forward MGPM avatar prediction. While MGPM produces visually reasonable Gaussian head avatars for unseen identities at test time, we observe missing avatar details,

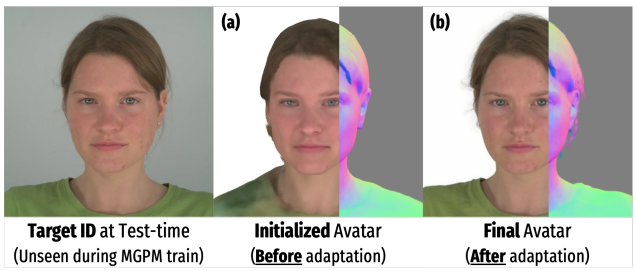


Figure 4. **Why need test-time avatar adaptation?** (a) Our learned Gaussian initialization provides a visually reasonable initial, but synthesizing a high-fidelity avatar from only a feed-forward path is challenging at test time. (b) After the test-time adaptation of the avatar prior model, we obtain a high-fidelity, authentic avatar.

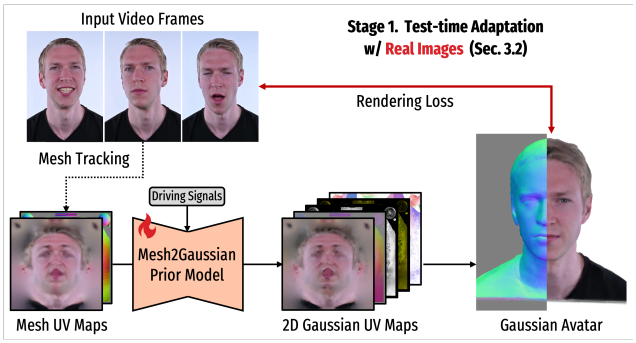


Figure 5. **Stage 1: Test-time adaptation w/ real images.** Given input video frames and offline-tracked head mesh UV maps, we obtain 2D Gaussian UV maps by Mesh2Gaussian Prior Model's (MGPM) feed-forward avatar initialization. We fine-tune MGPM by minimizing the rendering loss between the animated Gaussian avatar images and the sampled image frames within the input video.

as well as minor identity shifts (Fig. 4a). We attribute this mainly to the limited scale and diversity of MGPM's training dataset [14], which contains only about 400 identities, making it difficult for MGPM to perfectly generalize to unseen facial appearances, geometries, and expressions. Moreover, casual monocular video inputs provided at test time, *e.g.*, selfies and internet videos, exhibit significant domain gaps relative to the videos used for MGPM training. These practical limitations necessitate test-time avatar adaptation stages (Fig. 4b), which we describe in the following sections.

3.2. Stage 1:Test-time Adaptation with Real Images

We design a test-time adaptation stage to compensate for missing details and identity shifts from an initialized Gaussian avatar. Since the pre-trained MGPM already can generate an initial 2D Gaussian avatar from the mesh UV maps and driving signals, our test-time avatar adaptation essentially means the MGPM fine-tuning stage using the observed test time input video frames (Fig. 5).

Given a set of input video frames, $\mathbf{I}_{\text{real}}$, we first conduct off-line FLAME mesh tracking [29] to obtain canonical mesh UV maps and per-frame driving signals, *i.e.*,

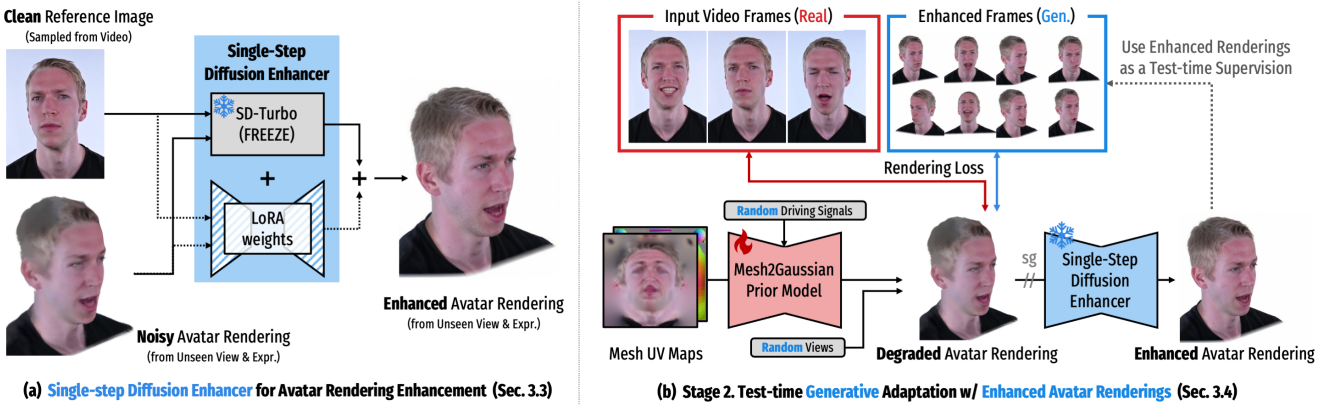


Figure 6. **Single-step diffusion enhancer & Test-time "generative" adaptation.** (a) We design a single-step diffusion enhancer that takes a degraded avatar rendering and a clean reference image as inputs, and efficiently generates a detail-enhanced and identity-preserving avatar rendering, within 0.3 seconds. (b) Using the generated images as test-time supervision, we conduct the stage 2 test-time avatar adaptation. After stage 2 adaptation, we obtain a final identity-specific avatar that generalizes across diverse poses, expressions, and viewpoints.

$[\mathbf{M}_{\text{tex}}, \mathbf{M}_{\text{geo}}, \mathbf{\Theta}] \leftarrow \texttt{Track}(\mathbf{I}_{\text{real}})$. We query $\mathbf{M}_{\text{tex}}, \mathbf{M}_{\text{geo}}, \mathbf{\Theta}$ to the pre-trained MGPM and obtain initialized 2DGS avatar in a feed-forward manner (Eq. (1)). Then, as in the MGPM training, we rasterize the 2DGS avatar into image space and compute reconstruction losses (Eq. (2)), using the estimated camera parameters. By backpropagating the loss gradients to the pre-trained MGPM, we adapt the general-purpose prior model $\mathcal{F}_\phi$ to an identity-specific prior model $\mathcal{F}_\phi^*$. In practice, we sample N_{real} frames ($N_{\text{real}} = 3$ unless noted otherwise) from the input video for computational efficiency and use a learning rate $0.05\times$ that of the MGPM training stage.

