Pixel3DMM: Versatile Screen-Space Priors for Single-Image 3D Face Reconstruction

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Figure 1: We present Pixel3DMM, a set of two ViTs Dosovitskiy et al. (2020), which are tailored to predict per-pixel surface normals and uv-coordinates. Here, we demonstrate the fidelity and robustness of Pixel3DMM on challenging inputs. From top to bottom we show input RGB, predicted normals, 2D vertices extracted from the uv-coordinate prediction, and our FLAME fitting results.

Abstract

We address the 3D reconstruction of human faces from a single RGB image. To this end, we propose Pixel3DMM, a set of highly-generalized vision transformers which predict per-pixel geometric cues in order to constrain the optimization of a 3D morphable face model (3DMM). We exploit the latent features of the DINO foundation model, and introduce a tailored surface normal and uv-coordinate prediction head. We train our model by registering three high-quality 3D face datasets against the FLAME mesh topology, which results in a total of over 1,000 identities and 976K images. For 3D face reconstruction, we propose a FLAME fitting opitmization that solves for the 3DMM parameters from the uv-coordinate and normal estimates. To evaluate our method, we introduce a new benchmark for single-image face reconstruction, which features high diversity facial expressions, viewing angles, and ethnicities. Crucially, our benchmark is the first to evaluate both posed and neutral facial geometry. Ultimately, our method outperforms the state-of-the-art (SoTA) by over 15% in terms of geometric accuracy for posed facial expressions.

1 Introduction

3D reconstruction of faces, tracking facial movements, and ultimately extracting expressions for animation tasks are fundamental problems in many domains such as computer games, movie production, telecommunication, and AR/VR applications. Recovering 3D head geometry from a single image is a particularly important task due to the vast amount of available image collections.

Unfortunately, reconstructing faces from a single input image is also inherently underconstrained. Not only depth ambiguity renders this task challenging, but also ambiguities between albedo and lighting/shadow effects. In addition, properly disentangling identity and expression information – which is critical for many downstream applications – makes the problem difficult. Finally, occlusions and unobserved facial regions further complicate the problem in real application scenarios, thus highlighting the need for strong data priors.

A typical approach to single-image face reconstruction is to exploit 3D parametric head models (3DMMs) Blanz & Vetter (2023); Li et al. (2017) which provide a low-dimensional parametric representation for the underlying 3D geometry. Optimizing within a 3DMM's

disentangled parameter space heavily constrains the search space with built-in assumptions about plausible facial structure and expressions, and allows to extract disentangled identity and expression information. Nonetheless, despite relying on 3DMMs, many ambiguities remain and their simplifying assumptions about our world often cannot explain the complexity of the real world. This necessitates additional priors in order to obtain compelling fitting results such as sparse Sagonas et al. (2013) and dense Cao et al. (2013); Wood et al. (2022) facial landmarks, or UV coordinate predictions Taubner et al. (2024a).

In recent years, we have also seen significant progress in feed-forward 3DMM regressors Sanyal et al. (2019); Feng et al. (2021); Daněček et al. (2022); Retsinas et al. (2024); Zielonka et al. (2022); Zhang et al. (2023). However, it is complicated to extend feed-forward regressors, *e.g.* to a multi-view or temporal domain, and, as we will show later, they fall behind optimization-based approaches on inputs with strong facial expressions. Overall, accurate 3D face reconstruction from single images remains a challenging and highly relevant problem.

Therefore, we propose Pixel3DMM, a novel optimization-based 3D face reconstruction approach. Our main idea is to exploit and further develop broadly generalized and powerful foundation models to predict pixel-aligned geometric cues that effectively constrain the 3D state of an observed face. Given a single image at test time, we propose normal and uvcoordinate predictions as optimization constraints from which we fit a 3D FLAME model. Instead of a simple rendering loss of uv-coordinates, we then transfer the information into a 2D vertex loss, which offers a wider basin of attraction during optimization. We argue that this strategy is superior to traditional photometric terms, or sparse landmarks, which often struggle with extreme view points and facial expressions. In order to train our approach, we unify three recent, high-fidelity 3D face datasets Giebenhain et al. (2023); Zhu et al. (2023); Martinez et al. (2024) by registering them against the FLAME Li et al. (2017) model. Our approach outperforms all available normal estimators for human faces in the NeRSemble Kirschstein et al. (2023) dataset.

In order to advance the evaluation of single-image 3D face reconstruction methods, we further propose a new benchmark based on the multi-view video dataset NeRSemble Kirschstein et al. (2023), which includes a wider variety of facial expressions than existing benchmarks Sanyal et al. (2019); Zhu et al. (2023); Feng et al. (2018); Chai et al. (2022). Our benchmark is the first to allow for the simultaneous evaluation of posed and neutral facial geometry. This enables a more direct comparison of methods, especially regarding fitting fidelity and ability to disentangle expression and identity information. Finally, we show that compared to our strongest baselines, our approach improves the L2-Chamfer reconstructions loss by over 15% for posed geometry, while slightly improving over neutral geometry predictions.

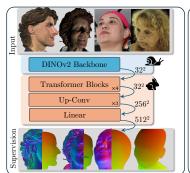
To summarize, our main contributions are as follows:

- A new formulation to exploit foundation model features for 3D-related, pixelaligned predictions, facilitating SoTA normal estimations for human faces.
- A novel 3D face reconstruction approach based on predicted uv-map correspondences and surface normals.
- A 3D face reconstruction benchmark and evaluation protocol from high-fidelity multi-view face captures.

We plan to make the model, code, and our new benchmark publicly available to promote progress in single image 3D face reconstruction and encourage quantitative benchmarking on challenging facial expressions.

2 Related Work

Single-Image 3DMM Fitting Tracking morphable models from single images is a well-studied problem in the context of 3D face reconstruction and tracking. Early works Blanz & Vetter (1999); Paysan et al. (2009); Li et al. (2017), introduced statistical shape and texture priors to estimate 3D face geometry from 2D images. Such methods rely on photometric fitting and subsequent approaches improve modeling capabilities using learned implicit representations Lin et al. (2023); Giebenhain et al. (2024). While some methods Thies et al.



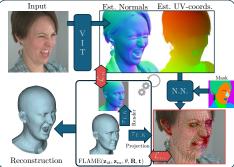


Figure 2: **Method Overview:** Pixel3DMM consists of (a) learning pixel-aligned geometric priors (left) and (b) test-time optimization against predicted uv-coordinates and normals (right). On the left we show our network architecture and training examples. On the right we depict the process of finding per-vertex 2D locations using a nearest neighbor (N.N.) look up, and our loss terms.

(2016); Grishchenko et al. (2020) favor a high tracking frame rate for real-time applications, others favor reconstruction accuracy Zielonka et al. (2022).

Facial Landmark Prediction Numerous reconstruction methods Li et al. (2017); Cao et al. (2013) for faces rely on accurate landmark predictions, which are usually coupled with vertices of a template mesh. Pioneering work on detecting such landmarks already relies on statistical learning Cootes et al. (2001) and more recent models exploit large datasets Wood et al. (2021); Wu et al. (2018) and neural networks to improve the performance Bulat & Tzimiropoulos (2017); Bazarevsky et al. (2019). MediaPipe Bazarevsky et al. (2019), for instance, uses a convolutional network inspired by MobileNet Howard et al. (2017). Another line of work focuses on densely aligning template mesh and 2D predictions. To achieve this FlowFace Taubner et al. (2024a) employs a vision-transformer backbone and iteratively refines the flow from UV to image space.

