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Feed-forward Gaussian Registration for Head Avatar Creation and Editing

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Figure 1. Given calibrated multi-view images as input, MATCH infers static Gaussian splat textures in 0.5 seconds. The resulting Gaussians are in dense semantic correspondence across subjects and expressions. This enables diverse downstream applications such as fast head avatar creation, interpolation, semantic editing, and expression transfer. For visualization, we show 6 of the 12 input images, display predicted Gaussians for three separate frames, and apply a checkerboard semantic texture to highlight the dense correspondence.

Abstract

We present MATCH (Multi-view Avatars from Topologically Corresponding Heads), a multi-view Gaussian registration method for high-quality head avatar creation and editing. State-of-the-art multi-view head avatars require time-consuming head tracking followed by expensive avatar optimization, resulting in creation times exceeding one day. In contrast, MATCH directly predicts Gaussian splats in correspondence from calibrated multi-view images in 0.5 seconds per frame. While the learned intra-subject correspondence across frames allows us to quickly build personalized head avatars, correspondence across subjects enables expression transfer, optimization-free tracking, semantic editing, and interpolation. We establish these correspondences with a transformer that predicts textures of Gaussian splats. To this end, we introduce a novel attention block, in which each UV map token attends exclusively to image tokens depicting its corresponding mesh region. MATCH outperforms existing methods for novel-view synthesis, geometry registration, and head avatar generation, the latter being 10× faster than the qualitatively closest baseline. The code and model weights are available on the project website.

*Work partially done while Malte Prinzler was an intern at Google.

1. Introduction

The growing demand for realistic digital humans in telepresence, film, and gaming has intensified the need for scalable methods that can rapidly create controllable, photorealistic head avatars. Obtaining state-of-the-art head avatars from multi-view in-studio captures typically relies on a two-stage pipeline. This involves first establishing cross-view and temporal correspondence via mesh-based tracking before optimizing surface-attached primitives, such as Gaussian splats [21, 23], to model appearance [17, 49, 66]. Despite its high-fidelity results, this two-stage process is a major computational bottleneck, as creating a single personalized avatar typically requires hours, or even days, of optimization. Consequently, scaling to a large number of subjects becomes prohibitively expensive.

Our method MATCH overcomes these limitations by directly predicting Gaussian splats in dense semantic correspondence from multi-view images in 0.5 seconds per frame. In this context, dense semantic correspondence means that all output Gaussian textures share a fixed topology in which a specific Gaussian consistently represents the same semantic region (e.g., the nose tip), regardless of identity or expression. Crucially, this correspondence enables downstream applications such as building lightweight

head avatars in the form of linear Gaussian Eigen Models (GEM) [66], or performing direct expression transfer and semantic editing (see Figure 1). By bypassing both time-consuming mesh tracking (10.7 hours) and animatable Gaussians optimization (27.7 hours), our approach reduces the total GEM avatar creation time by a factor of 10.

MATCH employs a transformer architecture inspired by Large Reconstruction Models (LRM) [52, 61, 63]. The UV texture map and input images are tokenized and processed by a sequence of transformer blocks. However, naïvely attending to all image and UV tokens [20, 56, 57, 59] is computationally expensive and leads to poor generalization on unseen subjects [27]. Instead, we introduce a novel registration-guided attention block. It restricts each UV token to attend only to image tokens displaying the relevant head region, which reduces compute complexity while simultaneously improving synthesis quality.

In summary, MATCH represents heads with Gaussian textures in dense semantic correspondence that are regressed directly from multi-view input images using a novel registration-guided attention mechanism. These textures can subsequently be processed into lightweight GEM [66] avatars, drivable by monocular videos. Finally, we show that dense Gaussian correspondence enables further applications, such as semantic editing and expression transfer.

2. Related Work

Head correspondences. The concept of correspondence across head captures was introduced by early methods such as Blanz and Vetter [4] two decades ago, followed by extensive research on the optimization-based alignment of a common mesh topology to unstructured 3D head scans [2, 4, 22, 32, 42, 44, 50]. Recent learning-based approaches have moved towards predicting registered meshes directly from the raw scans [3, 37, 65], calibrated multi-view input images [5, 15, 29, 33, 38], or even monocular in-the-wild images [18]. While these works are restricted to geometry reconstructions, our method infers registered Gaussian splats representing both geometry and appearance.

Registered head scans enable the construction of 3D morphable models (3DMM) [4], which are used to establish temporal and spatial correspondences across single- or multi-view video frames through subject-specific head tracking [34, 48, 53]. Our method allows us to avoid this slow optimization process (12 s/frame for VHAP [48]) by directly predicting registered Gaussians in 0.5 s per frame.