3.3. Single-step Diffusion Enhancer for Test-time Avatar Rendering Enhancement

The previous test-time avatar adaptation yields plausible avatar rendering results for the views and expressions seen in stage 1 (inset-a). However, when the avatar is rendered from unseen views and expressions, the rendered results are often degraded (inset-b). Therefore, we follow the principle of 2D generative prior approaches, where we leverage a diffusion model to provide augmented facial images from unseen views and expressions and use them as test-time supervision.


(a) **Clean renderings** from **Seen view & expr.** in Stage 1


(b) **Degraded renderings** from **Unseen view & expr.** in Stage 1

Gaussian avatars for grounded image generation. Previous works [40, 41] generate multi-view/-expression face images via full diffusion denoising from pure noise, which is slow and often hallucinates the identity. Our core idea is to leverage the degraded avatar renderings to *ground the generation* of novel view and expression images. Although degraded, we observe that the avatar renderings already contain rich appearance and geometry, which can serve as conditioning signals for a generative model, rather than pure noise. We approach this rendering-grounded image generation as a generative image enhancement and design an efficient diffusion image enhancer to enhance avatar renderings.

Single-step diffusion enhancer. Our single-step diffusion model enhances blurry, noisy avatar renderings and generate clean images by referencing the clean input frame (see Fig. 6a). After stage 1 adaptation, we render the avatar from random viewpoints and driving expression signals $\mathbf{\Theta}_{\text{rand}}$, and obtain degraded renderings, *i.e.*, $\mathbf{I}_{\text{gen}} \leftarrow \mathcal{F}_\phi^*([\mathbf{M}_{\text{tex}}, \mathbf{M}_{\text{geo}}], \mathbf{\Theta}_{\text{rand}})$. The single-step diffusion model $\mathcal{D}_\xi$ takes $\mathbf{I}_{\text{gen}}$, and a clean face image from input frames $\mathbf{I}_{\text{real}}$, then remove artifacts and add missing details in image space, as follows: $\mathbf{I}_{\text{gen}}^\star = \mathcal{D}_\xi([\mathbf{I}_{\text{gen}}, \mathbf{I}_{\text{real}}])$. Our design is inspired by the single-step diffusion enhancer for static 3D scene renderings, DIFIX [42]. Our enhancer is built to handle heterogeneous viewpoints and expressions between the clean reference image and the degraded avatar rendering. This is crucial in monocular video settings, where clean reference frames are mostly frontal while avatar renderings span diverse poses and expressions. Compared to the full diffusion denoising approach [41], our rendering-grounded image generation achieves $60\times$ faster image generation time, while better preserving identity-specific details (later discussed in Sec. 4.2). We train our model by fine-tuning the single-step image-translation diffusion model SD-Turbo [36] using our curated triplets of degraded avatar rendering, clean reference image, clean ground-truth image. Additional training details are provided in the supplementary material.

3.4. Stage 2: Test-time Generative Adaptation with Enhanced Avatar Renderings

After generating images from novel views and expressions, we use the generated images as test-time supervision to

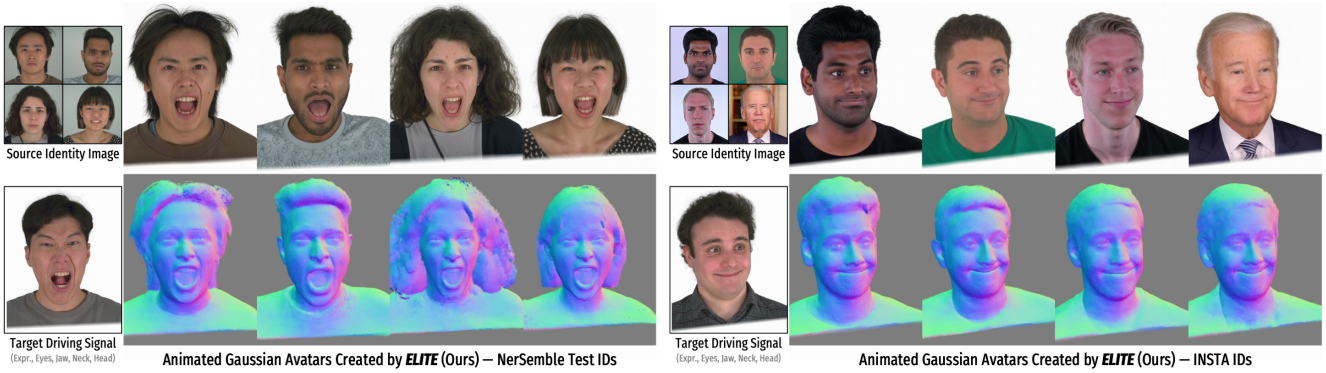


Figure 7. **ELITE: Qualitative results**. We show the animated rendering results (RGB and normal) of ELITE's generated 2DGS avatars for test IDs [14, 50]. ELITE synthesizes authentic, ID-preserving avatars for diverse attributes, *e.g.*, races, genders, ages, and hairstyles, even when trained on only 3 frames from an input monocular video. Please refer to the supplementary video for the dynamic animation results.

further fine-tune the avatar prior model. In other words, we perform the second-round test-time avatar adaptation using the generated images as additional supervision; we call this *test-time **generative** adaptation* (see Fig. 6b).

Given N_{gen} enhanced avatar images $\{\mathbf{I}^{\star}_{\text{gen}}\}$, we add them to the test-time adaptation dataset, *i.e.*, we use $N_{\text{real}}+N_{\text{gen}}$ images for test-time fine-tuning. Since we create $\{\mathbf{I}^{\star}_{\text{gen}}\}$ conditioned on the sampled viewpoints and driving signals, we already have accurately aligned pairs of images, camera parameters, and driving signals. As in Stage 1, we query the mesh UV maps and driving signals (Eq. (1)), rasterize the 2DGS avatar, and compute reconstruction losses (Eq. (2)), to further fine-tune the prior model $\mathcal{F}^{*}_{\phi} \rightarrow \mathcal{F}^{\star}_{\phi}$. Finally, the identity-specific avatar prior model $\mathcal{F}^{\star}_{\phi}$ can generalize to diverse poses, expressions, and viewpoints.

Rendering the final avatar. After test-time generative adaptation, we use the identity-specific avatar prior model $\mathcal{F}^{\star}_{\phi}$ to animate the target identity's 2DGS avatar given any FLAME driving signals in a feed-forward manner.

