

Instant Volumetric Head Avatars

Wojciech Zieleńka Timo Bolkart Justus Thies
 Max Planck Institute for Intelligent Systems, Tübingen, Germany
 {wojciech.zielonka, timo.bolkart, justus.thies}@tuebingen.mpg.de

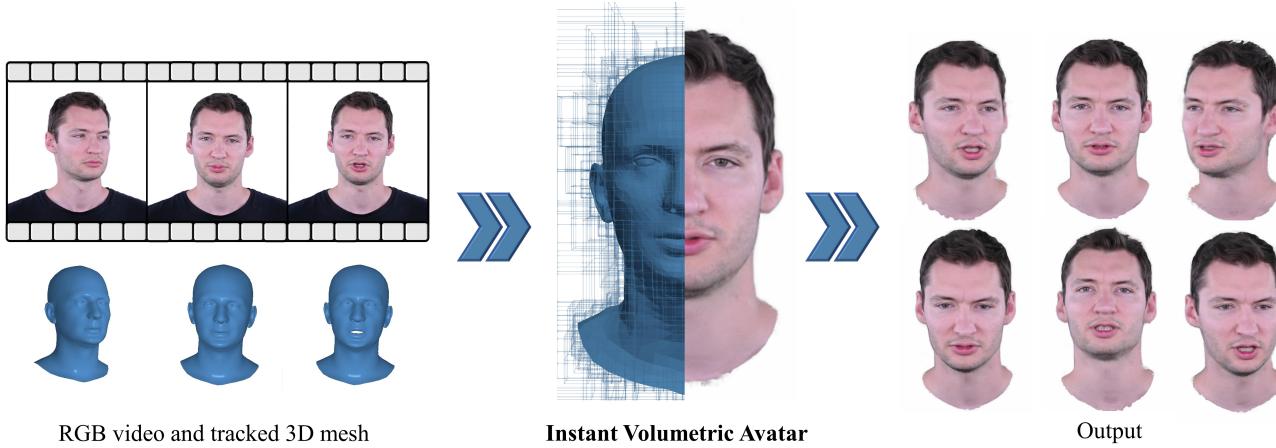


Figure 1. Given a short monocular RGB video, our method instantaneously optimizes a deformable neural radiance field to synthesize a photo-realistic animatable 3D neural head avatar. The neural radiance field is embedded in a multi-resolution grid around a 3D face model which guides the deformations. The resulting head avatar can be viewed under novel views and animated at interactive frame rates.

Abstract

We present *Instant Volumetric Head Avatars (INSTA)*, a novel approach for reconstructing photo-realistic digital avatars instantaneously. *INSTA* models a dynamic neural radiance field based on neural graphics primitives embedded around a parametric face model. Our pipeline is trained on a single monocular RGB portrait video that observes the subject under different expressions and views. While state-of-the-art methods take up to several days to train an avatar, our method can reconstruct a digital avatar in less than 10 minutes on modern GPU hardware, which is orders of magnitude faster than previous solutions. In addition, it allows for the interactive rendering of novel poses and expressions. By leveraging the geometry prior of the underlying parametric face model, we demonstrate that *INSTA* extrapolates to unseen poses. In quantitative and qualitative studies on various subjects, *INSTA* outperforms state-of-the-art methods regarding rendering quality and training time. Project website: <https://zielon.github.io/insta/>

1. Introduction

For immersive telepresence in AR or VR, we aim for digital humans (avatars) that mimic the motions and facial expressions of the actual subjects participating in a meeting. Besides the motion, these avatars should reflect the human's shape and appearance. Instead of prerecorded, old avatars, we aim to instantaneously reconstruct the subject's look to capture the actual appearance during a meeting. To this end, we propose Instant Volumetric Head Avatars (*INSTA*), which enables the reconstruction of an avatar within a few minutes (~ 10 min) and can be driven at interactive frame rates. For easy accessibility, we rely on commodity hardware to train and capture the avatar. Specifically, we use a single RGB camera to record the input video. State-of-the-art methods that use similar input data to reconstruct a human avatar require a relatively long time to train, ranging from around one day [20] to almost a week [16, 60]. Our approach uses dynamic neural radiance fields [16] based on neural graphics primitives [38], which are embedded around a parametric face model [25], allowing low training times and fast evaluation. In contrast to existing methods, we use a metrical face reconstruction [61] to ensure that the avatar has metrical dimensions such that it can be viewed in an

AR/VR scenario where objects of known size are present. We employ a canonical space where the dynamic neural radiance field is constructed. Leveraging the motion estimation employing the parametric face model FLAME [25], we establish a deformation field around the surface using a bounding volume hierarchy (BVH) [12]. Using this deformation field, we map points from the deformed space into the canonical space, where we evaluate the neural radiance field. As the surface deformation of the FLAME model does not include details like wrinkles or the mouth interior, we condition the neural radiance field by the facial expression parameters. To improve the extrapolation to novel views, we further leverage the FLAME-based face reconstruction to provide a geometric prior in terms of rendered depth maps during training of the NeRF [36]. In comparison to state-of-the-art methods like NeRFace [16], IMAvatar [60], or Neural Head Avatars (NHA) [20], our method achieves a higher rendering quality while being significantly faster to train and evaluate. We quantify this improvement in a series of experiments, including an ablation study on our method.

In summary, we present Instant Volumetric Head Avatars with the following contributions:

- a surface-embedded dynamic neural radiance field based on neural graphics primitives, which allows us to reconstruct metrical avatars in a few minutes instead of hours or days,
- and a 3DMM-driven geometry regularization of the dynamic density field to improve pose extrapolation, an important aspect of AR/VR applications.

2. Related Work

INSTA is reconstructing animatable digital human avatars from monocular video data based on 3D neural rendering [49]. Current solutions are using implicit representations [8, 16, 29, 36, 40, 41] optimized via differentiable volumetric rendering, or are based on explicit models [5, 7, 20, 51] for instance, triangle or tetrahedral meshes using differentiable rasterization [10, 22, 30, 33]. For a concise overview of neural rendering methods and face reconstruction, we point the reader to the state-of-the-art reports by Zollhöfer et al. [62], and Tewari et al. [48, 49].