3DMM Regression DECA Feng et al. (2021) trains a regressor to predict 3DMM parameters from an image . An extension of this work is presented in EMOCA Daněček et al. (2022), which emphasizes the reconstruction of emotion-rich expressions. Similarly, SPECTRE Filntisis et al. (2022) aims at temporal consistency and reconstructing lip motion. SMIRK Retsinas et al. (2024) introduces a neural synthesis component, reducing the domain gap between real and rendered images. Since the aforementioned methods don't assume 3D training data, it is easy to scale them to large datasets. As a downside, the lack of 3D information impedes accuracy and leaves depth ambiguity. In order to address this, MICA Zielonka et al. (2022) supervises directly in 3D space. TokenFace Zhang et al. (2023) is a transformer-based method that can be trained on both 2D and 3D data.

Face Reconstruction Benchmarks The Stirling Feng et al. (2018) dataset contains 2000 images of 135 subjects. Unfortunately, ground truth reconstructions are only available for neutral poses in this dataset. Similarly, the NoW Sanyal et al. (2019) benchmark provides reconstructions only in the neutral expression. It has 2054 images of 100 subjects. Both the FaceScape Zhu et al. (2023) and the REALY Chai et al. (2022) dataset contain posed scans. While the former has 10 identities, the latter has 100 subjects. Neither of these two benchmarks measures disentanglement by additionally evaluating against neutral geometry.

3 Pixel3DMM

In this work we address the challenges of single-image face reconstruction by learning powerful priors of pixel-aligned geometric cues. In particular we train two vision transformer networks, which predict uv-coordinates and surface normals against which we fit FLAME Li et al. (2017) parameters at inference time. In section 3.1 we describe our Pixel3DMM networks, our data acquisition, and how we train them for accurate surface normal and uv-coordinate prediction. Afterwards, in section 3.2, we elaborate on our single-image fitting approach, which is purely based on our surface normal and uv-coordinate predictions.

3.1 Learning Pixel-Aligned Geometric Cues

Despite recently released high-quality 3D face datasets Zhu et al. (2023); Kirschstein et al. (2023); Giebenhain et al. (2023); Martinez et al. (2024), such data is still relatively scarce, especially w.r.t. the number of different identities, ethnicities, age distribution and lighting variation. We therefore take inspiration from recent achievements on fine-tuning foundational and large generative models to become experts on a constrained domain, *e.g.* Hu et al. (2022); Ruiz et al. (2023).

In particular we train two expert networks

$$\mathcal{N}: \mathbb{R}^{512\times512\times3} \rightarrow [-1,1]^{512\times512\times3} \quad \text{and} \quad \mathcal{U}: \mathbb{R}^{512\times512\times3} \rightarrow [\ 0,1]^{512\times512\times2} \tag{1}$$

which, given a single input image I, predict surface normals $\mathcal{N}(I)$ and uv-space coordinates $\mathcal{U}(I)$, respectively.

3.1.1 Network Architecture

We build Pixel3DMM on top of the foundational features from a pre-trained DINOv2 Oquab et al. (2023) backbone. As depicted in fig. 2, we extend the ViT architecture using a simple prediction head. It consists of four additional transformer blocks, three up-convolutions which lift the feature map resolution from 32 to 256×256 . Finally, we use a single linear layer to increase the feature dimensionality and unpatchify the predictions to $512 \times 512 \times c$, where $c \in \{3,2\}$ for normals and uv-coordinate prediction tasks, respectively.

3.1.2 Data Preparation

To train our networks, we opt for three recent, high-quality 3D face datasets: NPHM Giebenhain et al. (2023), FaceScape Zhu et al. (2023), and Ava256 Martinez et al. (2024). We follow the non-rigid registration procedure from NPHM, register all datasets into a uniform format and topology. fig. 2 shows pairs of input views with the associated supervision signal for surface normals and uv-coordinates.

Dataset Numbers In total, our dataset comprises 470 identities from NPHM in 23 expression and 40 renderings each (376K rgb, normal and uv images in total). For FaceScape we use 350 subjects, observed under 20 different expressions and 50 cameras each (350K rgb, normal and uv images in total). Since Ava256 is a video dataset, we leverage furthest point sampling to select the 50 most diverse expressions per person. For each person we choose a random subset of 20 cameras (250K rgb and uv images in total).

Diffsion-based Lighting Variations Since FaceScape and Ava256 are both studio datasets, which are captured at rather homogeneous lighting conditions, we leverage IC-Light Zhang et al. (2025), an image conditioned diffusion model Rombach et al. (2022), which alters the lighting condition based on a text prompt or background image.

3.1.3 Training

We train our models $\mathcal{M} \in \{\mathcal{N}, \mathcal{U}\}$ using a straight forward image translation formulation

$$\underset{\Psi_{\mathcal{M}}}{\operatorname{argmin}} \sum_{k \in \mathcal{D}} \sum_{p \in M^k} \| f(I^k)_p - Y_p^k \|_2, \tag{2}$$

where $\Psi_{\mathcal{M}}$ denotes the network's parameters, $k \in \mathcal{D}$ is a sample from our dataset, I^k and Y^k are input rgb and target images, respectively, and $p \in M^k$ are all pixels in the associated foreground mask.

Note, that instead of freezing the parameters of our DINOv2 backbone altogether, we set their learning rate ten times lower, in order to encourage prior preservation but enable stronger domain adoption.

Compared to Sapiens Khirodkar et al. (2024), a recent SoTA foundation model for human bodies and faces, training our models is cheap and can be realized using 2 GPUs and training for 3 days. Additionally, all our data is publicly available. The relatively low

computational burden and data accessibility, will hopefully inspire more research to follow in a similar direction.

3.2 SINGLE-IMAGE FLAME FITTING

Given a single image I, we leverage our prior networks to obtain predicted surface normals $\mathcal{N}(I)$ and uv-coordinates $\mathcal{U}(I)$. Using these predictions we aim to recover 3DMM parameters. In particular, we optimize for FLAME Li et al. (2017) identity, expression, and jaw parameters, as well as, camera rotation, translation, focal length and principal point:

$$\Omega_{\text{FLAME}} = \{ \mathbf{z}_{\text{id}} \in \mathbb{R}^{300}, \mathbf{z}_{\text{ex}} \in \mathbb{R}^{100}, \theta \in \mathcal{SO}(3) \}$$
 (3)

$$\Omega_{\text{cam}} = \{ \mathbf{R} \in \mathcal{SO}(3), \mathbf{t} \in \mathbb{R}^3, \mathbf{fl} \in \mathbb{R}^+, \mathbf{pp} \in \mathbb{R}^2 \}.$$
 (4)

