

PSAvatar: A Point-based Morphable Shape Model for Real-Time Head Avatar Creation with 3D Gaussian Splatting

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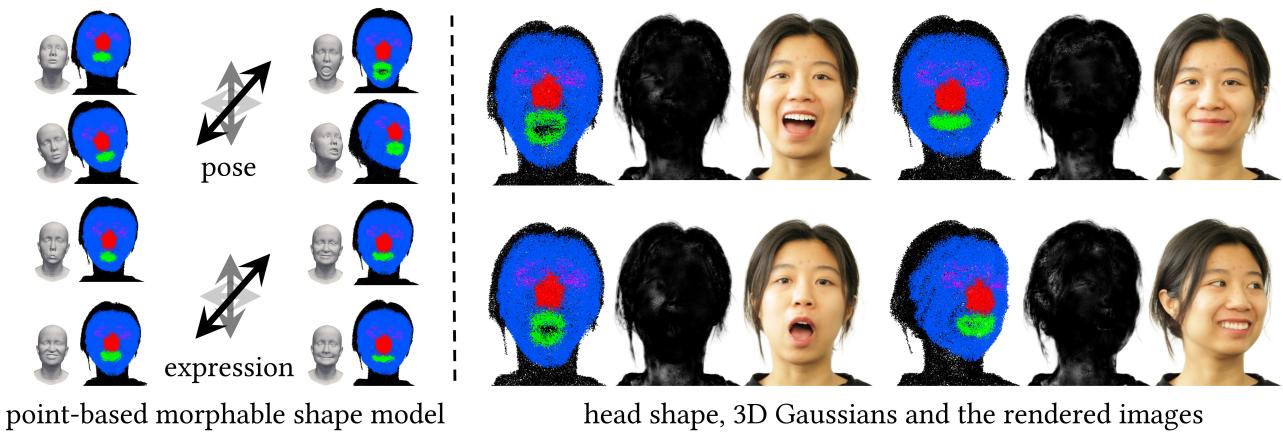


Figure 1. PSAvatar learns the shape with pose and expression variations based on a point-based morphable shape model, and employs 3D Gaussian for fine detail representation and efficient rendering. Given monocular portrait videos, PSAvatar can create head avatars that enable real-time (≥ 25 fps at 512×512 resolution) and high-fidelity rendering.

Abstract

Despite much progress, achieving real-time high-fidelity head avatar animation is still difficult and existing methods have to trade-off between speed and quality. 3DMM based methods often fail to model non-facial structures such as eyeglasses and hairstyles, while neural implicit models suffer from deformation inflexibility and rendering inefficiency. Although 3D Gaussian has been demonstrated to possess promising capability for geometry representation and radiance field reconstruction, applying 3D Gaussian in head avatar creation remains a major challenge since it is difficult for 3D Gaussian to model the head shape variations caused by changing poses and expressions. In this paper, we introduce PSAvatar¹, a novel framework for animatable head avatar creation that utilizes discrete geometric primitive to create a parametric morphable shape model and employs 3D Gaussian for fine detail representation and high fidelity rendering. The parametric morphable shape model is a Point-based Morphable Shape Model (PMSM) which uses

points instead of meshes for 3D representation to achieve enhanced representation flexibility. The PMSM first converts the FLAME mesh to points by sampling on the surfaces as well as off the meshes to enable the reconstruction of not only surface-like structures but also complex geometries such as eyeglasses and hairstyles. By aligning these points with the head shape in an analysis-by-synthesis manner, the PMSM makes it possible to utilize 3D Gaussian for fine detail representation and appearance modeling, thus enabling the creation of high-fidelity avatars. We show that PSAvatar can reconstruct high-fidelity head avatars of a variety of subjects and the avatars can be animated in real-time (≥ 25 fps at a resolution of 512×512)².

1. Introduction

Creating animatable head avatars has wide applications and has attracted extensive interests in academia and industries. Many methods based on explicit representations, e.g., 3D

¹<https://github.com/pcl3dv/PSAvatar>

²Test is conducted based on Nvidia RTX 3090

morphable models (3DMMs) [1, 21], points [35, 41] and more recently 3D Gaussian [3, 17, 25]), and neural implicit representations, *e.g.*, Neural Radiance Field (NeRF) [10, 22, 42] and signed distance function (SDF) [37, 40]), have been developed in recent years. Whilst these methods have achieved very impressive results, there are still many unsolved problems.

3DMM-based methods allow efficient rasterization and inherently generalize to unseen deformations, but are limited by a priori-fixed topology and surface-like geometries, making them less suitable for modeling individuals with eyeglasses or complex hairstyles [3, 25]. Whilst neural implicit representations outperform 3DMM-based methods in capturing hair strands and eyeglasses [6, 40], they are computationally extremely demanding [15]. Furthermore, neural implicit representations need the deformer network or similar techniques to bridge the gap between the canonical and deformed spaces, making it challenging to achieve high deformation accuracy.

In contrast to neural implicit representations, both point and 3D Gaussian representations can be rendered efficiently with a splatting-based rasterization [3, 25, 41], and both are considerably more flexible than 3DMMs in representing complex volumetric structures, *e.g.*, eyeglass, hair strands, *etc.*. PointAvatar [41] initializes with a sparse point cloud randomly sampled on a sphere and periodically upsamples the point cloud by adding noises. The position of the points are updated to match the target geometry via backwards gradients. Points are rotation-invariant and isotropically scaled, making them easy to control. In comparison, 3D Gaussians can be rotated and scaled, making them more flexible than points for 3D representation. In order to achieve consistent 3D representations, 3D Gaussian rely on carefully designed controlling strategy. In GaussianAvatar [25], each triangle of the mesh is initialized with a 3D Gaussian, and the positional gradient is utilized to move and periodically densify the Gaussian splats. A major difficulty in applying 3D Gaussian to head avatar creation is modeling the head shape variations caused by changing poses and expressions.