Optimization-based head avatars. Current personalized head avatars require 3DMM tracking to establish correspondences before avatar optimization. These methods attach appearance representations, such as RGB textures [19], localized radiance field primitives [39], or Gaussian splats [17, 28, 60, 66], to the tracked geometry and optimize them against training images. GEM [66] shows that such high-quality avatars can be distilled into lightweight PCA-based representations. The high quality of the reconstructed avatars comes at the cost of long optimization times (45 h per avatar for GEM). We show that MATCH's predictions can be used to significantly accelerate the reconstruction of lightweight head avatars to 4.6 h per avatar.

Inference-based head avatars. One way to avoid the compute-heavy registration process is to infer animatable head avatars directly from one or a few images, typically at the cost of inferior synthesis quality. While early methods in this field focused on direct 2D image generation [6, 11, 51], recent works have moved towards 3D representations such as texturized meshes [24], Neural Radiance Fields [16, 46, 47], animatable triplanes [7, 10, 12, 13, 55], or 3DMM-attached Gaussian splats [20, 31, 59]. Similar to our approach, LAM [20] and FastAvatar [59] estimate Gaussians with a fixed UV location on a template mesh. However, their Gaussians are predicted in an unposed canonical space, while our method reconstructs the observed expression as-is in posed space with improved fidelity. Avat3r [27] and Facelift [40] predict pixel-aligned Gaussians [36, 52, 61, 63]. Unlike our method, these do not exhibit any cross-frame correspondences.

3. Method

This section presents MATCH, a feed-forward method for reconstructing photorealistic 3D heads as textures of registered Gaussian splats from calibrated multi-view images. We first describe the components of MATCH and then show how it can be applied to speed up the reconstruction process of lightweight, subject-specific head avatars (Section 3.2).

3.1. MATCH

Given V multi-view input images $\mathcal{I} \in \mathbb{R}^{H_{\text{img}} \times W_{\text{img}} \times 3}$ with known camera parameters, MATCH predicts a UV texture of Gaussian splat attributes $\mathcal{G}_{\{\mathbf{c},\boldsymbol{\alpha},\boldsymbol{\phi},\boldsymbol{\sigma},\boldsymbol{\theta}\}} \in \mathbb{R}^{H_{\text{uv}} \times W_{\text{uv}} \times C}$. Every texel is a C-vector that encodes RGB color $\mathbf{c}$, opacity $\boldsymbol{\alpha}$, location $\boldsymbol{\phi}$, anisotropic scale $\boldsymbol{\sigma}$, and rotation quaternion $\boldsymbol{\theta}$ of a Gaussian splat. An overview of MATCH's pipeline is presented in Figure 2.

Image tokenization. Following recent works [27, 63], we convert the high-resolution images $\mathcal{I}$ into image tokens $\mathcal{T}_{\text{img}}$ within low-resolution grids $\in \mathbb{R}^{H'_{\text{img}} \times W'_{\text{img}} \times d}$ that can be processed by the transformer. First, the images are concatenated with Plücker ray coordinates [45]. The result is split into patches and converted into tokens using a 2D convolutional layer with stride and kernel size equal to the patch size p_{img}. Following Avat3r [27], we fuse the image tokens with Sapiens [25] features through concatenation and linear projection, which yields the final tokens of dimension d.

Coarse mesh registration. Before computing the UV tokens, TEMPEH's [5] global stage without head localization is used to estimate a coarse mesh $\mathcal{M} \in \mathbb{R}^{N_{\text{vert}} \times 3}$ from the

