I M Avatar: Implicit Morphable Head Avatars from Videos

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Abstract

Traditional morphable face models provide fine-grained control over expression but cannot easily capture geometric and appearance details. Neural volumetric representations approach photo-realism but are hard to animate and do not generalize well to unseen expressions. To tackle this problem, we propose I Mavatar (Implicit Morphable avatar), a novel method for learning implicit head avatars from monocular videos. Inspired by the fine-grained control mechanisms afforded by conventional 3DMMs, we represent the expression- and pose-related deformations via learned blendshapes and skinning fields. These attributes are pose-independent and can be used to morph the canonical geometry and texture fields given novel expression and pose parameters. We employ ray tracing and iterative root-finding to locate the canonical surface intersection for each pixel. A key contribution is our novel analytical gradient formulation that enables end-to-end training of I Mavatars from videos. We show quantitatively and qualitatively that our method improves geometry and covers a more complete expression space compared to state-of-the-art methods.

1. Introduction

Methods to automatically create animatable personal avatars in unobtrusive and readily available settings (i.e., from monocular videos) have many applications in VR/AR games and telepresence. Such applications require faithful renderings of the deforming facial geometry and expressions, detailed facial appearance and accurate reconstruction of the entire head and hair region. Conventional methods \cite{15, 17, 19, 20, 41, 43, 45, 47} based on morphable mesh models \cite{3, 27, 36} can fit the shape and texture parameters to images for a given subject. However, mesh-based approaches suffer from an inherent resolution-memory trade-off, and cannot handle topological changes caused by hair, glasses, and other accessories. Recent methods build on neural radiance fields \cite{30} to learn personalized avatars \cite{18, 34, 35} and yield high-quality images, especially if the generated expressions are close to the training data. A key challenge for building animatable facial avatars with implicit fields is the modeling of deformations. Previous works either achieve this by conditioning the implicit representation on expressions \cite{18} or via a separate displacement-based warping field \cite{34, 35}. Such under-constrained formulations limit the generalization ability, requiring large sets of training poses.

In this paper, we propose Implicit Morphable Avatar (IMavatar), a novel approach for learning personalized, detailed and 3D consistent facial avatars from monocular videos.
In summary, we contribute:

- extrapolation ability over poses and expressions.
- Our method produces more accurate geometry and generalizes better to unseen poses and expressions. When applied to real video sequences, IMavatars reconstruct the in-allocation of the geometry and deformation networks from videos.
- a differentiable rendering approach that enables end-to-end learning from videos,
- and a synthetic video dataset consisting of 10 subjects rendered with meaningful and diverse expressions.

We will release code and models for research purposes.

2. Related work

3D Face Models and Avatar Reconstruction. Estimating 3D shape from monocular input is an ill-posed problem, traditionally addressed for faces by employing strong statistical priors learned from real data. The seminal work of Blanz and Vetter [3] used principal component analysis (PCA) to model facial appearance and geometry on a low-dimensional linear subspace, known as the 3D Morphable Model (3DMM). Extensions to this idea included multilinear models for shape and expression [6, 55], full-head PCA models [13, 27, 37], deep non-linear models [40, 52] and fully articulated head models with linear blend skinning (LBS) and corrective blendshapes [27]. 3DMM and its variants have been widely used within optimization-based [20, 41, 44, 50] or deep learning-based approaches [15–17, 26, 43, 45, 47–49] to recover a coarse mesh and appearance representation. These methods can obtain overall accurate estimates of the facial area but typically lack details, do not model the entire head, and cannot properly represent eyes, teeth, hair, and accessories.

A related line of research estimates personalized rigs from single images or videos, i.e. 3D representations of the human head along with a set of controls that can be used to animate the geometry. This has been traditionally addressed by recovering a personalized set of expression bases known as blendshapes, obtained through deformation transfer [7, 19, 21, 22, 46] or deep neural networks [1, 9, 58]. Other rigging techniques have also been investigated, such as joint-based representations [17, 21, 54] and muscle-based models [40, 52] and fully articulated head models with linear blend skinning (LBS) and corrective blendshapes [27]. 3DMM and its variants have been widely used within optimization-based [20, 41, 44, 50] or deep learning-based approaches [15–17, 26, 43, 45, 47–49] to recover a coarse mesh and appearance representation. These methods can obtain overall accurate estimates of the facial area but typically lack details, do not model the entire head, and cannot properly represent eyes, teeth, hair, and accessories.