Static Neural Radiance Fields. Mildenhall et al. [36] and its many follow-up works [3, 4, 28, 35, 39, 44, 46, 53, 58], synthesize novel views of a complex static scene using differentiable volumetric rendering. Many methods suffer from a long training time (1-5 days). To this end, different acceleration methods have been proposed to improve the training time. Yu et al. [15] achieved 100 \times speedup by using a sparse voxel grid storing density and spherical harmonics coefficients at each node. The final color is the composition of tri-linearly interpolated values of each voxel in-

tersecting with the ray. TensorRF [9] factorizes the 4D NeRF scene into multiple compact low-rank tensor components achieving high performance and compactness. The coordinate-based MLP is replaced with a voxel grid of features, and the final color is its vector-matrix outer product. Müller et al. [38] introduced a new computer graphics primitive in the form of tiny MLPs which benefit from a multi-resolution hashing encoding. The key idea is similar to Yu et al. [15]. The space is divided into an independent multi-level grid with feature vectors at the vertices of the grid. A spatial hash function [47] is used to store the voxel grid efficiently. Each point sampled on the ray is encoded by the interpolated feature vector of the corresponding grid level and passed to a tiny neural network to synthesize the final color. Our method uses this efficient architecture to model the face in a canonical space.

Some of the static NeRF methods [2, 13, 44, 54] use additional depth maps to improve alignment and quality for static scenes. The depth priors help guide the ray sampling and better estimate the transmittance, resulting in improved geometry and color recovery. While we are working with RGB images only, our method leverages the geometry prior of the 3DMM to guide the depth estimation during training, which results in an improved extrapolation ability w.r.t. view changes.

Deformable Neural Radiance Fields. After the introduction of NeRF [36] for static scenes, a natural research direction was to generalize it to dynamic, time-varying ones [14, 26, 40, 41, 43, 52]. The reconstruction problem is divided into two different spaces, the deformed scene, and the canonical space, with a neural network as the mapper between them. For human body modeling, a series of approaches have been proposed that leverage the kinematic chain of the SMPL [32] body model to condition the mapping function. Peng et al. [42] proposed to learn blend weights to estimate the linear blend skinning-based warping field between canonical and deformed space based on the body skeleton. Similarly, Neural Actor [29] uses a 3D body mesh proxy to learn pose-dependent geometric deformation and view-dependent appearance effects defined in the canonical space. Lombardi et al. [31], which defines surface-aligned neural volumes to improve the rendering speed. Garbin et al. [18] build a tetrahedral deformation graph around a radiance field based on the underlying mesh on which the deformations are defined, effectively transforming sampled points according to the current cage state. Xu et al. [55] propose surface-aligned neural radiance fields by projecting points in space to the surface of the body mesh. Our idea is based on a similar principle. However, instead of projecting points onto the mesh surface, we construct a 3D space around the head and deform points based on the deformation defined by the nearest triangles.

In contrast to modeling the deformation explicitly, Gafni

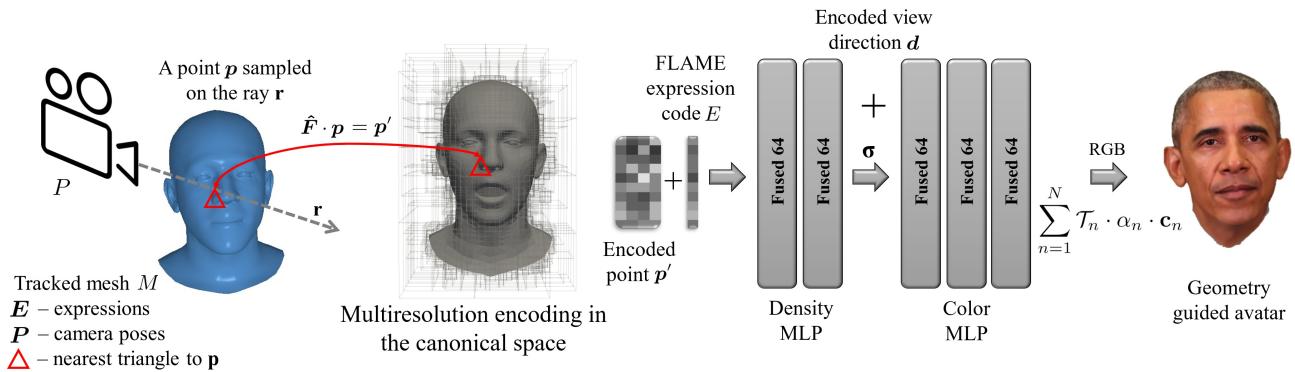


Figure 2. **Overview.** INSTA follows differentiable volumetric optimization introduced in [36, 38]. For each sampled point $p \in \mathbb{R}^4$ in deformed space (in homogeneous coordinates), we are computing the nearest neighbor triangle on the mesh $T_{def} \in \mathcal{M}_i$ and its topological corresponding twin in the canonical space $T_{canon} \in \mathcal{M}^{canon}$. The deformation gradient of the triangle from deformed space to canonical space $\hat{F} \in \mathbb{R}^{4 \times 4}$ defines the deformation field. Specifically, p is transformed to the canonical space by $p' = \hat{F} \cdot p$. After canonicalization, the point is encoded using a multi-resolution hashing [38]. This feature is passed to fully fused multi-layer perceptrons [37] with additional conditioning on the facial expressions E_i and the encoded view direction d .

et al. [16] implicitly model the facial expressions by conditioning the NeRF MLP with the global expression code obtained from 3DMM tracking [51] and by optimizing per latent frame codes to increase the network capacity for overfitting. In our approach, we leverage the idea of dynamic neural radiance fields to improve the mouth region’s rendering, which is not represented by the face model motion prior. Inspired by 3DMMs, IMAvatar [60] learns the subject-specific implicit representation of texture together with expression blendshapes and blend skinning weights. They optimize an implicit surface by incorporating ray marching from Yariv et al. [56] with root-finding of the occupancy function [11] to locate canonical correspondence of deformed points. However, we found the training time-consuming (~ 5 days) and unstable (can diverge). In a concurrent work, Gao et al. [17] create personalized blendshapes using neural graphics primitives, where for each of the blendshape, a multi-resolution grid [38] is trained.

3. Instant Deformable Neural Radiance Field

Our goal is to create instant digital avatars which can be learned in a few minutes and rendered in interactive time. For this purpose, we are using a geometry-guided deformable neural radiance field embedded into a multi-resolution hashing grid [38], exploiting differentiable volumetric rendering [36] (see Fig. 2).