4. Experiments

In this section, we provide visualizations of our synthesized avatars and compare ELITE with the recent competing methods. We also conduct ablation studies to support our core design choices. For all experiments, we train our Mesh2Gaussian Prior Model (MGPM) on NerSemble-V2 [14], and use in-the-wild monocular videos from the INSTA [50] for testing and comparison.

4.1. Qualitative Results

In Fig. 7, we visualize synthesized Gaussian avatars for unseen IDs animated using various driving signals. ELITE faithfully synthesizes high-fidelity, authentic avatars that reliably reflect source visual details (*e.g.*, facial spots or cloth patterns) and accurately follow the driving signals (*e.g.*, gaze directions or laugh lines). Even under variations in source human attributes (races, genders, ages, hairstyles) and challenging driving signals with rich, expressive facial motions, ELITE maintains strong generalization.

Table 1. **Self re-enactment comparison.** We compare the visual quality of the avatars for INSTA identities [50]. ELITE (Ours) shows superior reconstruction quality and ID preservation.

Method	Duration	PSNR (↑)	SSIM (↑)	LPIPS (↓)	CSIM (↑)
FlashAvatar [43]	10 mins.	20.875	0.8338	0.1420	0.5823
SplattingAvatar [37]	15 mins.	24.838	0.8831	0.0893	0.6406
CAP4D [41]	400 mins.	19.478	0.8675	0.0992	0.7064
ELITE (Ours)	20 mins.	25.220	0.8771	0.0732	0.7396

4.2. Comparison with Competing Methods

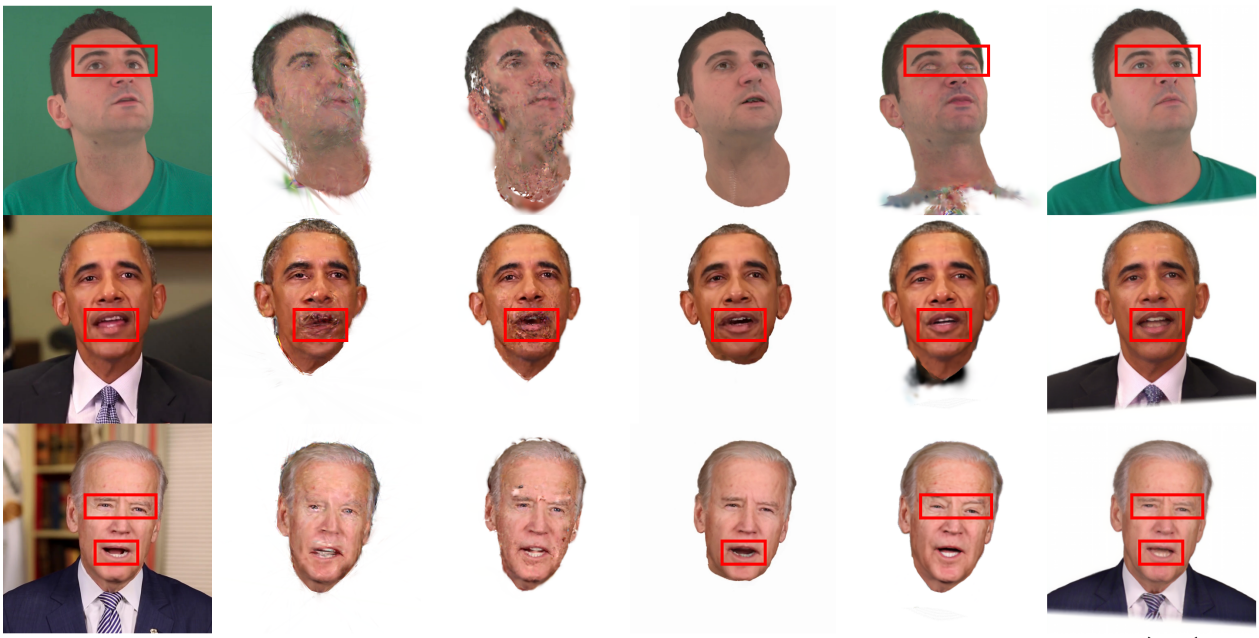
We compare ELITE with recent competing methods in terms of visual quality and quantitative metrics.

Competing methods. We compare the avatar synthesis quality of ELITE from the in-the-wild face videos from INSTA dataset [50] against recent competing methods, including: overfitting-based method (FlashAvatar [43], SplattingAvatar [37]), 3D data prior method (SynShot [51][1]), and 2D generative prior method (CAP4D [41]).

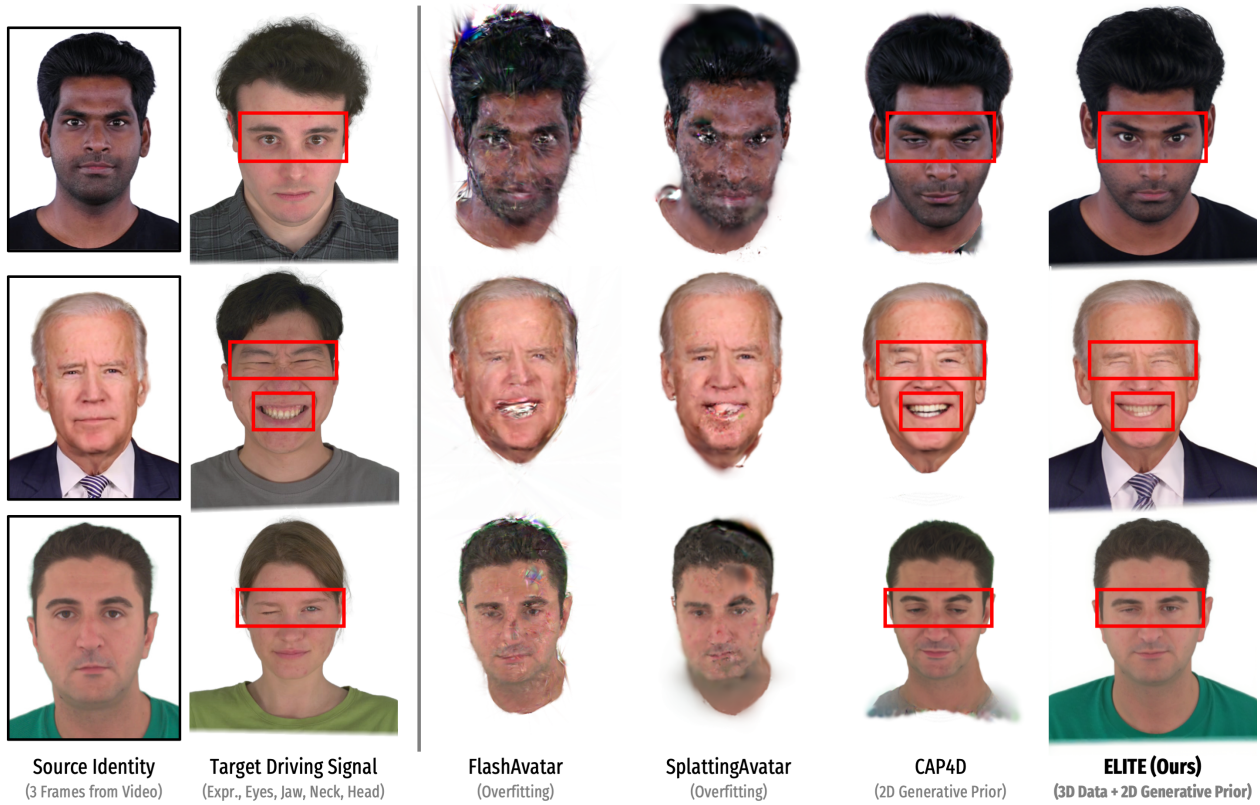
Monocular avatar self/cross re-enactment. Following the avatar synthesis protocol from [51], we synthesize avatars using only three supervision frames, excluding the last 600 test frames. For self re-enactment, we animate the synthesized avatars using the driving signals from the 600 test frames for quantitative evaluation. For cross re-enactment, we instead use driving signals from other sequences.