3.2.1 2D Vertex Loss

Using the estimated uv-coordinates $\mathcal{U}(I)$, we aim to extract the 2d location p_v^* for each visible vertex $v \in V$ of the FLAME mesh. To this end we first run a facial segmentation network Zheng et al. (2022), in order to mask out the background, eyeballs and mouth interior. Then we find correspondences for each vertex $v \in V$ using a nearest neighbor lookup into $\mathcal{U}(I)$. To be more specific let $T_v^{\mathrm{uv}} \in [0,1]^2$ denote the uv-coordinate of v in the template mesh T. Then we find the pixel location

$$p_v^* = \underset{p \in P}{\operatorname{argmin}} \|T_v^{\text{uv}} - \mathcal{U}(I)_p\| \tag{5}$$

as the pixel with the closest uv prediction. Finally, we define

$$\mathcal{L}_{uv} = \sum_{v \in V} \mathbb{1}_{\|T_v^{uv} - \mathcal{U}(I)_p\| < \delta_{uv}} \cdot |p_v^* - \pi(v)|$$
(6)

to be our 2d vertex loss, where 1 denotes the indicator function which masks out vertices with a nearest neighbor distance larger than δ_{uv} . $V = \text{FLAME}\left(\Omega_{\text{FLAME}}\right)$ is the current estimate of the FLAME parametric model, and π denotes the projection implied by the current estimate of the camera parameters Ω_{cam} .

3.2.2 Optimization

Next to the 2d vertex loss \mathcal{L}_{uv} , we include the normal loss $\mathcal{L}_n = |\mathcal{N}(I) - \mathtt{render}_n(V)|$, where \mathtt{render}_n denotes a rendering of surface normals of the FLAME mesh. The regularization term $\mathcal{R} = \lambda_{\mathrm{id}} \|\mathbf{z}_{\mathrm{id}} - \mathbf{z}_{\mathrm{id}}^{\mathrm{MICA}}\|_2^2 + \lambda_{\mathrm{ex}} \|\mathbf{z}_{\mathrm{ex}}\|_2^2$ completes our overall energy term

$$E = \lambda_{uv} \mathcal{L}_{uv} + \lambda_n \mathcal{L}_n + \mathcal{R}. \tag{7}$$

Here $\mathbf{z}_{\mathrm{id}}^{\mathrm{MICA}}$ denotes MICA's Zielonka et al. (2022) identity prediction.

3.3 Monocular Video Tracking

Next to the single-image scenario, tracking faces in monocular videos is a fundamental task in computer vision. To address this problem, we simply extend our optimization strategy from section 3.2.2 globally over all images in a video sequence $\{I_t\}_{t=1}^T$. Using our prior networks, we first obtain normal predictions $\{\mathcal{N}(I_t)\}$ and uv-predictions $\{\mathcal{U}(I_t)\}$ After obtaining an initial estimate for $\Omega_{\text{FLAME}}^{(0)}$ and $\Omega_{\text{cam}}^{(0)}$ on the first frame by optimizing for eq. (7), we freeze \mathbf{z}_{id} , fl and \mathbf{pp} . We then sequentially optimize for all remaining attributes in $\Omega_{\text{FLAME}}^{(t)}$ and $\Omega_{\text{cam}}^{(t)}$. Using the results from the sequential optimization pass as initialization, we extend eq. (7) to a batched version using randomly sampled frames. Note, that the parameters \mathbf{z}_{id} , fl and \mathbf{pp} are shared for all frames. In order to enforce smoothness across all per-frame optimization targets we add a smoothness term

$$\mathcal{L}_{\text{smooth}}^{\Phi} = \frac{\lambda_{\text{smooth}}^{\Phi}}{2 * B} \sum_{t \in P} \|\Phi^{(t-1)} - \Phi^{(t)}\|_{2}^{2} + \|\Phi^{(t)} - \Phi^{(t+1)}\|_{2}^{2}$$
 (8)

to the energy E, where $\Phi^{(t)} \in \{\mathbf{z}_{ex}^{(t)}, \theta^{(t)}, \mathbf{R}^{(t)}, \mathbf{t}^{(t)}\}$ denotes any of the per-frame variables.

4 3D Face Reconstruction Benchmark

Constructing a benchmark that covers the variety of facial geometry and its complex deformations is a challenging endeavor. Compared to existing benchmark, ours focuses on strong facial expressions, and is the first to jointly evaluate *posed* and *neutral* face reconstruction. Our benchmark contains 21 subjects, each in its neutral state and in 20 different and diverse facial expressions. We e hope that our proposed benchmark will be adopted as a standard by the community to encourage better quantitative comparisons across methods. For more information we refer to appendix A.1.

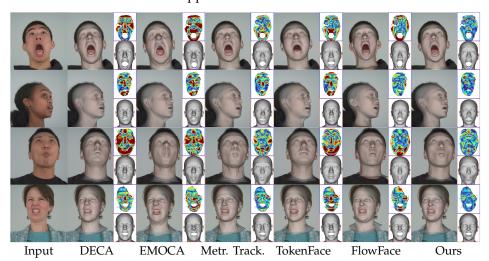


Figure 3: **Qualitative Comparison (Posed):** We show overlays of the reconstructed meshes. Insets with a blue border depict L_2 -Chamfer distance as an error map, rendered from a frontal camera. Red insets show the reconstructed mesh from the same camera. We encourage the reviewers to watch our supplementary material for additional visualizations.

4.1 Task Description and Evaluation Protocol

Our benchmark consists of *posed* and *neutral* 3D face reconstruction. The posed reconstruction task aims to measure the fidelity of a 3D reconstruction. Given any expressive face image, the underlying geometry shall be recovered. The neutral reconstruction task measures how well a reconstruction method can disentangle the effects of shape and expression. Specifically, the task is to reconstruct the face under neutral expression given an image of the person under any arbitrary expression. Both tasks are evaluated using standard practice, and refer to appendix A.1 for more details.

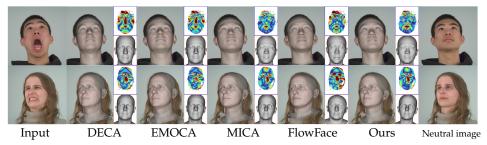


Figure 4: Qualitative Comparison (Neutral): Alignment against the neutral expression.

5 Experimental Results

5.1 Implementation Details

Prior Learning We train Pixel3DMM using the Adam Kingma & Ba (2014) optimizer, a batch size of 40, and 2 A6000 GPUs, which takes 3 days until convergence. We use a learning

Table 1: **Results on our benchmark.**

	Neutral			Posed			
	L1↓	NC↑	$R^{2.5} \! \uparrow$	L1↓	NC↑	$R^{2.5} \!\!\uparrow$	
MICA	1.68	88.3	91.0	-	-	-	
TokenFace	-	-	-	2.62	86.5	76.8	
DECA	2.07	87.6	84.5	2.38	87.0	79.8	
EMOCAv2	2.21	87.3	82.4	2.63	86.0	75.8	
Metr. Tracker	-	-	-	2.03	87.8	85.7	
NHA (stage1)	2.35	86.9	80.6	2.67	86.4	76.2	
VHAP (stage1)	2.95	84.7	71.0	3.04	84.8	69.9	
FlowFace	1.93	87.8	87.0	1.96	87.9	87.9	
Ours	1.66	88.3	91.2	1.66	88.4	91.6	

Table 2: Existing benchmarks.