In this paper, we introduce PSAvatar, a novel framework for animatable head avatar creation that utilizes discrete geometric primitive to create a parametric morphable shape model to make it possible to employ 3D Gaussian for fine detail representation and high fidelity rendering. Such a parametric morphable shape model, referred to as Point-based Morphable Shape Model (PMSM), relies on points instead of meshes for 3D representation to achieve enhanced representation flexibility. PMSM is created based on FLAME to inherit its morphable capability. Specifically, PMSM converts the FLAME mesh to points by uniformly sampling points on the surface of the mesh. However, FLAME is incapable of representing individuals with eye-

glasses or complex hairstyles. To address this, PMSM samples points off the FLAME mesh to enhance the representation flexibility. PMSM splats the points onto screen and minimizes the difference between the rendered and ground truth images. After removing the invisible points, the remaining points are then aligned with the head shape. PSAvatar models the appearance by employing 3D Gaussian in combination with the PMSM to reconstruct the underlying radiance field and to achieve high-fidelity rendering. Our contributions are as follows:

- We present PSAvatar, a method for creating animatable head avatars using a point-based morphable shape model for shape modeling and employing 3D Gaussian for fine detail representation and appearance modeling.
- We have developed a Point-based Morphable Shape Model for 3D head representation that is capable of modeling facial shapes with pose and expression variations and capturing complex volumetric structures *e.g.*, hair strands, glasses, *etc.*.
- We show that PSAvatar can reconstruct high-fidelity head avatars of a variety of subjects and the avatars can be animated in real-time (≥ 25 fps at 512×512 resolution).

2. Related Work

Head Avatar Creation with Implicit Models Implicit models reconstruct the face by neural radiance field in combination with volumetric rendering or using implicit surface functions (*e.g.*, signed distance functions). A popular approach to creating animatable head avatar is to condition the NeRF on low-dimensional facial model parameters such as expression, pose and camera setting [10, 11, 34]. NeRF-Blendshape [12] models the dynamic NeRF by linear combinations of multiple NeRF basis one-to-one corresponding to semantic blendshape coefficients. Despite achieving impressive performances, such an approach could either fail to disentangle pose and expression or fail to generalize well to novel poses and expressions [7, 10, 16, 26, 30, 32, 33]. Another paradigm is to establish the target head model in the canonical space and synthesize the dynamics by deformation [19, 20, 38]. INSTA [42] deforms the query points from the observation space to the canonical space by using the bounding volume hierarchy (BVH) and employs InstantNGP to accelerate rendering. IMAvatar [40] represents the deformation fields via learned expression blendshapes and solves for the mapping from the observed space to the canonical space via iterative root-finding. AvatarMAV [36] defines motion-aware neural voxels, and models deformations via blending a set of voxel grid motion bases according to an input 3DMM expression vector. In addition, a variety of powerful techniques such as triplane [39], Kplane [9], deformable multi-layer meshes [6] have been utilized in head avatar creation to improve training efficiency and rendering quality.

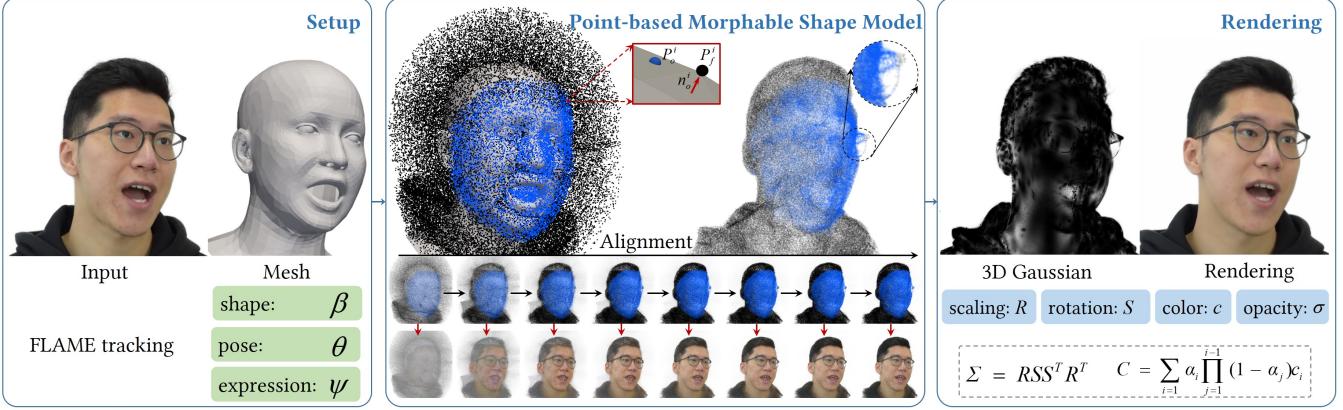


Figure 2. Overview. Given a monocular portrait video, we conduct FLAME tracking to obtain the parameters. The point-based morphable shape model (PMSM) first converts the FLAME mesh to points. It performs sampling on the surfaces (blue points) and additionally generates samples off the meshes by offsetting the samples on the meshes along their normal directions (black points). These points are then aligned with the head shape in an analysis-by-synthesis manner. The inclusion of points on meshes and off meshes enables the PMSM to reconstruct not only surface-like structures but also complex geometries that are beyond the capability of 3DMMs. Combining the PMSM with 3D Gaussian allows the reconstruction of the radiance field for efficient rendering.