In Table 1, we report the photometric metrics (PSNR, SSIM, and LPIPS) and ID-consistency metric (CSIM) for self re-enactment. ELITE ourperforms all competing methods across most metrics, while showing comparable performance in SSIM. Notably, ELITE achieves superior perfor-

[1]No 3D data prior methods [1, 2, 48, 51] released codes and models. SynShot only provides videos without metrics; we only compare visual results.



(a) **Monocular self re-enactment comparison.**



(b) **Monocular cross re-enactment comparison.**

Figure 8. **Monocular self (a) and cross (b) re-enactment comparisons.** We synthesize 3D head avatars using ELITE (Ours) and competing methods [37, 41, 43, 51] ($N_{\text{real}} = 3$ input images), and evaluate both self and cross re-enactment using test split or held-out driving signals. ELITE produces Gaussian avatars with *better identity preservation* (iris color, hair style), as well as *stronger generalization* to novel head poses and fine-grained expressions, including gaze changes and one-eye winking.

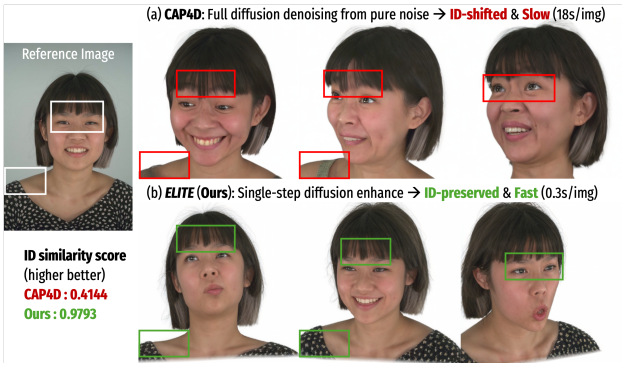


Figure 9. **Comparison of ID preservation of generated images.** CAP4D severely hallucinates IDs and slow (18 secs./image). Our rendering-guided single-step enhancement leads to significantly better ID preservation, with 60× faster image generation speed.

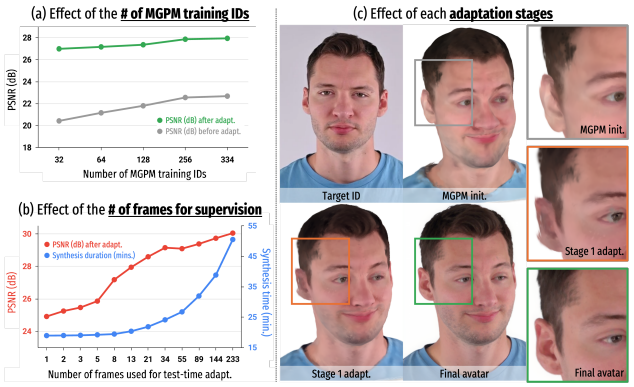


Figure 10. **Ablation Study.** (a) Scaling up the number of training identities for MGPM leads to better quality and generalization at test time. (b) Using more video frames for supervision improves quality but sacrifices the synthesis speed. (c) Our proposed modules, learned 3D avatar initialization & test-time generative adaptation, enable high-fidelity and generalizable avatar synthesis.

mance in identity preservation, which is a crucial component of avatar personalization. Since INSTA [50] primarily consists of speech-oriented videos with low variation in head pose, overfitting-based approaches [37, 43] can achieve favorable metric results. However, they fail under unseen views or expressions[2] (see Fig. 8). Another crucial requirement for a practical avatar system is the synthesis speed. Although CAP4D provides strong visual fidelity, it requires over six hours per identity because it relies on slow diffusion-based image generation, making it less suitable for practical use. ELITE strikes a favorable balance between fidelity and speed: it synthesizes avatars at a speed comparable to overfitting-based methods while surpassing existing methods in visual fidelity, both quantitatively and qualitatively.

While SynShot and CAP4D produce reasonable avatars, they fail to capture detailed appearance and geometry and do not model complete avatars, *i.e.*, missing torso. CAP4D fails to generalize to extreme and fine-grained facial expressions (See Fig. 8b). In contrast, ELITE crafts high-fidelity, authentic, and more complete (including torso) avatars that generalize well across diverse identities and expressions. Please refer to the supplementary material for more results.

ID preservation of generated images. Both CAP4D [41] and ELITE (Ours) generate synthetic face images for supervising the avatar synthesis, yet CAP4D often hallucinates the identity ($\text{CSIM}_{\text{CAP4D}}$=0.4144) and takes 18 seconds/image generation. In contrast, ELITE generates ID-preserving images ($\text{CSIM}_{\text{ours}}$=0.9793), with 60× faster speed, *i.e.*, 0.3 seconds/image. Our generative single-step enhancement, anchored by avatar renderings, achieves both high identity consistency and rapid avatar personalization (see Fig. 9).

4.3. Ablation Study

We discuss the effects of design choices in each module.

[2]We follow their exact inference instructions, but we use N_{real}=3 images for a fair comparison. We discuss the effects of N_{real} in the supplementary.