Method	No	oW	FaceScape			
	Med.↓	Mean↓	CD↓	MNE↓	CR↑	
Dense	1.02	1.28	-	-	-	
PRNet	-	-	3.56	.126	89.6	
3DDFAv2	-	-	3.60	.096	93.1	
DECA	1.09	1.38	4.69	.108	99.5	
MICA	0.90	1.11	-	-	-	
FlowFace	0.87	1.07	2.21	.083	-	
TokenFace	0.76	0.82	3.70	.101	93.8	
Ours	0.87	1.07	1.76	.077	98.0	

rate of 1×10^{-4} for the prediction head and 1×10^{-5} for the DINO backbone. For simplicity we choose a light-weight network head. Using a DPT Ranftl et al. (2021) head instead resolves the last remaining patch artifacts of the ViT-Base backbone but drastically increases runtime whithout improving down-stream reconstruction performance. Similarly, we find that replacing ViT-Base with Sapiens-300M Khirodkar et al. (2024) backbone (the smallest available Sapiens model) incurs high computational costs without reconstruction benefits. We use 10% of the subjects as validation set, and exclude all the subjects from our benchmark from the training set.

FLAME Fitting We use the Adam optimizer with $lr_{id} = 0.001$ and $lr_{ex} = 0.003$. We set $\lambda_{uv} = 2000$, $\lambda_n = 200$, $\lambda_{id} = 0.15$ and $\lambda_{ex} = 0.01$. We perform 500 optimization steps which takes 30 seconds in our unoptimized implementation.

5.2 Baselines

Feed-Forward FLAME Regressors The first category of approaches we compare against are feed-forward neural networks trained to predict FLAME parameters. In this category of baselines, we choose DECA Feng et al. (2021) and EMOCA Daněček et al. (2022) which are trained on 2D data only. Additionally, we compare against MICA Zielonka et al. (2022), which is trained on 3D data and only predicts identity parameters \mathbf{z}_{id} , and TokenFace Zhang et al. (2023) which istrained on a mixture of 2D and 3D data.

Optimization-Based Approaches We compare against MetricalTracker Zielonka et al. (2022), which optimizes against two sets of facial landmark predictions Bulat & Tzimiropoulos (2017); Cao et al. (2013) and a photometric term. Additionally, we compare against Flow-Face Taubner et al. (2024a), a recent method that predicts flow from the uv-space into image space, in order to predict 2D image-space vertex positions. Similar to Pixel3DMM, FlowFace also uses a dense 2D vertex loss, but predicts them in a quite different manner. Finally, we compare against VHAP (Qian et al., 2024) and Neural Head Avatars (NHA) (Grassal et al., 2022), which start by optimizing within FLAME space (stage1) and continue by optimizing for vertex offsets (stage2).

Normal Estimation We compare against recent large-scale industry-born surafce normal estimators Sapiens-2B (Khirodkar et al., 2024) and concurrent work DAViD (Saleh et al., 2025). Additionally, we compare against Deep Face Normals (DFN) (Abrevaya et al., 2020) and Diff-E2E (Martin Garcia et al., 2025), which distill a normal estimator from StableDiffusion (Rombach et al., 2022)

5.3 Our Benchmark

Posed Face Reconstruction We present quantitative and qualitative results for the posed reconstruction task (see section 4.1) in table 1 and fig. 3, respectively. Quantitatively, Pixel3DMM outperforms all baselines by a large margin. In general, the feed-forward predictors (DECA, EMOCAv2, TokenFace) perform significantly worse than the optimization based approaches (MetricalTracker, FlowFace and Ours). Visually, DECA and TokenFace seem to underfit facial expressions, while EMOCAv2 exaggerates them. Compared to our approach, FlowFace sometimes exhibits performance drops for extreme facial expressions.

Figure 5: Surface Normal Estimation: Qualitative comparison to SoTA surface normal estimators.

Table 3: Ablation Study.						
	Neutral			Posed		
	L1↓	L2↓	$R^{2.5} \!\!\uparrow$	$L1\downarrow L2\downarrow R^{2.5}\uparrow$		
Lmks.	1.68	1.14	91.1	2.02 1.37 85.7		
Lmks.+Pho.	1.69	1.14	90.8	2.05 1.38 85.4		
Ours+Lmks.+Pho.	1.68	1.14	91.0	1.86 1.26 88.3		
only ${\cal U}$	1.66	1.11	91.3	1.72 1.16 90.6		
only ${\cal N}$	1.69	1.12	90.7	1.70 1.14 91.0		
only Sapiens	1.72	1.16	90.2	1.81 1.23 89.0		
Ours	1.66	1.12	91.2	1.66 1.11 91.6		
no MICA	1.90	1.29	87.2	1.74 1.17 90.1		

Table 4: Normal Estimation.								
Method	H3DS	MultiFace	NeRSemble					
DFN	0.878	0.914	0.907					
Diff-E2E	0.889	0.933	0.911					
sapiens	0.902	0.950	0.911					
David	0.903	0.943	0.927					
Ours	0.905	0.958	0.931					
Ours*	0.912	0.962	0.934					

Neutral Face Reconstruction Results on the neutral reconstruction task (see section 4.1) are provided in fig. 4 and table 1. First of all, we can observe that the significantly better posed reconstruction metrics of FlowFace and Pixel3DMM do not immediately translate to the neutral reconstruction. We attribute this to the ambiguities between identity and expression in the optimization process. Note that both FlowFace and Pixel3DMM rely on MICA predictions to initialize identity parameters \mathbf{z}_{id} . While FlowFace ends up with worse neutral reconstructions, our approach is able to improve upon MICA by a small margin. Nevertheless, we highlight the importance of using MICA to help disambiguate between \mathbf{z}_{id} and \mathbf{z}_{ex} , as ablated in section 5.7. Note, that TokenFace is missing from the neutral evaluation, since TokenFace's authors only provided posed meshes.

5.4 Results on Existing Benchmarks

FaceScape Benchmark Zhu et al. (2023) The FaceScape benchmark only evaluates the posed reconstruction task. The relative performance across methods matches with results on our benchmark, see table 2. Our method outperforms all baselines by a large margin w.r.t. chamfer distance (CD) and mean normal error (MNE), and has a slightly worse completeness rate (CR) than DECA, see Zhu et al. (2023) for more details.

NoW Benchmark Sanyal et al. (2019) On the NoW benchmark, which only evaluates the neutral reconstruction task, we achieve the same metrics as FlowFace, which is the best-performing optimization based approach, but perform worse than TokenFace. Note, however, that on FaceScape and our benchmark, we significantly outperform TokenFace. Similarly to the results on our benchmark, Pixel3DMM can only improve a small amount on top of the MICA predictions. We hypothesize that our prior significantly helps posed reconstructions, but struggles to guide the optimization to properly disentangle between \mathbf{z}_{id} and \mathbf{z}_{ex} .