Head Avatar Creation with Explicit Models The seminal work of 3D Morphable Model (3DMM) [1] uses principal component analysis (PCA) to model facial appearance and geometry on a low-dimensional linear subspace. 3DMM and its variants [2, 8, 14, 21, 24] have been widely applied in optimization-based and deep learning-based head avatar creation [4, 5, 13, 31]. Neural Head Avatar [15] employs neural networks to predict vertex offsets and textures, enabling the extrapolation to unseen facial expressions. ROME [18] estimates a person-specific head mesh and the associated neural texture to enhance local photometric and geometric details. 3DMM-based methods produce geometrically consistent avatars that can be easily controlled, however, they are limited to craniofacial structures and can fail to represent hair and glasses. To address this, PointAvatar [41] explores point-based geometry representation with differential point splatting, allowing for high quality rendering and representation of hair and eyeglasses. Although point-based representations are easy to handle, they lack flexibility. In comparison, 3D Gaussian [17] offers improved flexibility. MonoGaussianAvatar [3] replaces the point cloud in PointAvatar with Gaussian points to improve representation flexibility and rendering quality. GaussianAvatars [25] pairs a triangle of the mesh with a 3D Gaussian and introduces densification and pruning strategies for sufficiently representing the geometry. In addition, it uses binding inheritance to ensure that the 3D Gaussian translates and rotates with the triangle to enable precise animation control via the underlying parametric model.

Both point and 3D Gaussian rely on the controlling strategy for achieving consistent 3D representation. PointAvatar [41] initializes sparse points by randomly sampling

on a sphere, and updates their positions to approximate the coarse shape. Besides, PointAvatar introduces a deformer network to bridge the gap between the canonical space and the deformed space. To model details, it periodically densifies points by adding noises. 3D Gaussians are considerably more flexible than points in 3D representation but are more difficult to control. In GaussianAvatars [25], each triangle of the mesh is initialized with a 3D Gaussian. For each 3D Gaussian with a large positional gradient, GaussianAvatars split it into two smaller ones if it is large or clone it if it is small. The newly generated 3D Gaussian is bound to the same triangle as the old one to enable binding inheritance during densification. A major difficulty in applying 3D Gaussian to head avatar creation is modeling the head shape variations caused by changing poses and expressions. Our new PSAvatar uses a point-based morphable shape model to capture the head dynamics and successfully achieve real-time head avatar animation.

3. Method

Fig. 2 shows the schematic of PSAvatar. The objective is to reconstruct an animatable head avatar with a monocular portrait video of a subject performing diverse expressions and poses. To achieve this, PSAvatar introduces a point-based morphable shape model (PMSM) for 3D representation to model pose and expression dependent shape variations (see section 3.2), and models the appearance by combining the PMSM and 3D Gaussian (see section 3.3).

3.1. Preliminary

Point and 3D Gaussian utilize discrete primitives for geometry representation. Points are parameterized by the radius



Figure 3. Shape variations for given poses and expressions. The reference images (taken from subject 2) on the left provide the pose and expression parameters, and the Point-based Morphable Shape Model (PMSM) can warp the points in a way that is consistent with the reference, *i.e.* the reference person turns his head around, the points follow the movements. Blue and black represent the points on and off the mesh respectively. To visualize the shape variation in a better way, points sampled based on the eye, nose and mouth regions are colored with pink, red and green, respectively.

r , the opacity σ and the color c . A 3D Gaussian is defined by a covariance matrix Σ centered at a point (mean) μ [17]:

$$G(x) = e^{-\frac{1}{2}(x-\mu)^T \Sigma (x-\mu)} \quad (1)$$

To guarantee that Σ is physically meaningful, the covariance matrix is constructed by a parametric ellipse with a scaling matrix S and a rotation matrix R :

$$\Sigma = RSS^T R^T \quad (2)$$

Identical to that in [17], the scaling and rotation matrix are represented by a scaling vector $s \in R^3$ and a quaternion $q \in R^4$, respectively. s and q can be trivially converted to their respective matrices, and they can be combined to make sure that the normalised q is a valid unit quaternion.

Both points and 3D Gaussian can be rendered via a differentiable splatting-based rasterizer, and the color C of a pixel is computed by alpha compositing:

$$C = \sum_{i=1} \omega_i c_i = \sum_{i=1} \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j) c_i \quad (3)$$

where ω_i is the weight for alpha compositing, c_i is the color of each point or 3D Gaussian and α is the blending weight. For points, α is calculated as $\alpha = \sigma(1 - d^2/r^2)$, where d is the distance from the point center to the pixel center. For Gaussians, α is given by evaluating the 2D projection of the 3D Gaussian multiplied by a per-point opacity σ .