Neural Face Models. While triangulated meshes remain the dominant representation for 3D facial geometry, the recent success of neural implicit shape representations [11, 25, 28, 31, 33, 59] has inspired a number of works that build 3D facial models within this new paradigm. Yenamandra et al. [60] propose an implicit morphable model that decouples shape, expression, appearance, and hair style. Ramon et al. [39] estimate a full head model from a few input images.
Given a pixel location, our method performs ray tracing in the deformed space. For each deformed point $x_d$, we conduct correspondence search to find the corresponding canonical point $x_c$ (left side of the second row). Our novel implicit morphing leverages predicted canonical blendshape and skinning-weight fields $E$, $W$ and $P$ to morph the canonical point $x_c$ to its deformed location $x_d$ given expression and pose conditions. After finding the nearest canonical surface intersection $x_c$, our novel implicit gradient formula allows efficient computation of gradients for the geometry and deformation fields. Finally, we predict the RGB values by querying the canonical texture MLP with the differentiable canonical location. Quantities in red circles denote supervised values. We omit the mask loss for simplicity, please check Sec. 3.4 for objective functions.

by pre-training signed distance fields on a large number of raw 3D scans. These works demonstrate an improved ability to represent the full head and torso along with detailed geometry that can be stored compactly, but the estimated shapes cannot be animated. In contrast, our implicit surface representation can be controlled via 3DMM parameters.

Neural volumetric representations such as NeRF [31] have been explored in the context of faces [8, 18, 56]. These representations enable the encoding of thin structures such as hair, and they can model complex surface/light interactions. To handle the large complexity of facial motions, Wang et al. [56] propose a localized compositional model that combines discrete low-resolution voxels with neural radiance fields. Their method requires a complex multi-view video system for training. The closest work to ours is NerFace [18], which recovers an animatable neural radiance field from a single monocular video by conditioning on the expression parameters from a 3DMM. While the method achieves visually compelling images on both novel views and expressions, it struggles to extrapolate to unseen expressions and the quality of the geometry is too noisy to be used in 3D settings (Fig. 6).

**Implicit deformation fields.** Modeling dynamic objects with implicit neural fields is an active research topic, as deforming continuous functions pose additional challenges compared to discrete representations. There are currently three main approaches. The first is to condition each frame on a latent code, e.g. a time stamp [57], a learned latent vector [34, 56], or a vector from a pre-computed parametric model [14, 18, 29, 42]. A second, possibly complementary approach, uses a “backward” deformation field. This is an additional neural network that first maps observations in deformed space to observations in a canonical space, where the implicit function is then evaluated [32, 34, 38, 42, 51, 53]. The deformation fields are usually modeled as velocity fields [32], translation fields [38, 51], rigid transformations [34], or skinning-weight fields [23, 29, 42]. While they have demonstrated an impressive capacity for learning correspondences even in the absence of ground-truth supervision, the backwards formulation makes them pose-dependent and hence requires a large dataset for learning, showing reduced generalization when deformations are too far away from the training set. To tackle the latter problem, forward deformation fields have been recently proposed [10]. These learn a dense forward skinning weight field, and corresponding canonical points are found using iterative root-finding. To improve generalization outside the scope of train-time expressions, here we extend the idea of forward skinning to the problem of facial deformations and propose a new analytical gradient formula that allows the deformation fields to be directly learned from videos.
3. Method

We propose IMavatar, an implicit animatable facial avatar method that equips implicit surfaces with fine-grained expression control by leveraging morphing-based deformation fields. In this section, we first recap the deformation formulation of the FLAME face model [27], followed by the representation for the canonical geometry, deformation, and texture fields. Then, we introduce correspondence search to find canonical points for image pixels and derive the analytical gradients for end-to-end training.