5.5 In-the-Wild Results

In fig. 1, we demonstrate the robustness of our prior networks and fitting algorithm on challenging in-the-wild examples, including strong appearance variation, various background contexts and surroundings, lighting/shadow effects, and occlusions such as glasses, head wear and hands. Ultimately, this demonstrates that our approach successfully generalizes, even beyond the training data distribution. We hope that this will inspire more work in a similar direction, especially since all data is available and 2 48GB GPUs are sufficient for training. For tracking results on in-the-wild monocular videos we refer the reader to our supplementary video.

5.6 Surface Normal Estimation

In table 4 and fig. 5, we show quantitative and qualitative comparisons against recent state-of-the-art normal estimation methods. Our network estimates more detailed and accurate normals than the baselines. DAViD, a concurrent work to ours train on a vast synthetic dataset, predicts the most competitive results. However, DAViD struggles to accurately predict skin creases caused by complex deformations (see fig. 5), highlighting the need for real data. We also train a version of Pixel3DMM on the union of our data and the DAViD data, denoted as "Ours*". For more qualitative results and in-the-wild estimates, we refer to appendix A.2.

5.7 Ablation Experiments

We conduct extensive ablations on different compositions of our optimization energy E in table 3. We start by using the simplest energy, with only the landmark loss from MetricalTracker, and our regularization term. Next we add a photometric term, as in MetricalTracker. As shown in table 3, these configurations achieve significantly worse posed reconstructions. Interestingly, adding landmarks and photometric terms to the complete our proposed energy deteriorates reconstruction performance. Next, we investigate the effect of only using the predictions from $\mathcal N$ and $\mathcal U$, respectively. Compared to our full model these variants showcase lower posed reconstruction scores. We also compare our normal predictor $\mathcal N$ against Sapiens-2B Khirodkar et al. (2024), which confirms that our improved normal predictions translate to better reconstructions. Finally, we ablate the effect of using the MICA prior. Without MICA's predictions of $\mathbf z_{\rm id}$ especially the neutral reconstruction metrics drop, indicating its importance for disentanglement between identity and expression.

5.8 Additional Results

We highly encourage the reviewers to watch our supplementary video, and qualitative video tracking comparisons against the most competitive baseline (as suggested by our benchmark), which has publicly available code.

6 Limitations and Future Work

While we demonstrate the effectiveness of our approach for single image 3D reconstruction, several limitations remain. While our optimization energy could be easily extended to incorporate observations from multiple viewpoints, our prior models cannot currently exploit multiview information. Future extensions of our architecture could include multiview inputs similar to DUSt3R Wang et al. (2024), or video inputs similar to RollingDepth Ke et al. (2024). Next, for training large-scale 3DMM conditioned generative models like 3D GANS Sun et al. (2023) or diffusion models Kirschstein et al. (2024); Prinzler et al. (2024); Taubner et al. (2024b), e.g. on the LAION-Face dataset Zheng et al. (2022), fast reconstruction speed would be desirable. One potential avenue could be the distillation of our per-pixel predictors into a feed-forward 3DMM predictor. Finally, our experiments showcase, that optimization based approaches cannot flawlessly disambiguate identity and expression parameters. Therefore, specifically crafted priors for disambiguation are required.

7 Conclusion

In this paper, we trained pixel-aligned geometric prior networks, by leveraging pre-trained, generalized foundational features on publicly available 3D face datasets, which we registered into a uniform format. Our trained networks successfully generalize beyond the diversity of the training data, and we experimentally show that our normal predictor significantly outperforms all available normal estimators. We designed a 3DMM fitting algorithm on top of our prior predictions, which results in state of the art single image 3D reconstruction. Finally, we introduce a new benchmark, which features diverse and extreme expressions and allows, for the first time, to simultaneously evaluate neutral and posed geometry.

REFERENCES

- Victoria Fernandez Abrevaya, Adnane Boukhayma, Philip H.S. Torr, and Edmond Boyer. Cross-modal deep face normals with deactivable skip connections. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.
- Valentin Bazarevsky, Yury Kartynnik, Andrey Vakunov, Karthik Raveendran, and Matthias Grundmann. Blazeface: Sub-millisecond neural face detection on mobile gpus. *arXiv* preprint arXiv:1907.05047, 2019.
- Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. In *Proceedings of the 26th annual conference on Computer graphics and interactive techniques*, pp. 187–194, 1999.
- Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. In *Seminal Graphics Papers: Pushing the Boundaries, Volume 2*, pp. 157–164. 2023.
- Adrian Bulat and Georgios Tzimiropoulos. How far are we from solving the 2d & 3d face alignment problem?(and a dataset of 230,000 3d facial landmarks). In *Proceedings of the IEEE international conference on computer vision*, pp. 1021–1030, 2017.
- Chen Cao, Yanlin Weng, Stephen Lin, and Kun Zhou. 3d shape regression for real-time facial animation. *ACM Transactions on Graphics (TOG)*, 32(4):1–10, 2013.
- Zenghao Chai, Haoxian Zhang, Jing Ren, Di Kang, Zhengzhuo Xu, Xuefei Zhe, Chun Yuan, and Linchao Bao. Realy: Rethinking the evaluation of 3d face reconstruction. In *Proceedings of the European Conference on Computer Vision (ECCV)*, 2022.
- Timothy F. Cootes, Gareth J. Edwards, and Christopher J Taylor. Active appearance models. *IEEE Transactions on pattern analysis and machine intelligence*, 23(6):681–685, 2001.
- Radek Daněček, Michael J Black, and Timo Bolkart. Emoca: Emotion driven monocular face capture and animation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 20311–20322, 2022.
- Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.
- Yao Feng, Haiwen Feng, Michael J Black, and Timo Bolkart. Learning an animatable detailed 3d face model from in-the-wild images. *ACM Transactions on Graphics (ToG)*, 40(4):1–13, 2021.
- Zhen-Hua Feng, Patrik Huber, Josef Kittler, Peter Hancock, Xiao-Jun Wu, Qijun Zhao, Paul Koppen, and Matthias Rätsch. Evaluation of dense 3d reconstruction from 2d face images in the wild. In 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), pp. 780–786. IEEE, 2018.
- Panagiotis P. Filntisis, George Retsinas, Foivos Paraperas-Papantoniou, Athanasios Katsamanis, Anastasios Roussos, and Petros Maragos. Visual speech-aware perceptual 3d facial expression reconstruction from videos, 2022.
- Simon Giebenhain, Tobias Kirschstein, Markos Georgopoulos, Martin Rünz, Lourdes Agapito, and Matthias Nießner. Learning neural parametric head models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 21003–21012, 2023.
- Simon Giebenhain, Tobias Kirschstein, Markos Georgopoulos, Martin Rünz, Lourdes Agapito, and Matthias Nießner. Mononphm: Dynamic head reconstruction from monocular videos. In *Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2024.
- Philip-William Grassal, Malte Prinzler, Titus Leistner, Carsten Rother, Matthias Nießner, and Justus Thies. Neural head avatars from monocular rgb videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18653–18664, 2022.