3.2. Point-based Morphable Shape Model

Given shape, pose and expression components, FLAME [21] can produce morphologically realistic faces in a convenient and effective way. This motivates us to build a point-based morphable shape model (PMSM) on FLAME to inherit its morphable capability. Since we focus on human facial avatars, we specifically model the pose and expression dependent shape variations and simplify the FLAME model $M(\theta, \psi)$:

$$M(\theta, \psi) = W(T_P(\theta, \psi), J(\psi), \theta, \mathcal{W}) \quad (4)$$

where θ and ψ denote the pose and expression parameters respectively. $W(\cdot)$ and $J(\cdot)$ define the standard skinning function and the joint regressor respectively. \mathcal{W} represents the per-vertex skinning weights for smooth blending, and T_P denotes the template mesh with pose and expression offsets, defined as:

$$T_P(\theta, \psi) = \bar{T} + B_P(\theta; \mathcal{P}) + B_E(\psi; \mathcal{E}) + \mathcal{G}(\theta, \psi) \quad (5)$$

where \bar{T} is the personalized template, B_P and B_E model the corrective pose and expression blendshapes, respectively. \mathcal{P} and \mathcal{E} denote the pose and expression basis, respectively. To model the inconsistency between FLAME and the head geometry, $\mathcal{G}(\theta, \psi)$ is introduced as the per-vertex geometry correction:

$$\mathcal{G}(\theta, \psi) = B_P(\theta; \mathcal{P}') + B_E(\psi; \mathcal{E}') \quad (6)$$

where \mathcal{P}' and \mathcal{E}' are learned pose and expression blendshape basis, respectively.

Because FLAME is incapable of modeling hair strands or eyeglasses, PSAvatar addresses this limitation by introducing the point-based morphable shape model (PMSM) which utilizes points instead of meshes to enhance the representation flexibility. Specifically, we first convert the FLAME mesh to points by uniformly sampling points on the surface of the mesh with a probability that is proportional to the face area:

$$P_o^i = \sum_{j=0}^2 \alpha_j^i v_j^i \quad (7)$$

where the superscript i denotes the i -th mesh, the subscript o represents sampling on the mesh. α_j^i and v_j^i with $j = \{0, 1, 2\}$ are the barycentric coordinate and the vertex of the i -th mesh, respectively. Since FLAME excels in modeling the facial dynamics, sampling is only conducted on the facial region. In addition, sampling is conducted off the FLAME meshes to capture complex structures ignored by the FLAME model. This is achieved by offsetting the sample on the mesh along its normal:

$$P_f^i = P_o^i + L_f^i \cdot n_o^i \quad (8)$$

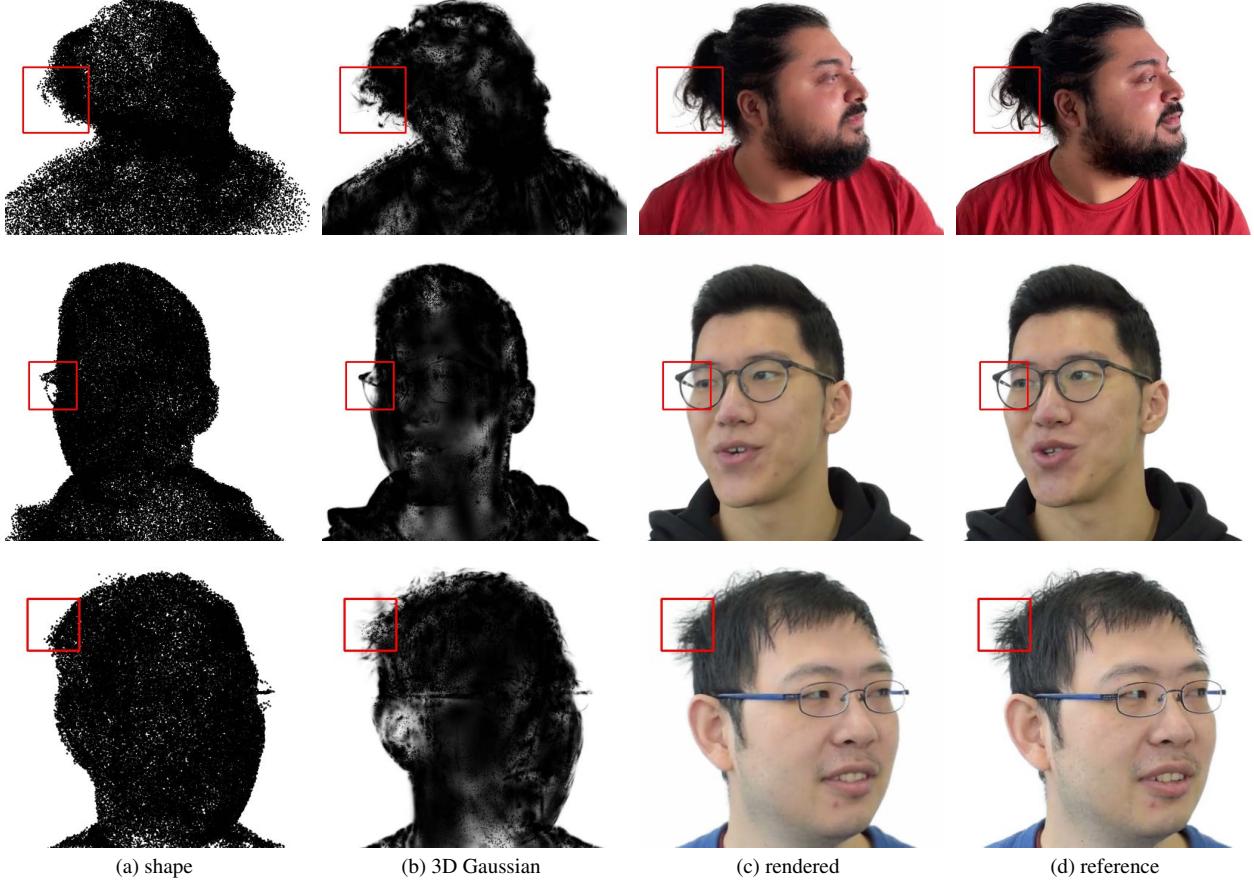


Figure 4. Visualization of each component in PSAvatar. (a) shows the learned point-based morphable shape model. (b) visualizes the 3D Gaussian, which shows improved representation flexibility over PMSM. (c) and (d) are the rendered and ground truth image, respectively.