For a given monocular video consisting of images $I = \{I_i\}$ along with optimized intrinsic camera parameters $K \in \mathbb{R}^{3 \times 3}$, tracked FLAME [25] meshes $M = \{M_i\}$ with corresponding facial expression coefficients $E = \{E_i\}$ and poses $P = \{P_i\}$, our goal is to build a controllable head avatar represented by a neural radiance field. To this end,

we employ a canonical space where the neural radiance field is constructed. To render specific facial expressions using volumetric rendering, we canonicalize the samples on a ray from the deformed space to query the radiance field in the canonical space.

Volumetric Rendering. We take advantage of the recent advances in interactive NeRF optimization and use neural graphic primitives [38] to represent the radiance field. The representation of the avatar is optimized using the differentiable volumetric rendering equation:

$$\hat{C} = \int_0^D \mathcal{T}(t) \cdot \sigma(t) \cdot \mathbf{c}(t) dt + \mathcal{T}(D) \cdot \mathbf{c}_{bg}, \quad (1)$$

where $\mathcal{T}(t_n) = \exp \left(- \int_0^{t_n} \sigma(t) dt \right)$ is the transmittance which indicates the probability of a ray traveling from $[0, t_n]$ without interaction with any other particles [36], $\sigma(t)$ is the density and $\mathbf{c}(t)$ is the radiance at position p_t . Note that the sample points p_t are canonicalized to access the actual radiance field. Following NeRFace [16], we condition every sample p_t on the ray with the 3DMM facial expression code $E_i \in \mathbb{R}^{16}$ of video frame i . Please note that in contrast to NeRFace [16] and IMAvatar [60], we do not use additional per-frame learnable codes. The viewing vector is encoded using spherical harmonics projection on four basis functions [1, 38]. We concatenate it with the ray direction vector resulting in the final viewing vector encoding $d \in \mathbb{R}^{12+4}$. While the viewing conditioning is applied on the entire avatar, the conditioning on facial expressions is bounded to the dynamically changing mouth region and is set to a constant vector $E_i = 1$ for the other regions.

Canonicalization. We define a mapping function $\Phi(p, M_i)$

that projects a point $\mathbf{p} \in \mathbb{R}^4$ from the time-varying deformed space (where the volumetric rendering is performed) to the canonical space. The mapping function leverages the time-varying surface approximation M_i and a predefined mesh in canonical space M^{canon} . We employ a nearest triangle search in deformed space to compute the deformation gradient $\mathbf{F} \in \mathbb{R}^{4 \times 4}$ which is used to map point \mathbf{p} to the canonical counterpart \mathbf{p}' . The deformation gradient \mathbf{F} is computed via the known Frenet frames of the deformed triangle $T_{def} \in M_i$ and the canonical triangle $T_{canon} \in M^{canon}$. Specifically, we compute the matrices $\{\mathbf{R}_{canon}, \mathbf{R}_{def}\} \in \mathbb{R}^{3 \times 3}$ based on the corresponding tangent, bitangent, and normal, and combine it with translations $\{\mathbf{t}_{canon}, \mathbf{t}_{def}\} \in \mathbb{R}^3$ to get the Frenet coordinate system frames \mathbf{L}_{canon} and \mathbf{L}_{def} (Eq. (2)). Please note that our \mathbf{R} matrices are not orthonormal since we include an anisotropic scaling factor to account for a potential triangle size change between deformed and canonical spaces. Finally, the deformation gradient is defined as:

$$\begin{aligned} \mathbf{F} &= \mathbf{L}_{canon} \mathbf{L}_{def}^{-1}, \\ \mathbf{L}_{def} &= \begin{bmatrix} \mathbf{R}_{def} & \mathbf{t}_{def} \\ 0 & 1 \end{bmatrix}, \\ \mathbf{L}_{canon} &= \begin{bmatrix} \mathbf{R}_{canon} & \mathbf{t}_{canon} \\ 0 & 1 \end{bmatrix}. \end{aligned} \quad (2)$$

To avoid transformation discontinuity, which arises from the local coordinate system of each triangle, for the selected area, we additionally perform exponentially weighted averaging of the transformations of the adjacent faces of the triangle's edges:

$$\hat{\mathbf{F}} = \frac{1}{\sum_{f \in A} \omega_f} \cdot \sum_{f \in A} \omega_f \mathbf{F}_f, \quad (3)$$

where $\omega_f = \exp(-\beta ||\mathbf{c}_f - \mathbf{p}||_2)$, $\beta = 4$ and A is the set of adjacent faces to \mathbf{T} (including \mathbf{T}) with corresponding centroids \mathbf{c}_f .

To achieve interactive rendering as well as instantaneous optimization of the neural radiance field, we leverage a classical bounding volume hierarchy (BVH) [12] to significantly increase the nearest triangle search speed for the sampled points \mathbf{p}_t on the ray. Note that methods like IMAvatar [60] performs heavy root-finding procedures to calculate surface points iteratively [11]. Our method builds a BVH based on the corresponding deformed mesh M_i of frame i to establish the mapping function to the canonical mesh. This gives a constant time $\mathcal{O}(1)$ for transformations between deformed and canonical space. Our BVH is implemented on GPU to utilize massively parallel nearest triangle search [23]. To alleviate the triangle search for highly tessellated FLAME regions, we simplified [19] the eyeballs and the eye region. Moreover, we added an additional set

of triangles in the mouth region to serve as a deformation proxy.

3.1. Training Objectives

The optimization of the neural radiance field is based on a color reproduction objective and a geometry prior based on the 3DMM. Following NeRF [36], we redefine the volumetric rendering Equation (1) with piece-wise constant density and color and rewrite it in terms of alpha-compositing:

$$\hat{\mathbf{C}}(t_{N+1}) = \sum_{n=1}^N \mathcal{T}_n \cdot \alpha_n \cdot \mathbf{c}_n, \quad (4)$$

where $\mathcal{T}_n = \prod_{n=1}^{N-1} (1 - \alpha_n)$ and $\alpha_n \equiv 1 - \exp(-\sigma_n \delta_n)$. To measure the photometric error, we use a Huber loss [21] with $\delta = 0.1$:

$$\mathcal{L}_{color} = \begin{cases} \frac{1}{2} (\mathbf{C} - \hat{\mathbf{C}})^2 & \text{if } |(\mathbf{C} - \hat{\mathbf{C}})| < \delta \\ \delta((\mathbf{C} - \hat{\mathbf{C}}) - \frac{1}{2}\delta) & \text{otherwise} \end{cases} \quad (5)$$