Effects of number of training IDs for 3D data prior. Our MGPM, trained on the widest ID and expression coverage (334 IDs) achieves the best avatar synthesis for both before and after avatar adaptation. Intuitively, the MGPM exposed to more IDs during training is more likely to learn a generalizable appearance and expression prior, providing better 3D avatar initialization before the adaptation, and yields higher-fidelity avatars after the adaptation.

Effects of the number of frames used for supervision. We evaluate the fidelity of the synthesized avatars, using a varying number of frames from the video at test time. In Fig. 10b, the graph shows the trade-off: the more frames we use to supervise avatar synthesis, the better the fidelity, but at the cost of sacrificing the synthesis time.

Effects of each module. Figure 10c shows the improvements in the avatar's visual quality achieved by each module. The MGPM gives a strong 3D avatar initialization. The stage 1 adaptation using video frames gives better ID alignment. Finally, the stage 2 adaptation using a 2D generative prior yields high-fidelity details and generalization.

5. Conclusion and Limitations

We present ELITE, an efficient Gaussian head avatar synthesis from a casual video. We identify a reinforcing synergy of two priors: 2D generative prior helps 3D prior generalize better, and 3D prior guides fast, ID-consistent image generation for test time supervision. ELITE strikes the sweet spot between fidelity and speed, surpassing competing methods.

Currently, ELITE can be vulnerable to unusual lighting conditions: connecting ELITE with lighting priors [3, 19] could be an interesting research problem. Joint 3D initialization and adaptation for avatars and accessories, *e.g.*, glasses [16], would be a promising future direction.

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ELITE: Efficient Gaussian Head Avatar from a Monocular Video via Learned Initialization and TEst-time Generative Adaptation

— Supplementary Material —

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In this supplementary material, we provide additional details and results for our method, ELITE, that are not included in the main paper due to the space limit. Also, we **encourage readers to watch the attached video**, where we show dynamic avatar visualizations.

Contents

A. Video for Summary & Visual Results

In the attached video, we provide the following content:

- ELITE overview and differences from existing methods.
- Multi-view videos of avatars synthesized by ELITE.
- Visual comparisons w/ competing methods [37, 41, 43].

B. Details of ELITE Pipeline

B.1. Mesh2Gaussian Prior Model (Sec. 3.1)

Our Mesh2Gaussian Prior Model (MGPM) serves as the core component of our feed-forward 3D data prior. It provides a fast and stable initialization of 2D Gaussian primitives from tracked mesh observations, enabling reliable identity-preserving avatar synthesis before any test-time adaptation.

Architecture. MGPM is a U-Net-based architecture that accepts a conditioning embedding vector through FiLM modulation [27]. Since our goal is to translate the concatenated FLAME UV texture map and UV geometry map into UV-aligned 2D Gaussian parameters, we adopt the U-Net design from SplatterImage [39], a feed-forward per-pixel 3D Gaussian parameter predictor, and repurpose it for the UV domain to use the U-Net to translate per-texel color and geometry to per-texel 2D Gaussian parameters. Following SplatterImage, we use a variant of SongUNet [38] with built-in self-attention layers, enabling the model to capture long-range dependencies across the UV maps.

Note that the FLAME geometry map contains the UV-unwrapped surface points' coordinates in a three-channel UV map. Since it contains 3D coordinate information, it has distinct statistics compared to UV texture maps, which typically have a limited range from 0 to 255. To mitigate this statistic mismatch between UV texture and geometry maps, we pre-compute the mean and standard deviation of UV geometry maps across all NerSemble [14] identities, and standardize the UV geometry maps, so that we can balance the statistic between the texture and geometry. Also, we use independent convolution layers for UV texture and geometry maps, so that we can balance the feature statistic before querying them into the U-Net.

To account for expression- and pose-dependent changes in the resulting UV-aligned 2D Gaussian primitives, we use a dedicated driving signal encoder implemented as a combination of lightweight MLP projection layers. The encoder receives FLAME driving parameters, global head rotation ($\mathbb{R}^3$), jaw rotation ($\mathbb{R}^3$), eye rotations ($\mathbb{R}^6$), neck rotation ($\mathbb{R}^3$), and expression code ($\mathbb{R}^{100}$), projects each into a compact latent space, and aggregates them into a single embedding ($\mathbb{R}^{128}$). This embedding modulates the U-Net features via FiLM layers across multiple resolution levels.

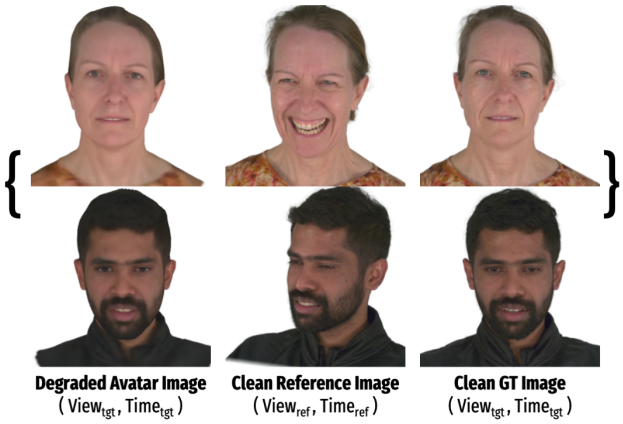

Figure S1. **Data samples for training diffusion enhancer.** We use the rendered Gaussian avatars, corresponding clean target images, and clean reference images from heterogeneous views and frames to build data triplet for training our diffusion enhancer.

Training. The full MGPM contains 36.2M learnable parameters: approximately 0.2M parameters belong to the driving signal encoder, and the remaining 36M to the U-Net. We train MGPM using four NVIDIA RTX A6000 GPUs (48GB) with Distributed Data Parallel (DDP) for two days.

B.2. Single-step Diffusion Enhancer (Sec. 3.3)

Our single-step diffusion enhancer serves as an essential module for achieving plausible generalization of an avatar across diverse views and expressions.

Dataset. To train such a diffusion enhancer, we need a paired dataset of {Degraded avatar rendering, Clean reference image, Clean ground-truth image}.