where the subscript f represents sampling off the mesh. L_f^i is a random offset from a uniform distribution $[0, L_{max}]$, where L_{max} is a hyperparameter, empirically taken as 0.30 for covering the entire head as much as possible. n_o^i is the normal on P_o^i , calculated by:

$$n_o^i = \sum_{j=0}^2 \alpha_j^i n_j^i \quad (9)$$

where n_j^i with $j = \{0, 1, 2\}$ are the vertex normal of the i -th mesh.

Samples on the mesh are parameterized by the face index i , the barycentric coordinates, the opacity σ and the color c . While samples off the mesh carry one additional parameter L_f^i . During shape acquisition, the color c is modeled by the RGB value for simplification. Such a parameterization guarantees samples across diverse poses and expressions are in one to one (or point to point) correspondence, thus enabling the PMSM to be morphable.

PMSM aligns the points and the target head in an analysis-by-synthesis manner, *i.e.*, all the samples are splatted onto the screen via the tile rasterizer in Equation (3), and the difference between the rendered image and the input are minimized. Samples with visibility below a predefined threshold are removed. For shape acquisition, point splatting instead of Gaussian splatting is applied as point has fewer parameters than Gaussian thus converging faster to model the shape (see section 4.3). As shown in Fig. 3 and the supplementary video sequences, the resulting shape model can represent the head geometry including the hair, and can be morphed with given poses and expressions.

3.3. Rendering

To represent the fine detail and model the appearance, PSAvatar employs 3D Gaussian in combination with the PMSM. Specifically, each Gaussian is parameterized by its rotation matrix R' , anisotropic scaling matrix S , color c and opacity σ . In contrast to that in PMSM, the color c for the Gaussian

Table 1. Quantitative comparison with state-of-the-art methods. Green and yellow indicates the best and the second, respectively.

Subject ID	subject 1 (yufeng)			subject 2 (marcel)			subject 3 (soubhik)		
Metrics	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
IMAvatar [40]	21.2437	0.8410	0.1608	21.0541	0.8409	0.2653	18.6646	0.7664	0.1822
INSTA [42]	17.7720	0.7888	0.1967	19.1923	0.8117	0.2261	16.4970	0.7607	0.2348
PointAvatar [41]	24.8368	0.8686	0.1519	24.1019	0.8525	0.1913	22.8175	0.8211	0.0996
Ours	29.3942	0.9212	0.0580	26.3734	0.8869	0.0930	27.4765	0.8901	0.0609
Subject ID	subject 4 (person_1)			subject 5 (person_2)			subject 6 (person_3)		
Metrics	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
IMAvatar [40]	20.2843	0.8785	0.1359	23.7250	0.9363	0.0924	24.9572	0.9052	0.1051
INSTA [42]	19.1685	0.8855	0.1478	22.7280	0.9324	0.0951	23.5286	0.9070	0.0861
PointAvatar [41]	25.2502	0.9212	0.0778	26.4185	0.9467	0.0524	29.953	0.9419	0.0481
Ours	31.5703	0.9667	0.0341	32.2534	0.9732	0.0254	32.3608	0.9675	0.0269

is modeled by the spherical harmonics.

As shown in Equation (7), samples in the PMSM are obtained based on the local coordinate determined by each mesh. To achieve rendering, Gaussians are supposed to be transformed from the local coordinate to the global coordinate by:

$$R = R' R^i \quad (10)$$

where R is the rotation matrix of the Gaussian in the global coordinate, and R^i is the local rotation matrix determined by the i -th mesh, which is calculated by the barycentric interpolation as well:

$$R^i = \sum_{j=0}^2 \alpha_j^i R_j^i \quad (11)$$

where R_j^i with $j = \{0, 1, 2\}$ is the rotation matrix of each vertex that can be derived by $W(\cdot)$ in Equation (4), i.e., R_j^i corresponds to the rotation part of $W(\cdot)$. The directoinal color is calculated based on the spherical harmonics which is rotated from the local coordinate to the global one using the method in [23]. Eventually, the tile rasterizer in Equation (3) splats the 3D Gaussians onto the screen to implement the rendering. Empirically, we have found that the performance of PSAvatar can be further improved with the guidance of the enhancement network. Considering this, a U-net [28] based enhancement is applied to the rendered image for improving the visual quality.