3.1. Recap: FLAME Face Morphable Model

The FLAME face model [27] parameterizes facial geometry with shape, pose, and expression components. Since we focus on personal facial avatars, we specifically represent the pose- and expression-dependent shape variations. The simplified FLAME mesh model is denoted by:

\[ M(\theta, \psi) = W(T_P(\theta, \psi), J(\psi, \theta), W), \]  

where \( \theta \) and \( \psi \) denote the pose and expression parameters, and \( W(\cdot) \) and \( J(\cdot) \) define standard skinning function and the joint regressor, respectively. \( W \) represents the per-vertex skinning weight for smooth blending, and \( T_P \) denotes the canonical vertices after adding expression and pose correctives, represented as:

\[ T_P(\theta, \psi) = \hat{T} + B_P(\theta; \mathcal{P}) + B_E(\psi; \mathcal{E}), \]  

where \( \hat{T} \) is the personalized canonical template. \( B_P(\cdot) \) and \( B_E(\cdot) \) calculate the additive pose and expression offsets using the corresponding corrective blendshapes \( \mathcal{P} \) and \( \mathcal{E} \) given the animation conditions \( \theta \) and \( \psi \). Our method extends the discretely defined \( W, \mathcal{E}, \) and \( \mathcal{P} \) to be continuous fields represented by MLPs, making it possible to morph continuous canonical representations.

3.2. IMAvatar

Our IMAvatar is represented by three canonical fields, defining the geometry, deformation, and texture of the person, as shown in Fig. 2. Details of the network architecture can be found in the Sup. Mat.

Geometry. We represent the canonical geometry using an MLP that predicts the occupancy values for each canonical 3D point. To account for the deformations that are not represented by FLAME expression parameters, we additionally condition the geometry network \( f_{\sigma_j} \) on a per-frame learnable latent code \( l \in \mathbb{R}^{n_l} \), similar to NerFace [18]. We also leverage positional encoding [31] to encourage high frequency details in the canonical geometry.

\[ f_{\sigma_j}(x, l) : \mathbb{R}^3 \times \mathbb{R}^{n_l} \rightarrow [0, 1]. \]  

Deformation. Following FLAME [27], our deformation network \( d_{\sigma_d} \) predicts the additive expression blendshape vectors \( \mathcal{E} \in \mathbb{R}^{n_e \times 3} \), the pose correctives \( \mathcal{P} \in \mathbb{R}^{n_p \times 9 \times 3} \), and the linear blend skinning weights \( W \in \mathbb{R}^{n_l} \) for each point in the canonical space, where \( n_e \) and \( n_p \) denote the number of expression parameters and bone transformations.

\[ d_{\sigma_d}(x) : \mathbb{R}^3 \rightarrow \mathcal{E}, \mathcal{P}, W. \]  

In a slight abuse of notation we reuse \( W, \mathcal{E}, \) and \( \mathcal{P} \) from FLAME, note that these denote continuous implicit fields from here on. For each canonical point \( x_c \), the transformed location \( x_d \) is:

\[ x_d = W(x_c + B_P(\theta; \mathcal{P}) + B_E(\psi; \mathcal{E}), J(\psi, \theta), W). \]  

This defines the forward mapping from canonical points \( x_c \) to corresponding deformed points \( x_d \). We detailed the construction of the inverse mapping from deformed to canonical space in Sec. 3.3.

Normal-conditioned texture. We leverage a texture MLP \( c_{\sigma_v} \) to map each location in the canonical space to an RGB color value. Since view-dependent effects change during expression and pose deformations, we additionally condition the texture network on the normal direction of the deformed shape. For implicit surfaces, the normal direction can be calculated as the normalized gradient of the occupancy field w.r.t. the 3D point location. In our case, the gradient of the deformed occupancy field is given by:

\[ \frac{\partial f_{\sigma_j}}{\partial x_d} = \frac{\partial f_{\sigma_j}}{\partial x_c} \frac{\partial x_c}{\partial x_d} = \frac{\partial f_{\sigma_j}}{\partial x_c} \left( \frac{\partial x_d}{\partial x_c} \right)^{-1}. \]  

Since the appearance in the mouth region cannot be modeled purely by warping due to dis-occlusions [34], our final predicted color is calculated from the canonical location \( x_c \), the normal direction of the deformed shape \( n_d \), and the related pose and expression parameters \( \theta \) and \( \psi \).

\[ c_{\sigma_v}(x_c, n_d, \theta, \psi) = c, \]  

where \( c \) denotes the color w.r.t. expression and pose.

3.3. Differentiable Rendering

To optimize the canonical geometry and texture field from videos with expressions and poses, we need to find the surface intersection in the canonical space. We first introduce ray tracing and correspondence search to find the canonical surface point for each ray, and introduce the analytical gradient that enables end-to-end training.