As a preliminary step, we first render animated Gaussian avatars from a pre-trained 3D prior model, MGPM (Sec. 3.1), for all the identities, viewpoints, and timeframes from NerSemble [14]. Then, we construct a data triplet by sampling two sets of viewpoints and the frame. First, we sample view v_{ref}, frame t_{ref}, and retrieve a clean image from the NerSemble dataset, where this image will serve as the "Clean reference image." Then, we sample view v_{tgt}, frame t_{tgt}, and render the avatar from the view and frame, and this will serve as the "Degraded avatar rendering." From the same view and frame (v_{tgt}, t_{tgt}), we also retrieve the corresponding clean image from the NerSemble dataset, which will serve as the "Clean ground-truth image." We collect total 10,688 triplets for training the single-step diffusion enhancer. We visualize the data triplet samples in Fig. S1. By sampling heterogeneous views and frames for the inputs, the model becomes robust across varying viewpoints and expressions.

Training. Following DIFIX [42], we train our cross-viewpoint and cross-expression single-step diffusion enhancer by fine-tuning the pre-trained single-step diffusion model SD-Turbo [36]. We freeze the VAE encoder and conduct LoRA finetuning for the decoder. During training, we supervise the model using L1, LPIPS [47], and Gram matrix losses [31], and conduct LoRA fine-tune [8] on DIFIX [42]. We use a single NVIDIA RTX A6000 GPU (48GB) for 6 hours to train the single-step diffusion enhancer model.

Test time. We mainly use the enhanced avatar images to supervise the test-time adaptation process, *i.e.*, we distill the 2D enhanced images back to 3D avatars. At test time, following DIFIX, we further enhance the rendering quality of the final synthesized avatar (after the stage 2 adaptation), by using our diffusion enhancer as the final post-processing step at test time. By only using the avatar rendering as an input, *without reference image* and fp16 precision, we achieve an interactive post-processing rate (∼80 ms per image) on a single NVIDIA RTX A6000 GPU.

C. More Ablation Studies

C.1. Effect of 3D Data & 2D Generative Priors

We analyze the contribution of each prior by evaluating four system variants: (a) an *overfitting baseline* without the 3D data prior or the 2D generative prior, (b) a *2D generative prior* variant without the 3D data prior, (c) a *3D data prior* variant without the 2D generative prior, and (d) our *hybrid* model combining both priors.

Table S1. **Ablation on the 3D data prior and the 2D generative prior (Self Re-enactment).** Our hybrid 3D data & 2D generative prior approach achieves the highest reconstruction performance on self re-enactment task, and achieves the most plausible appearance and geometry results on cross re-enactment (Fig. S2-right).

Variants	3D Data Prior	2D Gen. Prior	PSNR (↑)	SSIM (↑)	LPIPS (↓)	CSIM (↑)
(a)	✗	✗	25.08	0.8701	0.0948	0.6918
(b)	✗	✓	26.30	0.8759	0.0664	0.7237
(c)	✓	✗	28.26	0.8843	0.0742	0.7129
(d) Ours	✓	✓	28.68	0.8912	0.0585	0.7397

Fig. S2-left shows self re-enactment results, evaluated on held-out frames for which full metrics can be computed. For all the variants, we use three input frames for supervising the test-time adaptation. Quantitative comparisons for the self re-enactment PSNR, SSIM, LPIPS, and CSIM are provided in Table S1. Since the held-out frames are visually similar to the training data (speech-driven frames with limited pose variation), all the methods achieve comparable PSNR values. However, geometry quality differs significantly: methods (a) and (b), which lack a 3D data prior and optimize directly from a template mesh, overfit to RGB observations and converge to flattened, unrealistic facial geometry. In contrast, methods (c) and (d) benefit from the 3D prior and faithfully preserve plausible facial structure. Because the held-out frames are close to the training distribution, the influence of the 2D generative prior is less noticeable in this setting.

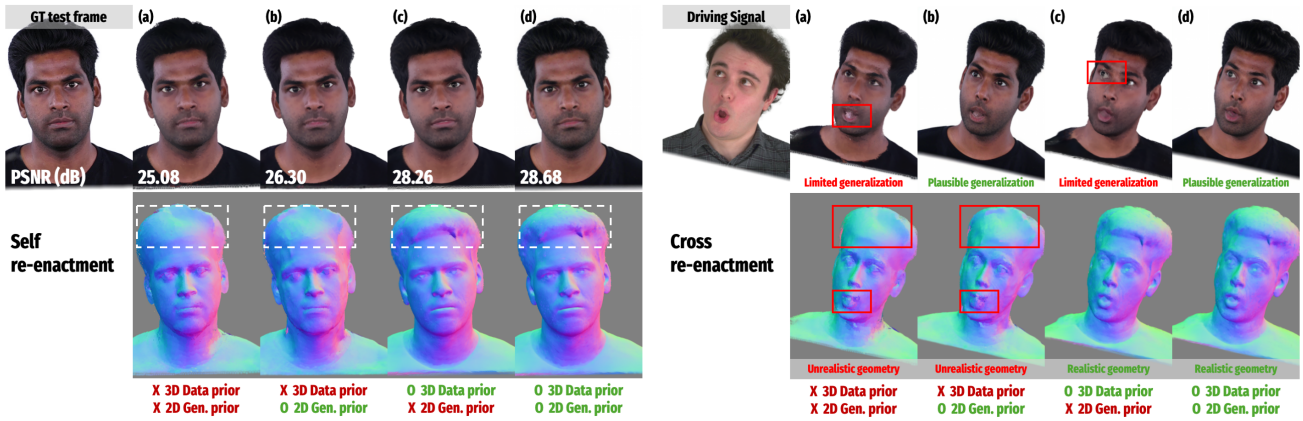

Figure S2. **Ablation on the 3D data prior and the 2D generative prior.** Self re-enactment (left) shows that methods without the 3D prior ((a),(b)) overfit and produce unrealistic geometry, while (c) and (d) preserve plausible structure. Cross re-enactment (right) highlights generalization differences: (a) fails in both geometry and appearance, (b) improves appearance but not geometry, (c) maintains geometry but lacks appearance generalization, and (d) (our proposed method) achieves both.

Fig. S2-right further evaluates cross re-enactment, where each avatar is driven by novel and challenging poses and expressions. This setting exposes clear differences in generalization performance. Variant (a) shows limited generalization in appearance due to the absence of any prior and producing noticeable geometric collapses. Variant (b) leverages the 2D generative prior and therefore plausibly generalizes to unseen poses and expressions, yet still suffers from unrealistic geometry because it lacks the 3D prior. Variant (c) produces realistic geometry thanks to the learned 3D prior, but its RGB appearance does not generalize well to out-of-distribution poses when trained solely on real monocular data. Finally, our hybrid approach (d), using both priors, achieves faithful geometry and appears to have strong view/expression generalization simultaneously, producing the most plausible re-enactment results.