3.4. Optimization and Regularization

The tile rasterizer in Equation (3) will output a rendered image I_r , and the U-net perform enhancement on the rendered image and produce the ultimate output I_{enh} . The RGB loss constrains the output image in the pixel domain:

$$\mathcal{L}_{RGB} = \|I_r - I_{GT}\| + \|I_{enh} - I_{GT}\| \quad (12)$$

where I_{GT} is the ground truth. Analogous to prior work [41], we adopt a VGG feature loss:

$$\mathcal{L}_{vgg} = \|F_{vgg}(I_r) - F_{vgg}(I_{GT})\| + \|F_{vgg}(I_{enh}) - F_{vgg}(I_{GT})\| \quad (13)$$

where F_{vgg} calculates the features from the first four layers of a pre-trained VGG network [29]. To avoid the scaling vector s growing unbounded, we regularize the scaling vector s by:

$$\mathcal{L}_{scaling} = \|s\| \quad (14)$$

Formally, the training objective for supervising PSAvatar is defined as:

$$\mathcal{L} = \mathcal{L}_{RGB} + \lambda_1 \mathcal{L}_{vgg} + \lambda_2 \mathcal{L}_{scaling} \quad (15)$$

where λ_1 and λ_2 are taken as 0.1.

4. Experiments

4.1. Setup

PSAvatar is applied for head avatar creation on video recordings of 6 subjects, in which subject 1 (yufeng) and 2 (marcel) are from IMAvatar [40] (captured by DSLR), subject 3 (soubhik) is from PointAvatar [41] (captured by smartphone), and subject 4-6 are from NerFace [10] (captured by DSLR). For fair comparisons, all these subjects share the same face-tracking algorithm for camera, pose and expression initializations.

We compare our method with three state-of-the-art methods for head avatar creation, each representing the head geometry in different ways. INSTA [42] establishes point-to-point correspondences between the canonical and deformed space based on the FLAME mesh, and relies on Instant-NGP for radiance field reconstruction. IMAvatar [40] uses SDF for 3D representation in the canonical space, while PointAvatar [41] represents the geometry via points instead. As the implementation code of GaussianAvatar

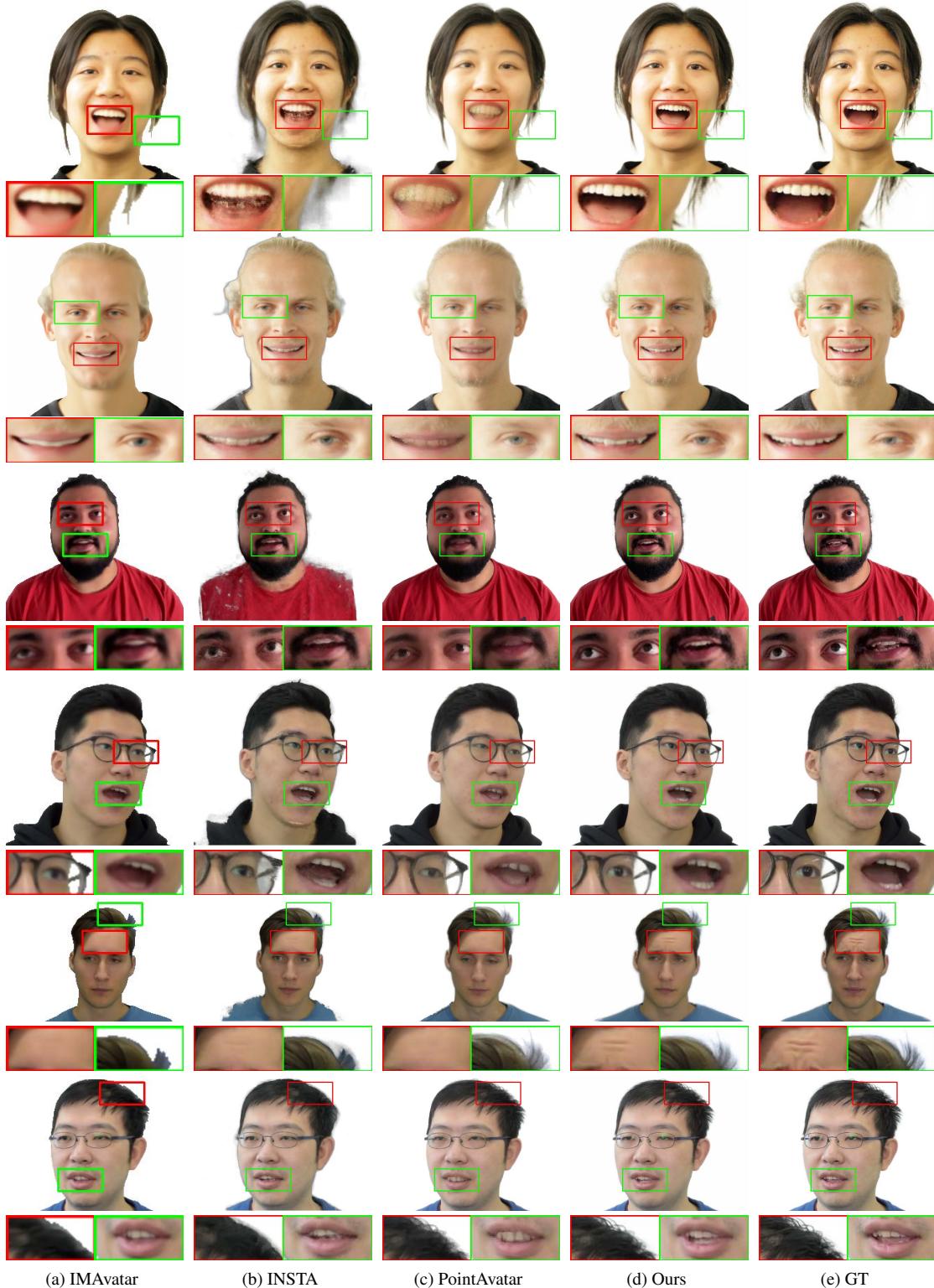


Figure 5. Qualitative comparison on subject 1-6 (from top to bottom). PSAvatar shows improved performances over strong baselines in capturing fine details such as hair strands, teeth, glasses, etc..