Ray tracing and canonical correspondence search. Given a camera location \( r_o \) and a ray direction \( r_d \) in the
deformed space, we follow IDR [59] and perform ray tracing by uniformly sampling 100 points between the near and far intersections with a predefined bounding sphere, and run 8 iterations of the secant algorithm. To determine the occupancy values for the sampled points $x_d$, we use Broyden’s method [4,10] to locate the canonical correspondence, whose occupancy values can be determined by querying the canonical geometry network. Thus, we can locate the canonical-surface intersection for each ray iteratively.

**Gradient.** To avoid back-propagation through the iterative process of correspondence search, we derive analytical gradients for the location of the canonical surface point $x_c$, which must satisfy the surface and ray constraints

$$f_{\sigma_f}(x_c) \equiv 0.5,$$

$$(x_d - r_o) \times r_d \equiv 0,$$ \hfill (8)

where 0.5 is defined as the level set for the surface and $x_d$ represents the deformed point, defined in Eq. 5. For convenience, we rewrite this equality constraint as:

$$F_{\sigma_f}(x_c) \equiv 0,$$ \hfill (9)

where $F_{\sigma_f}(\cdot)$ represents the function of $x_c$ that must be zero, and $\sigma_F = \sigma_f \cup \sigma_d$ includes the learnable parameters of the geometry and deformation networks. The function $F_{\sigma_f}(x_c) \equiv 0$ implicitly defines how the canonical surface intersection $x_c$ moves with the change of the canonical geometry and deformation networks. We leverage implicit differentiation to extract the gradient of $x_c$ w.r.t. the parameters of the geometry and deformation networks:

$$\frac{dF_{\sigma_f}(x_c)}{d\sigma_f} = 0$$

$$\Leftrightarrow \frac{\partial F_{\sigma_f}(x_c)}{\partial \sigma_f} + \frac{\partial F_{\sigma_f}(x_c)}{\partial x_c} \frac{\partial x_c}{\partial \sigma_f} = 0$$

$$\Leftrightarrow \frac{\partial x_c}{\partial \sigma_f} = -\left( \frac{\partial F_{\sigma_f}(x_c)}{\partial x_c} \right)^{-1} \frac{\partial F_{\sigma_f}(x_c)}{\partial \sigma_f}. \hfill (10)$$

### 3.4. Training Objective

The main supervision is an image reconstruction loss:

$$L_{RGB} = \frac{1}{|P|} \sum_{p \in P} \|C_p - c_{\sigma_c}(x_c)\|_1,$$ \hfill (11)

where $P$ denotes the set of training pixels, and $P^{\text{in}} \subset P$ denotes the subset of foreground pixels where a ray-intersection has been found. $C_p$ and $c_{\sigma_c}(x_c)$ represent the ground truth and predicted RGB values of pixel $p \in P^{\text{in}}$. We also leverage a mask loss to provide additional supervision for the geometry and deformation network:

$$L_M = \frac{1}{|P|} \sum_{p \in P \setminus P^{\text{in}}} CE(O_p, f_{\sigma_f}(x_c^*)),$$ \hfill (12)

where $CE(\cdot)$ is the cross-entropy loss calculated between the ground truth $O_p$ and predicted occupancy values $f_{\sigma_f}(x_c^*)$. The mask loss is applied to non-intersecting rays, and $x_c^*$ represents the nearest point to the surface.

Furthermore, we leverage prior knowledge about expression and pose deformations from FLAME [27] by supervising the deformation network with the corresponding values of the nearest FLAME vertices:

$$L_{FL} = \frac{1}{|P|} \sum_{p \in P^{\text{in}}} (\lambda_c \|E_{\sigma_p} - E_p\|_2^2 + \lambda_w \|W_{\sigma_p} - W_p\|_2^2),$$ \hfill (13)

where $E_p$, $W_p$, and $V_p$ denote the predicted values of the deformation network, and $E_{\sigma_p}$, $P_{\sigma_p}$ and $W_{\sigma_p}$ denote the pseudo ground truth defined by the nearest FLAME vertices. We set $\lambda_c = \lambda_w = 1000$, and $\lambda_w = 0.1$ for our experiments. Our final training loss is

$$L = L_{RGB} + \lambda_M L_M + \lambda_FL L_{FL},$$ \hfill (14)

where $\lambda_M = 2$ and $\lambda_FL = 1$.