Overall, this ablation confirms three key observations: (1) without a 3D data prior, monocular reconstruction easily overfits and produces inaccurate geometry even when the rendered appearance seems plausible; (2) without a 2D generative prior, appearance-space generalization to unseen poses and expressions remains limited; and (3) combining both priors yields a complementary effect, enabling ELITE to achieve realistic geometry and plausible re-enactment quality across both seen and unseen driving signals.

C.2. Effect of the Number of Real Video Frames

Figure S3 compares the cross re-enactment quality as we vary the number of real supervision frames N_{real}. Although self re-enactment metrics (e.g., PSNR) improve with more real frames (Sec. 4.3 & Fig. 10 in the main paper), we observe that ELITE already produces stable and high-quality cross re-enactment results even with a single supervision frame. We attribute this robustness to our 3D data prior,

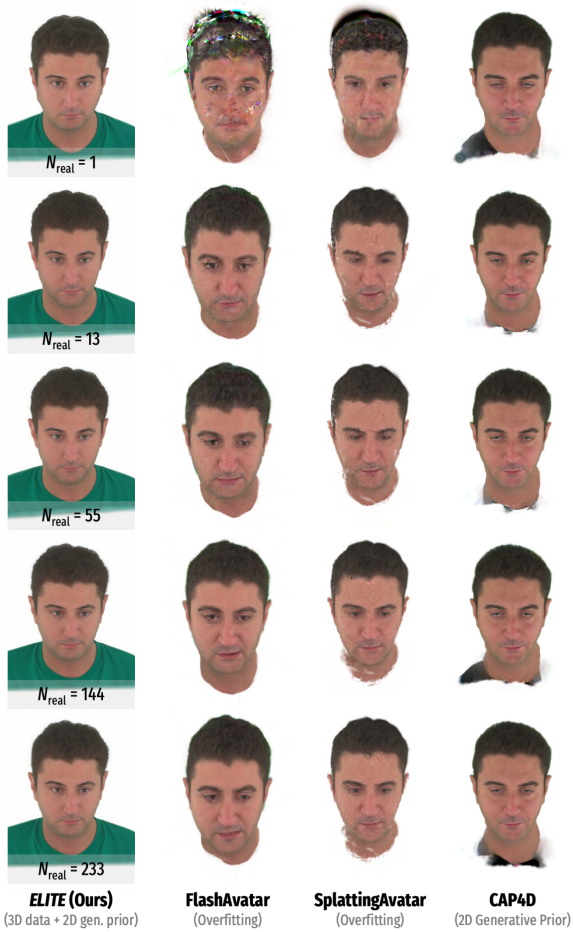

Figure S3. **Effect of the number of real frames.**

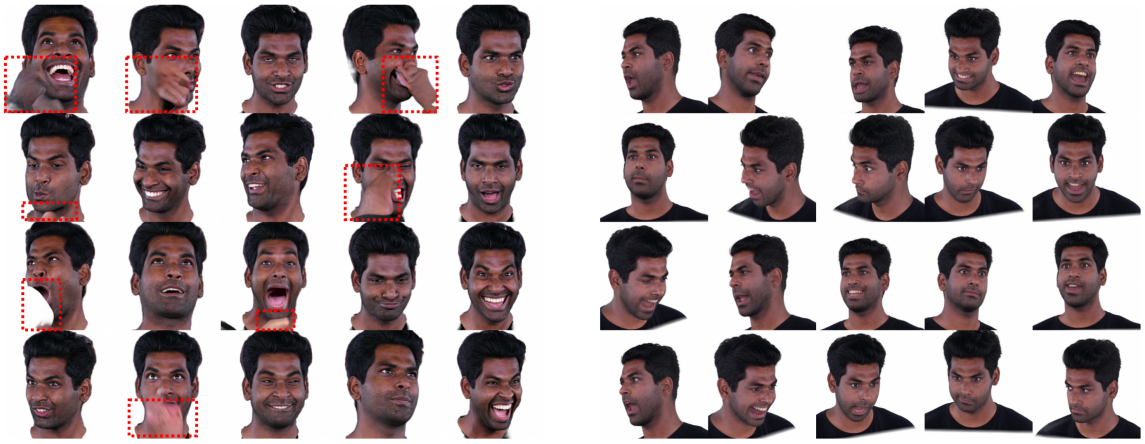

Figure S4. **Uncurated comparison of generated supervision images.** (a) CAP4D produces images via full denoising from pure noise, leading to severe artifacts and identity drift, whereas (b) our rendering-grounded single-step enhancer generates identity-preserving, artifact-free images with significantly higher consistency, with 60× faster generation speed.

which provides strong initialization, and to our generative adaptation stage, which supplies synthetic multi-view supervision regardless of N_{real}. In contrast, overfitting-based methods, FlashAvatar [43] and SplattingAvatar [37], show limited generalization to unseen expressions when N_{real} is small, as they rely solely on limited observations. CAP4D [41] benefits from synthetic views but still suffers from identity drift and limited expression fidelity. Overall, ELITE maintains strong cross-view and cross-expression generalization even under extremely sparse supervision.

D. More Results

D.1. Comparison of Generated Supervision Images

In Fig. S4, we qualitatively compare the uncurated sets of supervision images produced by CAP4D and our method.

Since CAP4D synthesizes each image by performing full diffusion denoising from pure noise, its outputs frequently exhibit severe artifacts (e.g., distorted facial regions, inconsistent geometry, or implausible textures) and suffer from noticeable identity drift. In contrast, our single-step diffusion enhancer is grounded on the rendered Gaussian avatar, providing strong geometric and appearance cues that guide the single-step generation process. As a result, our generated images preserve identity much more faithfully and contain significantly fewer visual artifacts. Moreover, by avoiding multi-step diffusion sampling, our method achieves **60× faster** generation while delivering cleaner and more reliable supervision for test-time adaptation.

D.2. Limitations on Modeling Accessories

Our method has room for improvement in modeling accessories such as eyeglasses. Because the underlying 3D data prior model, MGPM, is trained on NerSemble [14], and we filtered out few identities with accessories to focus on pure head geometry and appearance, ELITE did not have a chance to learn explicit geometry priors for glasses. As a result, while the RGB appearance partially follows the glasses in input frames, the rendered normal maps reveal that no corresponding 3D structure is reconstructed (see Fig. S5), meaning the glasses are effectively baked into the texture space rather than modeled as geometry. Extending the prior to jointly learn facial and accessory geometry remains an important direction for future work.