We enforce a depth loss to leverage the geometry prior of the reconstructed face based on the 3DMM FLAME. Specifically, we rasterize the depth of the tracking mesh M_i and apply an L1 distance between this map and the ray termination of the volumetric rendering. As the FLAME model does not contain details like hair, we restrict the geometry prior to the face region:

$$\mathcal{L}_{geom} = \sum_r |\mathbb{1}_{face}\{(z(r) - \hat{z}(r))\}|, \quad (6)$$

where $\hat{z} = \sum_{n=1}^N \mathcal{T}_n \cdot \alpha_n \cdot t_n$, and t_n is the current sample position, and $\mathbb{1}_{face}\{\cdot\}$ is a segmentation indicator function which enables the loss for the face region. The $\mathbb{1}_{face}$ function uses face parsing information [57] to decide a given pixel membership. The total loss \mathcal{L} is defined as:

$$\mathcal{L} = \sum_r \lambda_{color}(r) \mathcal{L}_{color}(r) + \lambda_{geom} \mathcal{L}_{geom}(r), \quad (7)$$

where $\lambda_{geom} = 1.25$ controls the influence of the geometry prior and $\lambda_{color}(r)$ weights the color loss contribution based on a face parsing mask. Specifically, we weight the color loss higher for the mouth region with $\lambda_{color} = 40$ and $\lambda_{color} = 1$ otherwise (see ablation studies for the influence of this weighting).

We implemented our animatable dynamic radiance field using the Nvidia NGP C++ framework [37]. We use two fully fused MLPs [37], each with 64 neurons, for color and density predictions. The density MLP outputs log-space values $\sigma \in \mathbb{R}^{16}$ which are later concatenated with the encoded viewing vector \mathbf{d} to be the input of the color network. For optimization, we used Adam [24] with an exponential moving average on the weights and fixed learning rate

$\eta = 2.5e-3$. In our experiments, we train the network for 32k optimization steps. We randomly sample 1700 frames from the whole dataset during the training and load them into the processing buffer. Every 1500 steps, we repeat the procedure and resample the dataset. In Table 1, we detail the hyperparameters of the hashing grid used to store the radiance field.

Parameter	Value
Number of levels	16
Hash table size	2^{17}
Number of feature per entry	8
Coarsest resolution	16
Finest resolution	2048

Table 1. Hyperparameters used for the hash encoding grid [38].

4. Dataset

Our method takes a single video as input to generate the volumetric avatar of the depicted subject. For our experiments, we recorded multiple actors with a Nikon Z6 II Camera as well as use sequences from Youtube, resulting in a set of twelve actors. For the in-house recordings, we captured around 2-3min of monocular RGB Full HD videos, which later were cropped, sub-sampled to 25fps, and resized to 512^2 resolution. We additionally use background foreground segmentation using robust matting [27] and an off-the-shelf face parsing framework [57] for image segmentation and clothes removal.

Dataset Tracking Generation. An essential part of this project is temporally stable face tracking of the monocular input data. To this end, we use the analysis-by-synthesis-based face tracker from MICA [61], based on Face2Face [51] using a sampling-based differentiable rendering. We extend the optimization with two extra blendshapes for eyelids and iris tracking using Mediapipe [34]. In contrast to MICA, we also optimize for FLAME shape parameters, with regularization towards MICA shape prediction instead of the average face shape as in Face2Face [51]. Note that for our prototype, we implemented the tracking in PyTorch, which is significantly slower than the original Face2Face implementation, which can track faces in real-time.

5. Results

In this section, we evaluate the quality of the synthesized digital human avatars generated by our method INSTA in comparison to state-of-the-art. For this purpose, we use the test sequences from our dataset, which consist of the last

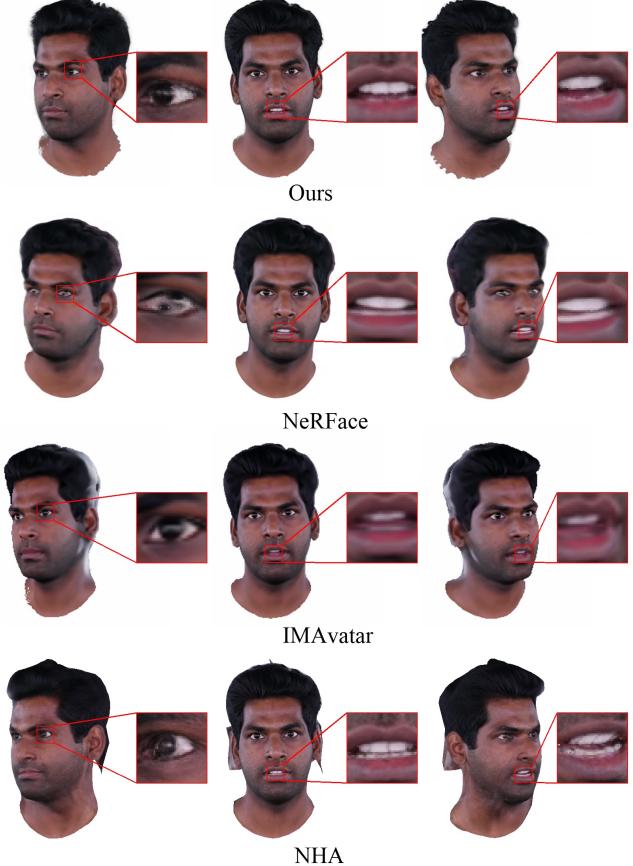


Figure 3. Qualitative comparison for novel view extrapolation. As can be seen, our method can better handle image synthesis under novel poses. NHA [20] suffers from degenerated geometry with many artifacts at the ear region. NeRFace [16] lacks high-frequency details for eyes and teeth, and IMAvatar [60] shows silhouette artifacts at grazing angles.

350 frames of each video. For more comparisons and results, please see the supplemental document and video.

5.1. Image Quality Evaluation

To evaluate our method in terms of the image quality and novel view extrapolation, we make a comparison to NeRFace [16], IMAvatar [60], and Neural Head Avatars (NHA) [20]. For this comparison, we use the original implementations of the authors. Note that for IMAvatar, we use the most recent version of the author's code, which contains additional semantic information for mouth interior and FLAME geometry supervision which is different from the original paper. Figure 4 depicts qualitative results evaluated on the test sequences. To evaluate the image quality of the results quantitatively, we use several pixel-wise metrics; mean squared error, SSIM, PSNR, and the perceptual metric LPIPS [59] (see Table 2). Note that IMAvatar is trained at a resolution of 256^2 due to its computational complexity; for the comparison, we upsample the results to 512^2 .