- Ivan Grishchenko, Artsiom Ablavatski, Yury Kartynnik, Karthik Raveendran, and Matthias Grundmann. Attention mesh: High-fidelity face mesh prediction in real-time. *arXiv* preprint arXiv:2006.10962, 2020.
 - Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.
 - Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. In *ICLR*. OpenReview.net, 2022. URL http://dblp.uni-trier.de/db/conf/iclr/iclr2022.html#HuSWALWWC22.
 - Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 4401–4410, 2019.
 - Bingxin Ke, Dominik Narnhofer, Shengyu Huang, Lei Ke, Torben Peters, Katerina Fragkiadaki, Anton Obukhov, and Konrad Schindler. Video depth without video models. *arXiv* preprint arXiv:2411.19189, 2024.
 - Rawal Khirodkar, Timur Bagautdinov, Julieta Martinez, Su Zhaoen, Austin James, Peter Selednik, Stuart Anderson, and Shunsuke Saito. Sapiens: Foundation for human vision models. In *European Conference on Computer Vision*, pp. 206–228. Springer, 2024.
 - Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2014. URL http://arxiv.org/abs/1412.6980. cite arxiv:1412.6980Comment: Published as a conference paper at the 3rd International Conference for Learning Representations, San Diego, 2015.
 - Tobias Kirschstein, Shenhan Qian, Simon Giebenhain, Tim Walter, and Matthias Nießner. Nersemble: Multi-view radiance field reconstruction of human heads. *ACM Transactions on Graphics (TOG)*, 42(4):1–14, 2023.
 - Tobias Kirschstein, Simon Giebenhain, and Matthias Nießner. Diffusionavatars: Deferred diffusion for high-fidelity 3d head avatars. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5481–5492, 2024.
 - Tianye Li, Timo Bolkart, Michael. J. Black, Hao Li, and Javier Romero. Learning a model of facial shape and expression from 4D scans. *ACM Transactions on Graphics*, (*Proc. SIG-GRAPH Asia*), 36(6):194:1–194:17, 2017. URL https://doi.org/10.1145/3130800.3130813.
 - Connor Lin, Koki Nagano, Jan Kautz, Eric Chan, Umar Iqbal, Leonidas Guibas, Gordon Wetzstein, and Sameh Khamis. Single-shot implicit morphable faces with consistent texture parameterization. In *ACM SIGGRAPH 2023 Conference Proceedings*, pp. 1–12, 2023.
 - Gonzalo Martin Garcia, Karim Abou Zeid, Christian Schmidt, Daan de Geus, Alexander Hermans, and Bastian Leibe. Fine-tuning image-conditional diffusion models is easier than you think. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 2025.
 - Julieta Martinez, Emily Kim, Javier Romero, Timur Bagautdinov, Shunsuke Saito, Shoou-I Yu, Stuart Anderson, Michael Zollhöfer, Te-Li Wang, Shaojie Bai, et al. Codec avatar studio: Paired human captures for complete, driveable, and generalizable avatars. *Advances in Neural Information Processing Systems*, 37:83008–83023, 2024.
 - Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv*:2304.07193, 2023.

- Pascal Paysan, Reinhard Knothe, Brian Amberg, Sami Romdhani, and Thomas Vetter. A 3d face model for pose and illumination invariant face recognition. In 2009 sixth IEEE international conference on advanced video and signal based surveillance, pp. 296–301. Ieee, 2009.
 - Malte Prinzler, Egor Zakharov, Vanessa Sklyarova, Berna Kabadayi, and Justus Thies. Joker: Conditional 3d head synthesis with extreme facial expressions. *arXiv preprint arXiv*:2410.16395, 2024.
 - Shenhan Qian, Tobias Kirschstein, Liam Schoneveld, Davide Davoli, Simon Giebenhain, and Matthias Nießner. Gaussianavatars: Photorealistic head avatars with rigged 3d gaussians. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 20299–20309, 2024.
 - Eduard Ramon, Gil Triginer, Janna Escur, Albert Pumarola, Jaime Garcia, Xavier Giro-i Nieto, and Francesc Moreno-Noguer. H3d-net: Few-shot high-fidelity 3d head reconstruction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 5620–5629, 2021.
 - René Ranftl, Alexey Bochkovskiy, and Vladlen Koltun. Vision transformers for dense prediction. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 12179–12188, 2021.
 - George Retsinas, Panagiotis P. Filntisis, Radek Danecek, Victoria F. Abrevaya, Anastasios Roussos, Timo Bolkart, and Petros Maragos. 3d facial expressions through analysis-by-neural-synthesis. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024.
 - Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10684–10695, 2022.
 - Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 22500–22510, 2023.
 - Christos Sagonas, Georgios Tzimiropoulos, Stefanos Zafeiriou, and Maja Pantic. 300 faces in-the-wild challenge: the first facial landmark localization challenge, 2013. URL https://nottingham-repository.worktribe.com/output/1000738.
 - Fatemeh Saleh, Sadegh Aliakbarian, Charlie Hewitt, Lohit Petikam, Xiao-Xian, Antonio Criminisi, Thomas J. Cashman, and Tadas Baltrušaitis. DAViD: Data-efficient and accurate vision models from synthetic data, 2025. URL https://arxiv.org/abs/2507.15365.
 - Soubhik Sanyal, Timo Bolkart, Haiwen Feng, and Michael Black. Learning to regress 3D face shape and expression from an image without 3D supervision. In *Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, pp. 7763–7772, June 2019.
 - Johannes Lutz Schönberger and Jan-Michael Frahm. Structure-from-motion revisited. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.
 - Jingxiang Sun, Xuan Wang, Lizhen Wang, Xiaoyu Li, Yong Zhang, Hongwen Zhang, and Yebin Liu. Next3d: Generative neural texture rasterization for 3d-aware head avatars. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 20991–21002, 2023.
- Felix Taubner, Prashant Raina, Mathieu Tuli, Eu Wern Teh, Chul Lee, and Jinmiao Huang. 3D face tracking from 2D video through iterative dense UV to image flow. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1227–1237, June 2024a.
- Felix Taubner, Ruihang Zhang, Mathieu Tuli, and David B Lindell. Cap4d: Creating animatable 4d portrait avatars with morphable multi-view diffusion models. *arXiv* preprint arXiv:2412.12093, 2024b.