### 4. Experiments

This section empirically evaluates the benefits of the proposed approach in terms of geometry accuracy and expression generalization. It is difficult to acquire ground-truth geometry for monocular videos. Hence, we ablate different design choices in a controlled setting on synthetic data with known geometry. We then conduct a similar ablation on real video sequences and compare with NerFace [18].

#### 4.1. Datasets

**Synthetic Dataset.** We conduct controlled experiments on a synthetic dataset by rendering posed and textured FLAME meshes. For the training set, we render a video that is representative of a speech sequence. We take FLAME expression parameters from the VOCA speech dataset [12] and head poses fitted from real videos. We build the test set with unseen, stronger expressions extracted from COMA [40]. Our synthetic dataset consists of 10 subjects with varied facial shapes and appearance, with an average of 5,368 frames for training and 1876 frames for testing per subject. For testing, we subsample every 10th frame. We will release the synthetic dataset for research purposes.

**Real Video Dataset.** We evaluate on real videos from a single stationary camera. We calculate foreground masks with MODNet [24] and estimate the initial FLAME parameters using DECA [17], which are refined by fitting to 2D facial keypoints [5]. Please see the Sup. Mat for more details. The
Figure 3. Qualitative results on synthetic data. As the expression strength increases from left to right, baseline methods either collapse to a neutral expression (D-Net, B-Morph) or produce invalid geometry (C-Net, Fwd-Skin). In contrast, our method successfully handles even the most extreme expressions.

real video dataset consists of 4 subjects, with roughly 4,000 frames for training and 1,000 frames for testing per subject. The training videos cover mostly neutral expressions in a speech video, while the test videos include unseen, difficult expressions such as jaw opening, big smiles, and more. We subsample every 10th frame for testing.

4.2. Ablation Baselines

This paper tackles the key difficulty in building animatable avatars from monocular videos: capturing the per-frame deformations with respect to the canonical shape. We compare our method with the commonly used previous approaches by replacing our deformation module with the following alternatives:

**Pose- and expression-conditioned network (C-Net).** The C-Net is inspired by NerFace [18] but is designed for implicit surfaces. It first applies a rigid transformation to the deformed shape, which brings the full upper body to the canonical space with the inverse head pose transformation; it then models other deformations by conditioning on the pose and expression parameters.

**Displacement warping (D-Net).** Similar to Nerfies [35], this baseline uses a deformation network that takes pose and expression parameters as input, and predicts a displacement vector from the deformed shape to the canonical shape, applied before querying the geometry and texture networks. We supervise the predicted displacement outputs with the corresponding values of the nearest FLAME vertices.

**Backward morphing (B-Morph).** Similar to our method, B-Morph leverages the morphing formulation of FLAME and predicts expression blendshapes, pose corrective vectors, and LBS weights. However, the deformation network is conditioned on the deformed location as well as pose and expression parameters and establishes correspondences by performing inverse morphing. In contrast, our deformation network takes as input only the canonical point, which is pose- and expression-independent, enabling better generalization [10]. The learned blendshapes and weights of this baseline are supervised in a similar way to our method.

**Forward skinning + expression-conditioning (Fwd-Skin).** This baseline is adapted from SNARF [10], which was originally proposed for human body avatars. Here, skinning is modeled in a similar way to our method, but the deformation network only predicts LBS weights, while the expression and pose-related correctives are handled by conditioning on the geometry and texture networks.

4.3. Metrics

The goal of this work is to obtain an animatable 3D head from a video, and hence we evaluate the geometric accuracy (only available for the synthetic dataset), image quality, and expression fidelity. Image quality is measured via the Manhattan distance ($L_1$), SSIM, PSNR and LPIPS [61] metrics, following the practice in NerFace [18]. To measure geometric consistency for synthetic data, we report the average angular normal error between the generated normal map and ground truth, denoted as the **Normals** metric in Tab. 1. Since we focus on modeling deformation-related geometry and texture, both normal consistency and image similarity metrics are measured in the face interior region. For both synthetic and real data, we measure the expression fidelity by calculating the distance between generated and pseudo ground truth (GT) facial keypoints. We estimate the facial keypoints of predicted images with [5], and pseudo GT keypoints are obtained from posed FLAME meshes.