Figure 4. Qualitative comparisons show that our method produces high-quality facial avatars which beat the state-of-the-art methods in terms of image quality (e.g., capturing fine details like lips and teeth) while being significantly faster to obtain (see Table 3).

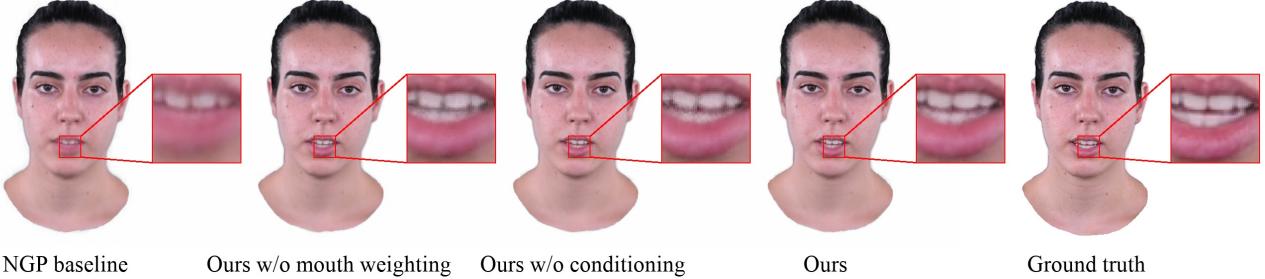


Figure 5. Embedding the neural radiance field around the deformable face model allows us to model dynamic sequences in contrast to the static radiance field of NGP [38]. Moreover, expression conditioning and face-parsing-based weighting in the mouth interior region help get sharper results for teeth.

Method	L2 ↓	PSNR ↑	SSIM ↑	LPIPS ↓
NHA [20]	0.0018	28.65	0.96	0.03
IMAvatar [60]	0.0014	29.10	0.95	0.06
NeRFace [16]	0.0010	30.87	0.96	0.05
Ours	0.0010	30.51	0.96	0.03

Table 2. Average photometric errors over all videos from our dataset (see Fig. 4). Our method is on par with NeRFace of Gafni et al. with respect to the pixel-wise error metrics. However, our approach achieves the lowest perceptual error in comparison to all methods while being significantly faster to train and evaluate. See Sup. Mat. for the video with qualitative comparison.

All methods produce sharp and photo-realistic images which are hard to distinguish from the ground truth. However, the most noticeable artifacts, especially for the ear regions, were generated by NHA. Moreover, IMAvatar, for some of the videos, had problems with convergence and stability, leading to diverging optimization and premature termination of the training. Compared to these methods, our approach can achieve the best image quality while being significantly faster to train (see Table 3).

Extrapolation to novel views is an essential aspect of 3D digital avatars that are used in AR or VR applications. In Figure 3, we depict a viewpoint extrapolation comparison with the baseline methods. We can observe that NeRFace [16] produces blurry results in the area of eyes and teeth. IMAvatar [60] exhibits artifacts at gracing angles at the silhouette, and NHA [20] suffers from degenerated geometry with strong artifacts at the ears. In contrast to these methods, our method can robustly generate photo-realistic images under novel poses and achieves high visual quality, especially in the skin and mouth region.

5.2. Ablation Studies

To analyze the different components of our pipeline, we conducted a series of ablation studies. Specifically, we are interested in the influence of localized expression conditioning for teeth quality (Figure 5), the influence of the geometric prior (Figure 8), especially for the novel view synthesis,

as well as the influence of our smooth mapping function from deformed to canonical space (Figure 6).

Smooth Mapping Function. To avoid discontinuities in the mapping from deformed to canonical space, we compute a weighted transformation based on the adjacent faces of the nearest triangle, as defined in Equation (3). In Figure 6, we depict this smoothing effect; discontinuities on the edges of the triangles are resolved with the interpolation.

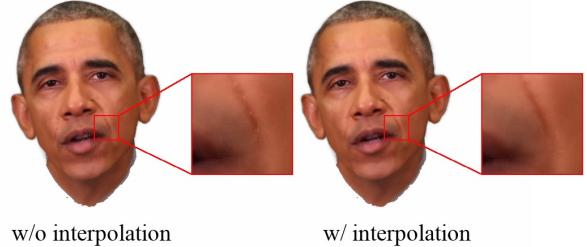


Figure 6. A smooth mapping function from deformed to canonical spaces helps to reduce artifacts introduced by the local coordinate frames of a single triangle.

Geometric Prior. We leverage the geometric prior of the 3DMM FLAME [25] to regularize the depth estimations of our volumetric rendering method. During training, we render depth maps of the per-frame 3DMM reconstructions and measure a loss between the estimated ray termination and the depth of the rendered face model. In Figure 8, we show an ablation study w.r.t. this geometric prior. The generated digital avatar is shown from an unseen profile view, an extreme extrapolation from the training data which observed views in a range of $\pm 40^\circ$. As can be seen, using the additional geometric prior greatly improves the stability and quality of the reconstruction.

Expression Conditioning. Most publicly available 3DMMs [6, 25] do not explicitly model teeth. However, this region is especially challenging for the reconstruction of 3D facial avatars due to highly dynamic lips, which can occlude the teeth depending on the given expressions. To compensate the missing geometry, we condition this region

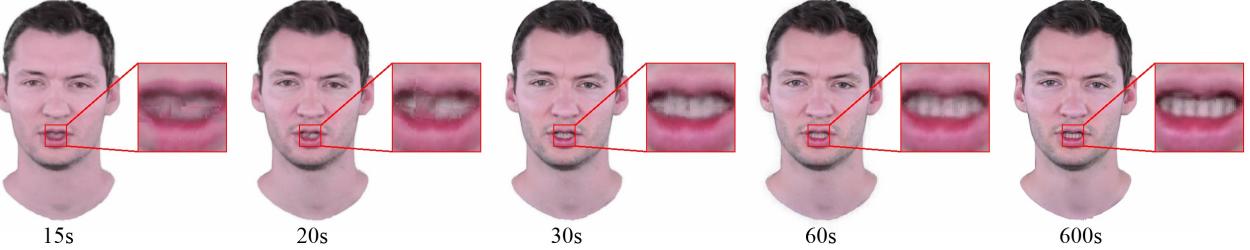


Figure 7. INSTA allows training personalized volumetric avatars from RGB videos within a couple of seconds. Already after 30 seconds of optimization, we achieve good results where the geometry and appearance match the input. To improve the reconstruction of high-frequency details like teeth, the method needs to train approximately 10 min.