- Justus Thies, Michael Zollhofer, Marc Stamminger, Christian Theobalt, and Matthias Nießner. Face2face: Real-time face capture and reenactment of rgb videos. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2387–2395, 2016.
- Shuzhe Wang, Vincent Leroy, Yohann Cabon, Boris Chidlovskii, and Jerome Revaud. Dust3r: Geometric 3d vision made easy. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 20697–20709, 2024.
- Erroll Wood, Tadas Baltrušaitis, Charlie Hewitt, Sebastian Dziadzio, Thomas J Cashman, and Jamie Shotton. Fake it till you make it: face analysis in the wild using synthetic data alone. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 3681–3691, 2021.
- Erroll Wood, Tadas Baltrušaitis, Charlie Hewitt, Matthew Johnson, Jingjing Shen, Nikola Milosavljević, Daniel Wilde, Stephan Garbin, Toby Sharp, Ivan Stojiljković, et al. 3d face reconstruction with dense landmarks. In *European Conference on Computer Vision*, pp. 160–177. Springer, 2022.
- Wayne Wu, Chen Qian, Shuo Yang, Quan Wang, Yici Cai, and Qiang Zhou. Look at boundary: A boundary-aware face alignment algorithm. In *CVPR*, 2018.
- Cheng-hsin Wuu, Ningyuan Zheng, Scott Ardisson, Rohan Bali, Danielle Belko, Eric Brockmeyer, Lucas Evans, Timothy Godisart, Hyowon Ha, Xuhua Huang, Alexander Hypes, Taylor Koska, Steven Krenn, Stephen Lombardi, Xiaomin Luo, Kevyn McPhail, Laura Millerschoen, Michal Perdoch, Mark Pitts, Alexander Richard, Jason Saragih, Junko Saragih, Takaaki Shiratori, Tomas Simon, Matt Stewart, Autumn Trimble, Xinshuo Weng, David Whitewolf, Chenglei Wu, Shoou-I Yu, and Yaser Sheikh. Multiface: A dataset for neural face rendering. In *arXiv*, 2022. doi: 10.48550/ARXIV.2207.11243. URL https://arxiv.org/abs/2207.11243.
- Lymin Zhang, Anyi Rao, and Maneesh Agrawala. Scaling in-the-wild training for diffusion-based illumination harmonization and editing by imposing consistent light transport. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=u1cQYxRI1H.
- Tianke Zhang, Xuangeng Chu, Yunfei Liu, Lijian Lin, Zhendong Yang, Zhengzhuo Xu, Chengkun Cao, Fei Yu, Changyin Zhou, Chun Yuan, et al. Accurate 3d face reconstruction with facial component tokens. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 9033–9042, 2023.
- Yinglin Zheng, Hao Yang, Ting Zhang, Jianmin Bao, Dongdong Chen, Yangyu Huang, Lu Yuan, Dong Chen, Ming Zeng, and Fang Wen. General facial representation learning in a visual-linguistic manner. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18697–18709, 2022.
- Hao Zhu, Haotian Yang, Longwei Guo, Yidi Zhang, Yanru Wang, Mingkai Huang, Menghua Wu, Qiu Shen, Ruigang Yang, and Xun Cao. Facescape: 3d facial dataset and benchmark for single-view 3d face reconstruction. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 2023.
- Wojciech Zielonka, Timo Bolkart, and Justus Thies. Towards metrical reconstruction of human faces. In *European conference on computer vision*, pp. 250–269. Springer, 2022.

A Appendix

In this appendix we provide additional information about our benchmark (see appendix A.1), and additional qualitative results for normal estimation and two more baselines, in sections A.2 and A.3, respectively. Additionally, we highly encourage the reviewers to watch out supplemental video, including qualitative comparisons for video tracking.

A.1 3D Face Reconstruction Benchmark

Human face geometry is complex due to the presence of thin structures, different textures and diverse shapes. Furthermore, humans can deform their facial geometry in a remarkable way, performing a wide range of expressions and emotions. Consequently, building a robust 3D face reconstruction pipeline that covers all potential states of a human face is a challenging endeavor. Several 3D face reconstruction benchmarks have been previously proposed to rank reconstruction methods in terms of quality and robustness.

Table 5: **Comparison of 3D Face Reconstruction Benchmarks.** We compare data capture year, whether the benchmark evaluates posed and/or neutral geometry, expression diversity, viewpoint diversity, number of persons (#pers.) and number of GT scans.

	Year	posed	neutral	expression diversity	viewpoint diversity	#pers.	#Scans
Stirling Feng et al. (2018)	2013		✓		✓	133	133
REALY Chai et al. (2022)	2015	\checkmark				100	100
NoW Sanyal et al. (2019)	2019		\checkmark		\checkmark	80	80
FaceScape Zhu et al. (2023)	2020	\checkmark		\checkmark	\checkmark	20	20
Ours	2023	\checkmark	\checkmark	\checkmark	\checkmark	21	441

In table 5 we present a comparison of popular single-image face reconstruction benchmarks. However, we find that most existing benchmarks rarely evaluate extreme facial expressions, an important aspect of human face geometry. This can be seen in fig. 6 where we retrieve the 5 most expressive images from the recent FaceScape benchmark Zhu et al. (2023) and the established NoW benchmark Sanyal et al. (2019). We do this by running EMOCA Daněček et al. (2022) on each image of the dataset, collecting the expression codes, and then performing furthest point sampling in EMOCA's expression space, starting from the expression with highest norm. We find that FaceScape only contains 20 different but relatively articulated expressions while the NoW benchmark is dominated by mostly neutral and smiling expressions. We therefore propose a new benchmark for 3D face reconstruction that is sourced from images of the recently published multi-view video dataset NeRSemble Kirschstein et al. (2023). For 21 diverse identities, we select 20 distinct expressions via furthest point sampling in expression space, for a total of 420 images. The corresponding ground truth 3D geometries are obtained by running COLMAP Schönberger & Frahm (2016) on the 16 full resolution 3208x2200 images. Additionally, we compute one pointcloud for a neutral frame of each person, yielding 441 ground truth 3D geometries in total.

A.1.1 TASK DESCRIPTION

Our benchmark consists of two 3D face reconstruction tasks, given a single image as an input: *posed* and *neutral* 3D face reconstruction. It is the first benchmark that evaluates both settings at the same time. The following briefly defines the differences of both tasks.

Posed Reconstruction: The posed reconstruction task aims to measure the fidelity of a 3D reconstruction. Given an image of a face under arbitrary facial expression, the underlying geometry shall be recovered. This requires images with paired ground truth geometries which are available in NeRSemble trough COLMAP.

Neutral Reconstruction The neutral reconstruction task on the other hand is specific to the face domain and measures how well a reconstruction method can disentangle the



Figure 6: **3D Face Reconstruction Benchmark Analysis.** We show the 5 most diverse images from each benchmark dataset, as measured by the expression codes of EMOCA Daněček et al. (2022). Our benchmark covers a richer diversity of facial expressions.

effects of shape and expression on a human 3D face. Specifically, the task is to reconstruct the geometry of a person's face under neutral expression given an image of the person under any arbitrary expression. Hence, the reconstruction method needs to understand the current facial expression, how it deforms the geometry and how the face would look like under neutral expression. On the other hand, this task does not *explicitly* measure whether a method can reconstruct expressions well.

Comparison to Existing Benchmarks The two established benchmarks from Feng et al. (2018) and Sanyal et al. (2019) capture images and a 3D scan separately, therefore the observed expression does not match the ground truth geometry. As a consequence, these benchmarks can only measure *neutral* reconstruction performance. In contrast, two other recent benchmarks ((Zhu et al., 2023; Chai et al., 2022)) merely evaluate posed reconstructions. Our benchmark is the first to evaluate both tasks at the same time.

A.1.2 EVALUATION PROTOCOL

To measure the performance of a reconstructed posed or neutral 3D face, we follow established practice and first rigidly align the prediction to the ground truth point cloud via landmark correspondences and ICP. Furthermore, we use segmentation masks Zheng et al. (2022) to remove non-facial areas (hair, neck, ears, and mouth interior) from the ground truth. We then compute three metrics: (i) uni-directional L1 Chamfer distance from GT points to the nearest mesh surface, (ii) cosine similarity (NC) of predicted mesh normals and GT point cloud normals, and (iii) Recall thresholded at 2.5mm (R^{2.5}) which is the percentage of GT points whose nearest mesh surface is 2.5mm or closer.