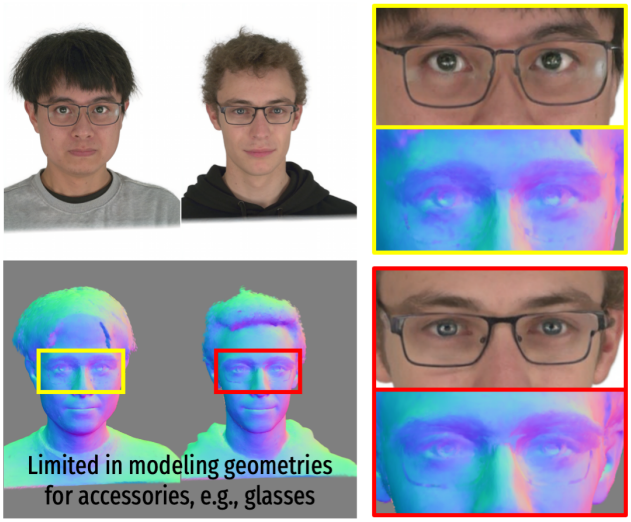

Figure S5. **Limitation in modeling accessories.** Although the RGB appearance from ELITE follows the eyeglasses in the input, the normal maps show no corresponding geometry, indicating that the glasses are baked into the texture.

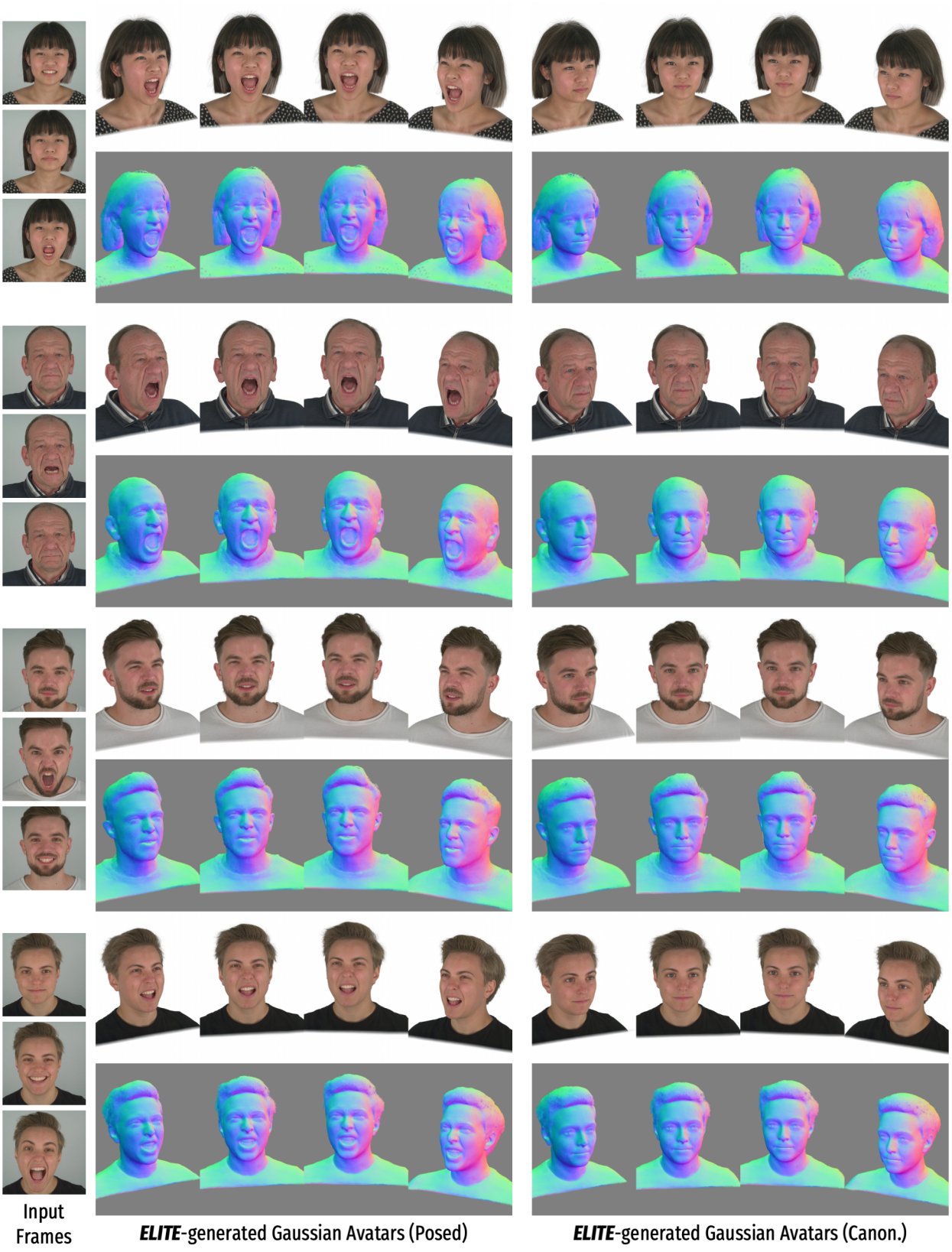

Figure S6. **Multi-view, Multi-expression Renderings of ELITE-generated Gaussian Avatars.**

Figure S7. **Multi-view, Multi-expression Renderings of ELITE-generated Gaussian Avatars.**

D.3. Multi-view/-expression Renderings

In Figs. S6 & S7, we show multi-view rendered images and normal renderings of the Gaussian avatars synthesized from our method. We use our held-out test identities from the NerSemble-V2 dataset and test identities from the INSTA dataset. For all the identities, we use three images from the videos as test-time supervision for avatar adaptation. Overall, our method synthesizes high-fidelity, authentic Gaussian avatars with faithful appearances and geometries that generalize across diverse expressions and viewpoints.

E. Broader Impacts & Ethical Considerations

Societal Impact. The primary goal of ELITE is to enabling accessible high-fidelity avatar synthesis for applications in telepresence, mixed reality, and we recognize the potential risks associated with misuse. To mitigate these risks, we advocate for the community's ongoing efforts in avatar fingerprinting [28] and digital media forensics [34] to support the detection of synthetic media. To promote transparency and reproducibility, we plan to release our code and models strictly for research purposes.

Data Considerations. ELITE utilizes open-sourced academic datasets (NerSemble-V2, INSTA) to learn geometric and appearance priors. While ELITE demonstrates plausible generalization across various identities, we are aware of the importance of continued improvements in dataset diversity.