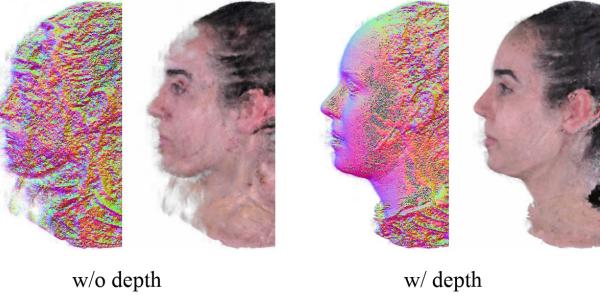


Figure 8. The incorporation of the geometric prior of the 3DMM-based face reconstruction helps for extrapolation to extreme novel views, in this case, 90°.

on FLAME expression coefficients. In Figure 5, we show that using this additional information helps to improve the synthesis of the mouth interior. Furthermore, we demonstrate that a higher color term weight on the mouth region (Equation (7)) improves the visual quality.

5.3. Training Time Evaluation

In Table 3, we present the average training times for each method. Our method uses a local gaming PC equipped with a modern GPU Nvidia RTX 3090 and requires about 10 min to reconstruct a volumetric avatar with high-frequency details (see Figure 7). For the baselines, we use their original configurations on a compute cluster. Specifically, an Nvidia Quadro 6000 was used for the single GPU methods [16,60], and for NHA [20], three Nvidia A100 40GB GPUs were used. While running on commodity hardware, our method is orders of magnitude faster than the others, making it more versatile and energy-saving.

6. Discussion

While our method INSTA shows better quality and speed compared to state-of-the-art RGB-video-based avatar generation techniques, there are still several challenges that need to be addressed in future work. Our model handles the dynamically changing facial expressions but does not capture dynamically changing hairs. Thus, the hair quality

Method	Time	Units	GPUs
IMAvatar [60]	~ 4	day	1
NeRFace [16]	~ 3	day	1
NHA [20]	~ 13	hour	3
Ours	~ 10	minute	1

Table 3. Average training times for the avatar creation at a resolution of 512^2 , except IMAvatar which is using 256^2 . Note that the dataset generation for each of the methods is not taken into consideration and only the avatar training time is measured.

is not on par with the face interior and still needs improvements in the level of detail. Furthermore, the used 3DMM does not model teeth geometry. A better approximation of the mouth region would increase the viewpoint extrapolation with improved quality of teeth. While our method achieves real-time frame rates for rendering at a resolution of 512^2 , the rendering speed needs to be improved to enable high-quality video conferences in AR or VR, especially when a higher resolution is required. With additional engineering, the training process of our method could be moved to a background process which would continuously refine our canonical avatar after an initial warm-up stage. For example, regions initially not visible could be captured during the conversation, and the avatar would be updated accordingly.

7. Conclusion

Instant Volumetric Head Avatars (INSTA) is a novel approach that instantaneously optimizes geometry-guided 3D digital avatars. Our method takes a monocular RGB video as input and optimizes a subject’s dynamic neural radiance field in less than 10 minutes using neural graphics primitives embedded around a 3DMM. In comparisons and ablation studies, we demonstrate the capabilities of INSTA, which enable us to instantaneously create avatars that reflect reality and not a prerecorded appearance that might deviate from the current look of the person. We believe this paradigm change to adaptable online avatars is a stepping stone toward immersive telepresence applications.

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Instant Volumetric Head Avatars – Supplemental Document –

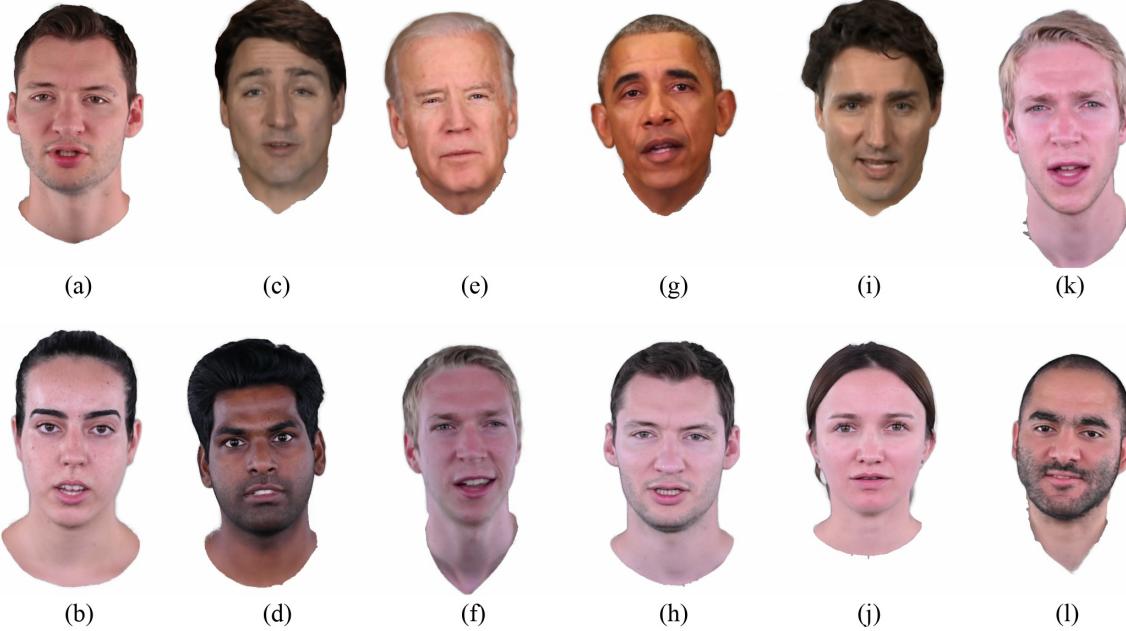


Figure 9. Our dataset consists of twelve sequences obtained from both in-house recordings and YouTube. Here, we present their respective volumetric avatars which INSTA optimizes in less than 10 minutes. As can be seen, our method works well in both cases producing photorealistic videos even for in-the-wild sources (c, e, g, i). Please see the supplemental video for animations of these avatars.