[25] and monoGaussianAvatar [3] is currently not available, comparisons with them are not included.

4.2. Head Avatar Reconstruction

Fig. 4 visualizes each component of the introduced PSAvatar. PMSM is capable of capturing the shape variation with poses and expressions, and can reconstruct the volumetric structures, *e.g.*, the glasses are well-reconstructed. However, PMSM struggles with the modeling of tiny hairs. To solve this, 3D Gaussians are employed to enhance the representation flexibility for fine details, and successfully model the complex geometry ignored by PMSM. Generally, PSAvatar can render sharp and realistic images even for extreme poses. In addition, the supplementary video sequences demonstrate that the reconstructed head avatars show good performances on high fidelity rendering and can be animated in real-time by the pose, expression and camera parameters.

For quantitative comparison, Table 1 lists the conventional metrics measured on the introduced PSAvatar and SOTA baselines. It is clearly seen that our approach outperforms others by a significant margin in terms of PSNR, SSIM and LPIPS [27]. Besides, we evaluate the reconstruction quality via qualitative comparison. As shown in Fig. 5, IMAvatar, based on implicit representation, is theoretically capable of modeling intricate details, but fails to reconstruct the complex hairstyles and the fine-grained teeth. PointAvatar shows improved performance over IMAvatar on rendering efficiency and quality. However, it still struggles with rendering sharp images, *e.g.*, the reconstructed teeth is blurry, and PointsAvatar is incapable of reproducing the tiny hair found in subject 1, 2 and 6. Both IMAvatar and PointAvatar warp points according to the deformation network, which potentially introduces geometric inconsistency, thus affecting the performance of 3D representation and the rendering quality. In another way, INSTA deforms points according to the nearest triangle, causing the misalignment between the FLAME mesh and the target geometry which greatly decrease the rendering quality. Hence, the neck, shoulder, mouth and eye regions synthesized by INSTA suffer from noises.

Owing to the representation capability provided by the point-based morphable shape model, PSAvatar can successfully model the surface-like topology in the face region and capture complex geometries introduced by diverse hairstyles and accessories. In addition, PSAvatar gains improved representation capability with the employment of 3D Gaussians during rendering. As seen in Fig. 5, PSAvatar shows plausible results on reproducing intricate details, *e.g.*, the tiny single hair of subject 1, the hair bun of subject 2, the glasses of subject 4 and 6. Remarkably, PSAvatar can reproduce the expression-dependent wrinkle in the forehead of subject 5, which is not observed in the

Table 2. Ablation study on subject 1. "PS" refers to rendering with point splatting, 'GS' refers to rendering with Gaussian splatting, and 'ENH' means that the enhancement network is used. Green and yellow indicates the best and the second, respectively.

Subject ID	subject 1 (yufeng)		
Metrics	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
w/o \mathcal{G}	25.7890	0.8951	0.0771
PS	28.4581	0.9016	0.0763
GS	29.1137	0.9126	0.0549
PS+ENH	29.0281	0.9183	0.0626
ours(GS+ENH)	29.3942	0.9212	0.0580

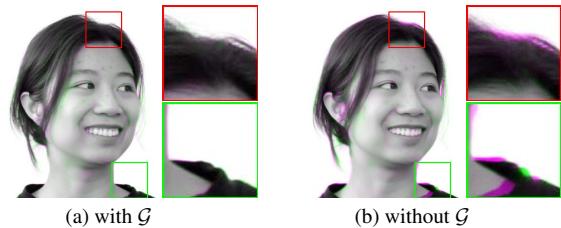


Figure 6. The effect of \mathcal{G} . The highlight pixels indicate the misalignment between the rendered image and the reference.

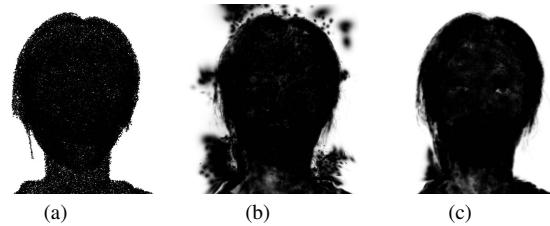


Figure 7. The difference between point and 3D Gaussian on modeling shape. (a) shows the points trained with 2 epochs, (b) and (c) show the Gaussians trained with 2 and 10 epochs, respectively. It is clear that points converge quickly to capture the head shape.

other head avatars and further demonstrates the improved performance of PSAvatar over the existing models.

4.3. Ablation Study

To validate the effectiveness of our method, we conduct experiments to measure the effect of each component, and report the quantitative results in Table 2.

G in Equation (5) INSTA [42] reconstructs the radiance field of human head based on the FLAME mesh as well, but neglect the misalignment between the FLAME mesh and the target geometry, thus causing the noises in the rendered images (see Fig. 5). To address this, \mathcal{G} is applied to learn the per-vertex geometry correction. As seen in Table 2 and Fig. 6, applying \mathcal{G} alleviates the misalignment problem, and contributes to the rendering quality.