4.4. Results on Synthetic Dataset

We train IMavatar and baseline methods for the 10 synthetic identities and measure geometry, expression and image reconstruction errors on 12 sequences with renderings from the COMA dataset. We outperform all baselines by a...
Table 1. Quantitative results for synthetic experiment. Compared with baselines, our method achieves more consistent surface normals, better image quality, and more accurate expressions.

| Method   | Expression ↓ | Normals ↓ | L1 ↓ | PSNR ↑ | SSIM ↑ | LPIPS ↓ |
|----------|--------------|-----------|------|--------|--------|--------|
| C-Net    | 3.248        | 9.108     | 0.02245 | 26.67  | 0.9829 | 0.03053 |
| D-Net    | 7.452        | 26.174    | 0.07881 | 19.62  | 0.9481 | 0.05881 |
| B-Morph  | 4.941        | 12.150    | 0.03293 | 24.95  | 0.9726 | 0.03340 |
| Fwd-Skin | 2.825        | 8.130     | 0.01920 | 27.30  | 0.9852 | 0.02812 |
| Ours     | 2.558        | 5.901     | 0.01807 | 28.75  | 0.9900 | 0.01581 |

Figure 4. Expression extrapolation. Performance of baseline methods worsen drastically as expressions become more extreme (higher norm). Geom. error denotes the angular error of the surface normals (lower is better, see Sec. 4.3).

Extrapolation. While other methods are limited to interpolation, our method is capable of extrapolating beyond seen expressions and poses. In Fig. 4, we plot the geometric error for different strength of expressions. Most methods perform well for mild expressions (small expression norm). For stronger expressions, however, their errors increase significantly. In contrast, our method only incurs a slight increase even for strong expressions (large norm). Analogous plot for the jaw pose is in Sup. Mat. Fig. 3 shows visual examples for neutral, medium, and strong expressions.

4.5. Result on Real Video sequences

To evaluate performance on real data, we compare to all baselines and NerFace [18]. Despite FLAME [27] not modeling hair or detailed geometries, our method can leverage this information from videos. Fig. 6 shows that all methods can generate realistic and correctly-posed images for easy expressions (row 1 and 2). For these easy expressions, our method and Backward Morphing (B-Morph) achieve the most accurate geometry because they leverage the morphing formulation of the FLAME face model. The FLAME-guided morphing field enables the joint optimization of a single canonical representation using information from all frames, even though they contain different expressions and poses. In contrast, C-Net, Fwd-Skin, and NerFace [18] model expression deformations via direct conditioning on the implicit fields, and do not enforce a shared canonical geometry for different expressions. These methods are too under-constrained to deal with the ill-posed problem of extracting geometry from monocular videos. D-Net, on the other hand, does model the correspondence between frames. However, given the high-frequency details of expression and pose conditions outside the training distribution.

Table 2. Quantitative results on real videos. We compare our method with the SOTA and baselines on test sequences with unseen expressions and poses. Our method reconstructs the expressions more accurately while being on par in terms of image quality. Although FLAME and B-Morph perform well for mild expressions (first expression component in FLAME [27]), and jaw (pitch) and neck (yaw) poses separately. For each parameter, we show generated images and the training data distribution with 5 vertical lines corresponding to the 5 samples.

![Image](image-url)
Figure 6. Qualitative comparison. Ours generates complete images and accurate geometry even when extrapolating expressions beyond the training data. The baselines cannot reproduce facial expressions or generate distorted outputs.

This shows that our method can generalize to expressions and poses far beyond the training distribution. More inter- and extrapolation examples can be found in Sup. Mat.

5. Conclusion

We propose IMavatar, an implicit morphable head avatar. IMavatar can be controlled via expression and pose parameters in a similar way to 3DMMs, while modeling diverse and detailed hairstyles and facial appearance. Our method—learned end-to-end from RGB videos—demonstrates accurate deforming geometry and extrapolates to strong expressions beyond the training distribution.

While our method contributes towards building controllable implicit facial avatars, some challenges remain. First, surface representations achieve detailed facial geometry, but
they cannot model transparencies of hair. Future work could potentially find a solution in a combination of volumetric representations [31] with animatable surfaces. Second, the appearance in the mouth interior region can be unrealistic (last two examples in Fig. 6). Special treatment of the mouth-interior may address this issue in the future.

Our method takes a step towards building controllable implicit facial avatars and makes personal avatars more accessible. We discuss potential negative societal impact in light of disinformation and deep-fakes in the Sup. Mat.

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