This document elaborates on additional results and potential applications beyond volumetric video conferencing. Specifically, we cover details about the acceleration structures for ray sampling with respect to the neural graphic primitives [38] (see Appendix A). We demonstrate facial expression transfer in Appendix B. In Appendix C, we show additional qualitative and quantitative results in terms of predicted normal and error maps.

A. Implementation Details

Accelerated Ray Marching. INSTA is based on NGP [38], which achieves significant speedup by adapting the sampling strategy utilizing occupancy grids. For a given scene, a separate grid of 128^3 is used to store an occupancy bit. During ray marching for a given sample point, a bit value is measured to determine if this position should be skipped. In this way, samples in empty spaces can be effectively omitted. The occupancy grid is continually updated during the training based on the density values that can be predicted from the neural graphic primitives. To accommodate dynamic scenes, we adapted this mechanism. Specifically, we construct the acceleration structure in the de-

formed space where we shoot rays, which is different from the canonical space where the neural graphic primitives are learned. Throughout the training, the acceleration structure converges to a Boolean union across all expressions in the training dataset.

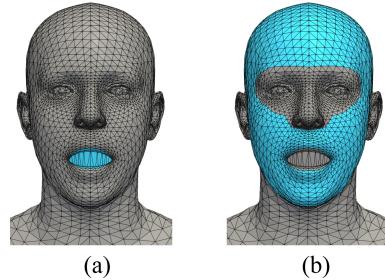


Figure 10. For the expression conditioning, we only consider the mouth region as depicted in (a). As the skin regions in (b) have large triangles, the mapping function from deformed to canonical space has to be smoothed in these regions.

FLAME masks. Our method uses two masks defined on the FLAME topology for expression conditioning (Section 3, main paper) and for the smooth mapping function (Equa-

tion 3, main paper). Figure 10 depicts these regions: the mouth region for the expression conditioning to handle the changing appearance of the mouth interior, and the skin region where large triangles lead to discontinuities in the mapping transformation, and thus, need to be smoothed.

B. Applications

Our volumetric avatars have many potential applications. Because they are controlled by a parametric face model, it can also be used for expression transfer. Expression transfer has been demonstrated in a variety of state of the art methods on facial avatar reconstruction [16, 20, 50, 51, 60]. Specifically, the expression from a source subject is captured and then applied to a facial avatar of a different person. Figure 11 shows that our method can be used for such an application.

C. Additional Results

In Figure 14, we present estimated geometry as normal maps. NeRF [36] can recover geometry, but it contains noise. Therefore, NeRFace [16], which is based on NeRF, inherits the same problem. In contrast, NHA [20] uses an explicit mesh representation based on the FLAME topology. However, NHA produces deformed geometry, especially, for the ears. Moreover, the optimized geometry is low-quality and misses many details, which are compensated by neural textures in the final image synthesis. IMAvatar [60] is able to recover high-quality geometry. The approach, based on IDR [56], can take up to several days to optimize the dynamic occupancy field. In contrast, our approach only needs a fraction of this time to optimize an avatar. In the face region, the geometry quality is on par with IMAvatar. However, at the hair region where we do not have access to a geometric prior, the quality is similar to NeRFace. In addition to the normal maps, we show the photo-metric error for a single frame in Figure 12 using an RGB-base ℓ_1 metric; a perceptual evaluation for the entire sequences are shown in Figure 13.

D. Broader Impact

INSTA synthesizes photo-realistic volumetric avatars from monocular RGB images and can extrapolate to novel views utilizing the 3DMM geometry prior. Since INSTA does not require sophisticated capture setups, it can be applied to standard videos that can be captured with a webcam or a smartphone or downloaded from YouTube. While our research focuses mainly on connecting people via teleconferencing, there is a risk of misuse. Specifically, our method could be abused to produce so-called DeepFakes, which can be used for misinformation, cyber mobbing, identity theft, or other harmful criminal acts. Unfortunately, we are not able to prevent the misuse of our technology. However,



Figure 11. Expression transfer: (a) source actor, (b-e) target subjects with expression from (a).

conducting research openly and transparently could raise awareness of nefarious uses. We will share our codebase to enable research on digital multi-media forensics, where synthesis methods are needed to produce a training corpus for forgery detection [45].

All participants in the study have given written consent to the usage of their video material for this publication.