PMSM In order to create the point-based morphable

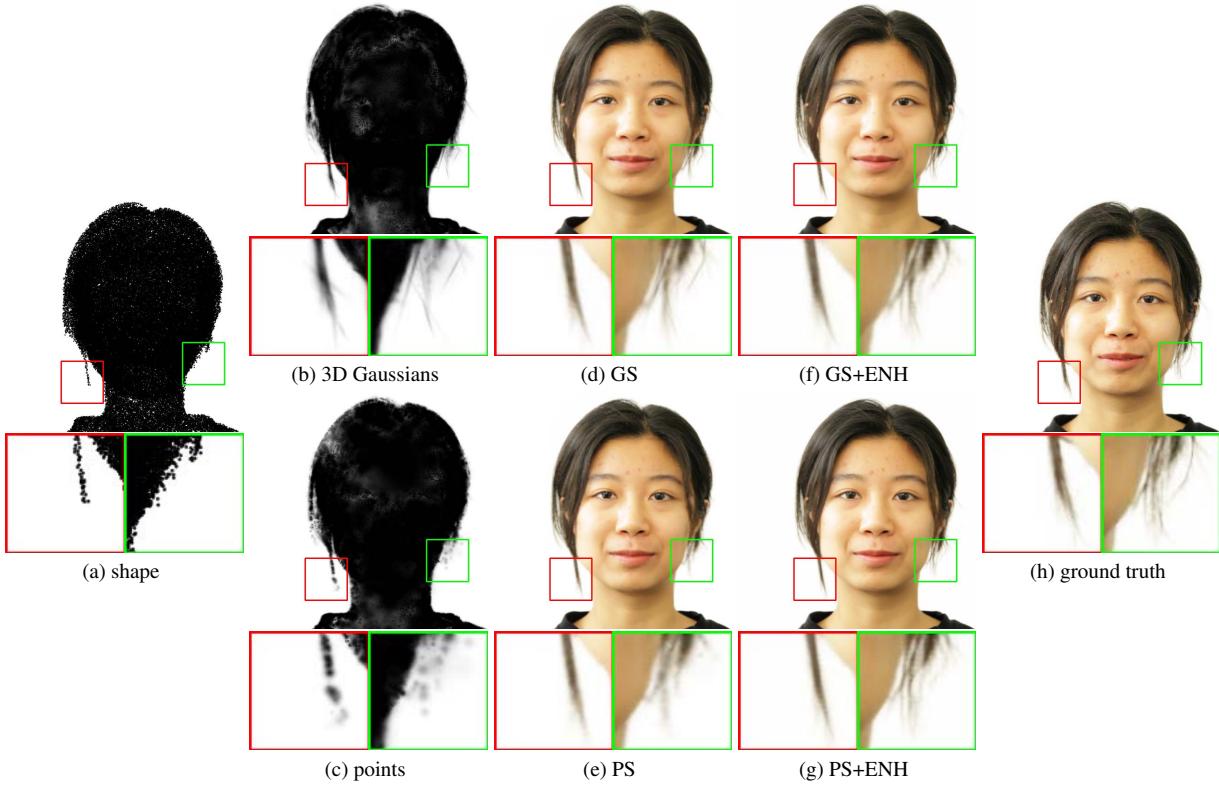


Figure 8. The effect of each component. (a) shows the shape obtained by the PMSM, (b), (d) and (f) are obtained by Gaussian splatting, where 'GS' refers to the image rendered by Gaussian splatting, 'ENH' refers to the enhancement operation, while (c), (e) and (g) are based on point splatting, where 'PS' refers to the image rendered by point splatting. (h) is the ground truth reference.

shape model, points are utilized to model the pose- and expression-dependent shape variation. Fig. 7 shows the differences between points and 3D Gaussians on the implementation of PMSM. It is clearly seen that points trained with 2 epochs can successfully reconstruct the geometry including the hair strands. However, Gaussian splatting fail to model the shape, even trained with 10 epochs. The points only optimize the color c and the opacity σ , in contrast to 3D Gaussians which are additionally parameterized by the rotation and scaling. Hence, points can converge quickly to approximate the shape of head. Considering this, the PMSM is achieved based on points instead of Gaussians.

3D Gaussian 3D Gaussian is utilized for fine detail representation in the rendering stage. To measure the effect of Gaussians, we replace Gaussian splatting with point splatting during rendering. Each point is parameterized by the color c , the opacity σ and the radius r . Fig. 8 shows the difference between Gaussians and points on capturing fine details. The introduced point-based morphable shape model can reconstruct the head including accessories like glasses, but struggles with the representation of single tiny hair. In

a similar way, point splatting suffers from fine detail representation, thus causing the blurry hair in the green box of Fig. 8(e). As a comparison, 3D Gaussian is considerable more flexible than points on 3D representation, and it can render sharp and realistic image.

Enhancement We have found that the U-net based enhancement can further improve the quality of the rendered image. As listed in Table 2, the enhancement network can quantitatively improve the visual quality in term of PSNR, SSIM and LPIPS. Fig. 8 indicates that the enhancement network can improve the visual quality of the rendered image.

5. Conclusion

We have developed PSAvatar, a novel framework for head avatar creation that facilitates flexible shape representation and efficient high-fidelity rendering. PSAvatar utilizes a newly developed Point-based Morphable Shape Model (PMSM) to reconstruct the surface-like geometry in the facial region and capture complex volumetric structures like glasses. The introduction of the PMSM makes it possible to exploit the powerful and flexible representation capabil-

ity of 3D Gaussian for fine detail representation and high-fidelity appearance modeling. We have shown that PSAvatar can create high-quality avatars of a variety of subjects and the avatars can be animated in real-time. Extensive experiments have demonstrated that PSAvatar has superior performances over strong baselines.

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