A.2 Surface Normal Estimation

In this section we provide additional qualitative surface normal estimation results.

A.2.1 In-the-Wild Normal Estimation

One central quality of surface normal estimators, which ultimately makes them valuable to our community, is their generalization to arbitrary in-the-wild images of human heads. Thus, fig. 8 provides additional estimation results on the FFHQ dataset (Karras et al., 2019). Here, we qualitatively compare against results of two recent industry foundational models, Sapiens (Khirodkar et al., 2024) and DAViD (Saleh et al., 2025), as well as, Diff-E2E (Martin Garcia et al., 2025), another recent surface normal estimator distilled from StableDiffusion (Rombach et al., 2022). While Sapiens, tends to produce blurry results,

DIff-E2E over-emphasizes geometric details, resulting in unnatural sharp edges. Finally, DAViD, a concurrent work to ours, produces the most competitive results on such images. However, similar to our findings in the main paper, the synthetic training data of DAViD is clearly noticeable in its predictions. This can especially be seen in the estimated geometry in the eye region, and the flatness of predicted wrinkles and creases of the skin. Pixel3DMM tends to produces the most visually pleasing results, while all methods produce fairly robust estimates.

A.2.2 Additional Visualizations

Furthermore, we provide additional visualizations in fig. 9, which corresponds to the quantitative evaluation in table 4. Here, we also show error maps, visualized using a turbocoloring scheme. Please note that the camera registration in the H3DS dataset Ramon et al. (2021) is slightly misaligned, which results in significantly higher errors, compared to the NeRSemble Kirschstein et al. (2023) and MultiFace Wuu et al. (2022) evaluations. The error maps confirm our error analysis of the previous subsection. In general, all methods perform similar on in-the-wild and studio images, confirming their generalization abilities.

A.3 Additional Baselines

Finally, we present qualitative comparisons to VHAP (Qian et al., 2024) and Neural Head Avatars (NHA) (Grassal et al., 2022) in fig. 10. While both methods were originally designed for monocular video tracking, they can still be executed on a single image. However, the increased sparsity of a single observations results in poor 3d reconstructions. In particular, both approaches consist of a two stage reconstruction paradigm: In the first stage reconstruction is performed in the FLAME latent space, which heavily regularized the optimization problem. In the second stage, both methods optimize for per-vertex offsets, which increases the representational capacity. Especially, the second stage tends to overfit to the single-view observation and degrade 3d accuracy.



Figure 7: **Benchmark Overview:**

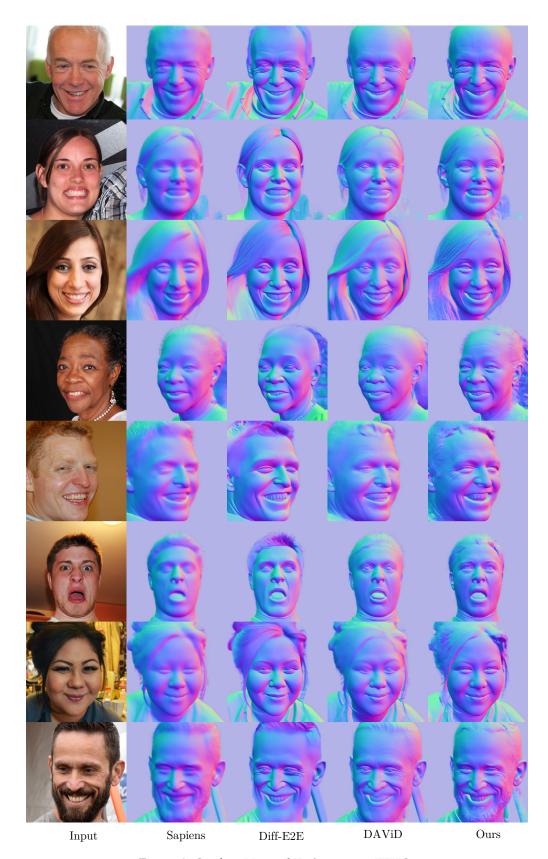


Figure 8: Surface Normal Estimates on FFHQ.

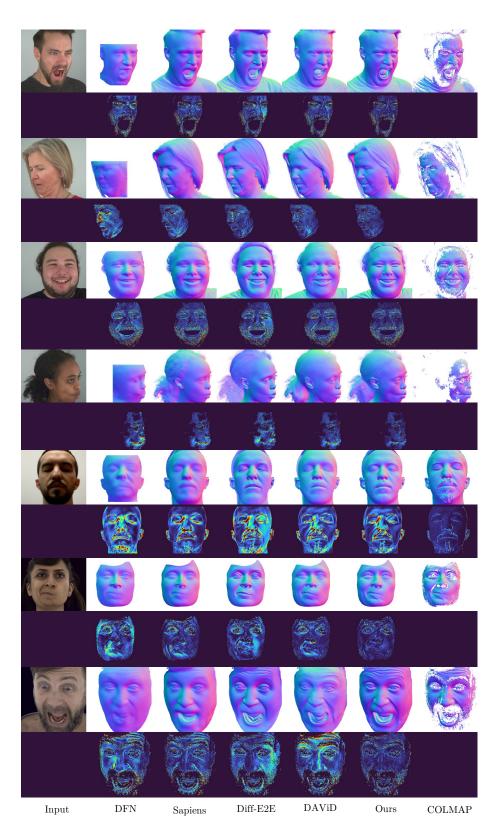


Figure 9: **Surface Normal Estimation:** The first four rows show results from NeRSemble, fllowed by one example from H3DS and two examples from MultiFace.

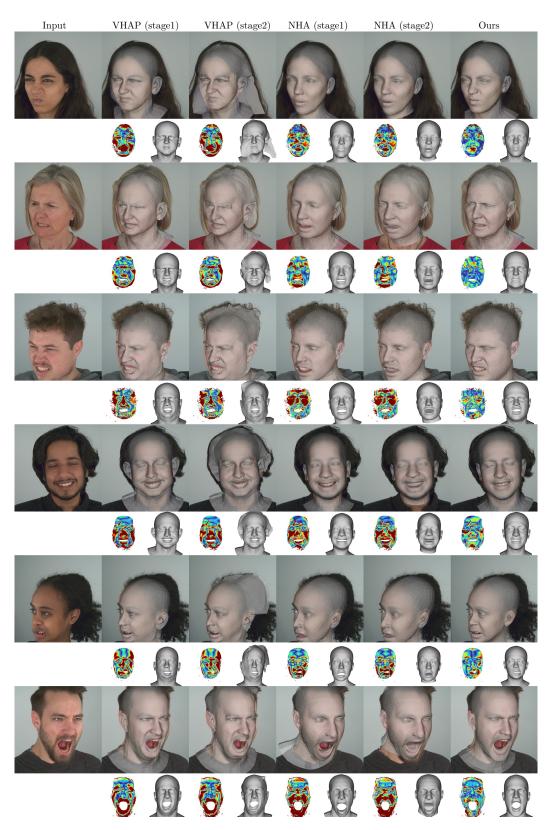


Figure 10: Additional Baselines: Posed reconstruction.