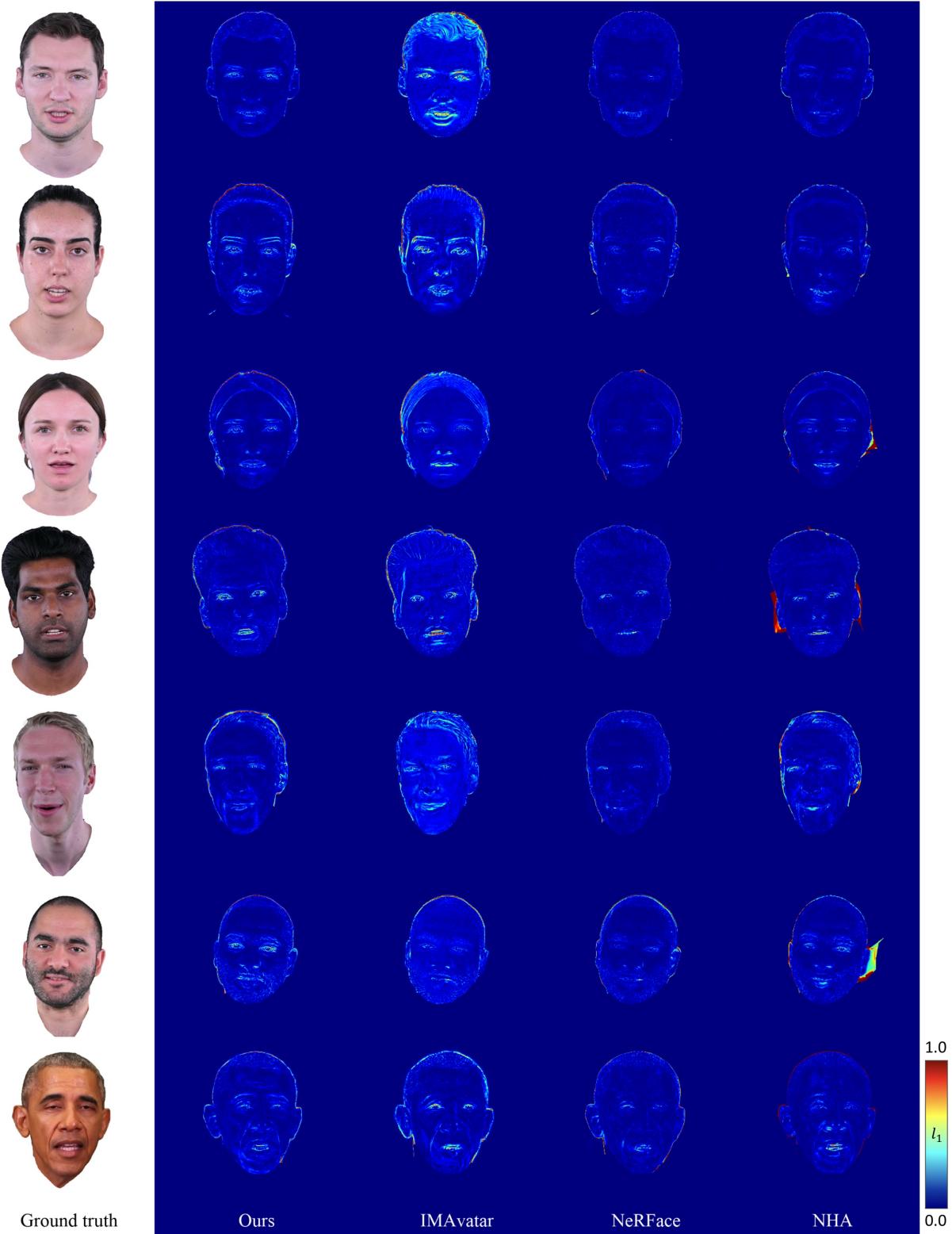


Figure 12. The heatmaps based on l_1 RGB distance represent photo metric errors on the test sequences. IMAvatar [60] synthesizes images with a low level of detail. Geometry mispredictions of NHA [20] create artifacts around the ear region.

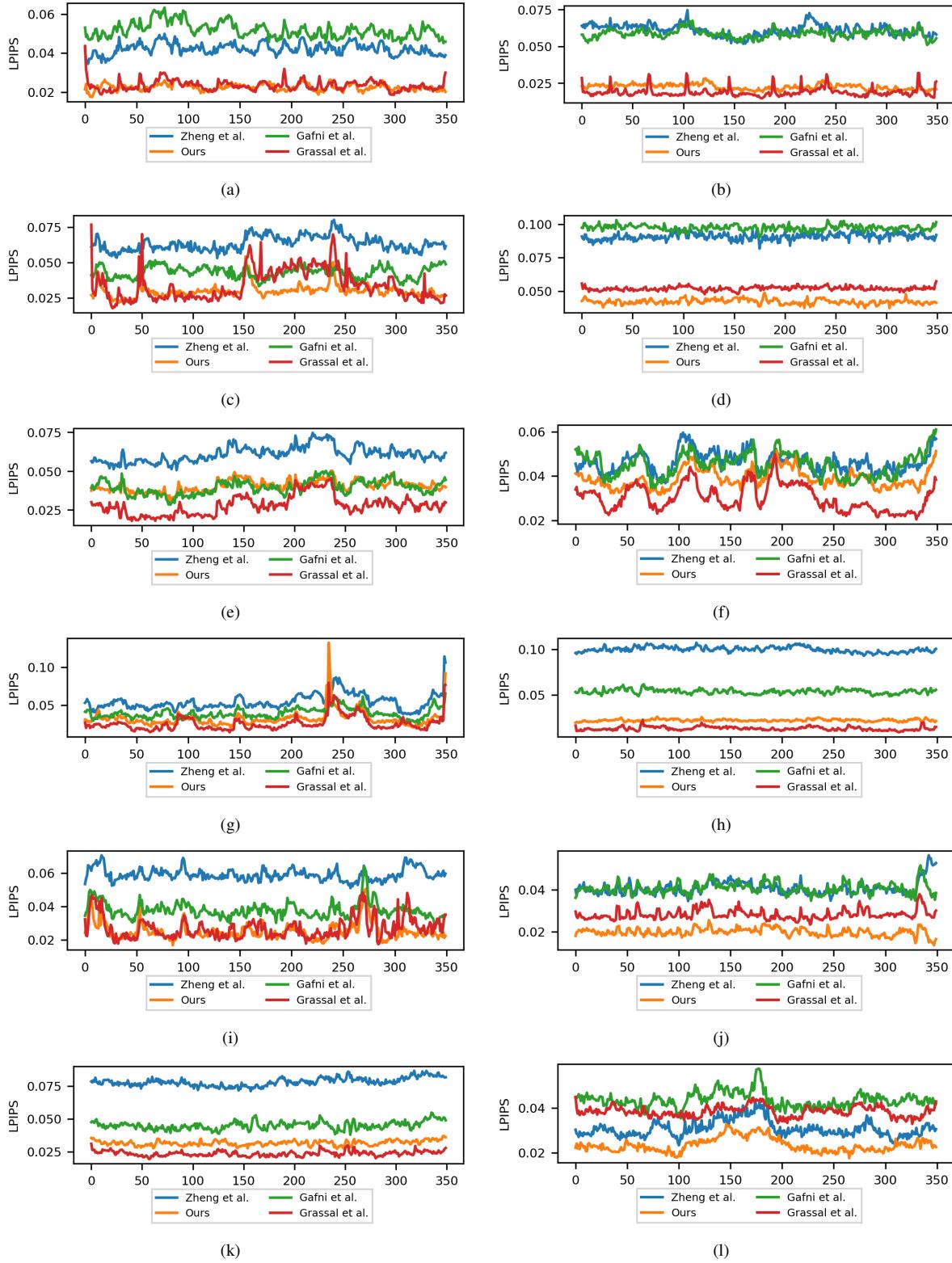


Figure 13. Evaluation of the perceptual error for each of the volumetric avatars from our dataset on the test sequence. The alphanumeric order matches Figure 9. Our method achieves the lowest errors for color reconstruction and captures well even high-frequency details like freckles or wrinkles.



Figure 14. NeRF [36] produces noisy normals maps, which can be seen in the results of Gafni et al. Our method uses additional geometric prior, which helps reduce the noise in specific areas, however, regions like hair are still problematic. The best results are achieved by IMAvatar [60], which is based on a modified version of IDR [56] approach. However, it takes a few days to achieve this result, while ours reaches similar quality, especially, in the face region, in about 10min.