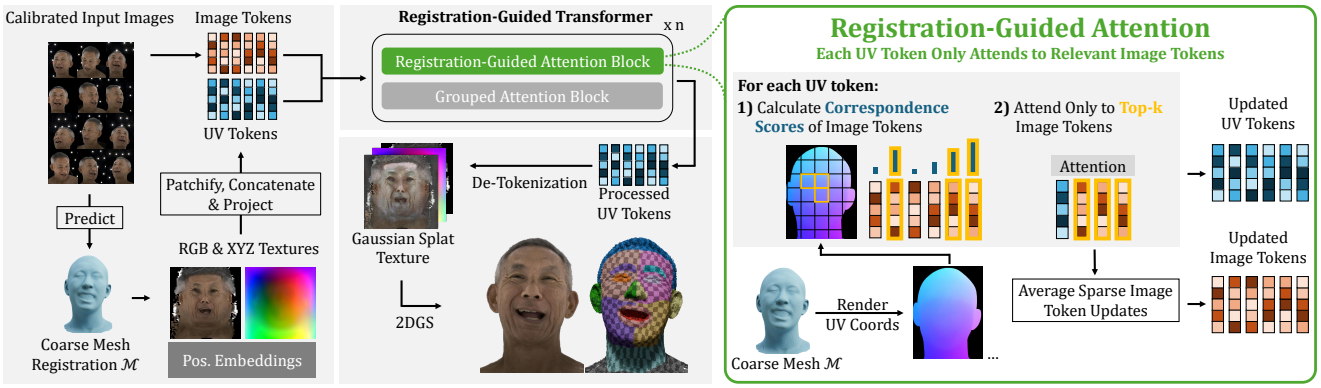


Figure 2. **Overview**. Given calibrated multi-view input images, MATCH first predicts a coarse mesh registration using a pretrained network. We obtain RGB and XYZ textures combined with learnable positional embeddings to encode UV tokens and follow GS-LRM [63] to tokenize the input images. The image and UV tokens serve as input to a transformer with two alternating attention blocks. In the novel registration-guided attention block, we render UV coordinate images from the input views, and for each UV token restrict the attention to image tokens displaying the relevant mesh region. The subsequent grouped attention block performs attention across the UV tokens and the tokens of each input image separately. The transformer outputs processed UV tokens that are projected into a texture of Gaussians.

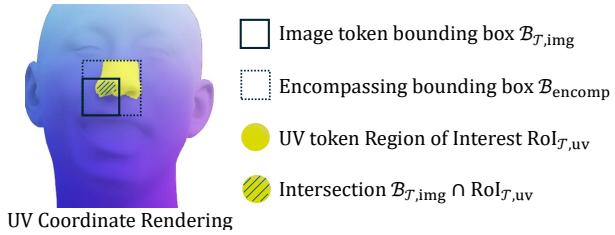


Figure 3. Correspondence score estimation between image tokens and UV tokens. To ease visualization, the full mesh is rasterized in overlay with the UV renders and patch sizes are increased.

input images. TEMPEH is trained against the ground-truth vertices of the Ava-256 dataset [41], including hair proxy geometry, and adopts the provided mesh topology.

UV tokenization. During UV tokenization, a high-resolution UV texture is encoded as a set of UV tokens $\mathcal{T}_{\text{uv}}$ in a low-resolution grid $\in \mathbb{R}^{H'_{\text{uv}} \times W'_{\text{uv}} \times d}$ that can be processed by the transformer. We first calculate a dense 3D location texture through per-texel barycentric interpolation of $\mathcal{M}$'s vertex locations. Second, we obtain an RGB texture by reprojecting the input images onto $\mathcal{M}$. These RGB and 3D location textures are concatenated and divided into non-overlapping patches of size p_{uv}. Finally, they are flattened, concatenated with learnable positional embeddings, and linearly projected to yield d-dimensional UV tokens.

Registration-guided attention. The image and UV tokens are processed by a transformer that contains alternating blocks of registration-guided attention and grouped attention. The registration-guided attention blocks constrain each UV token to only attend to image tokens of the corresponding head region (Figure 2 right). To determine which tokens should attend to each other, we estimate a correspondence score for each pair of UV and image tokens: We use the coarse mesh $\mathcal{M}$ to rasterize UV coordinates onto the input image planes. Since each UV token represents a texture patch, we can filter the rasterized UV coordinates by the respective coordinate range to obtain a region of interest $\text{RoI}_{\mathcal{T},\text{uv}}$ for that UV token, shown in yellow in Figure 3. Now let $\mathcal{B}_{\mathcal{T},\text{img}}$ denote the bounding box of a particular image token, and $\mathcal{B}_{\text{encomp}}$ the bounding box that includes both $\mathcal{B}_{\mathcal{T},\text{img}}$ and $\text{RoI}_{\mathcal{T},\text{uv}}$. The correspondence score S between the UV- and image token is defined as:

$$S\left(\mathcal{T}_{\text{uv}}, \mathcal{T}_{\text{img}}\right) = \frac{\text{RoI}_{\mathcal{T},\text{uv}} \cap \mathcal{B}_{\mathcal{T},\text{img}}}{\mathcal{B}_{\mathcal{T},\text{img}}} + \lambda \cdot \frac{\text{RoI}_{\mathcal{T},\text{uv}}}{\mathcal{B}_{\text{encomp}}}, \quad (1)$$

where the arithmetic is performed on the respective areas in pixels. The first term measures the ratio of pixels within $\mathcal{B}_{\mathcal{T},\text{img}}$ coinciding with $\text{RoI}_{\mathcal{T},\text{uv}}$, while the second term accounts for image tokens in $\text{RoI}_{\mathcal{T},\text{uv}}$'s vicinity (weighted by $\lambda = 0.1$). After evaluating $S(\cdot)$ across all image tokens, for each UV token, we only attend to the $k_{\mathcal{T},\text{img}}$ highest-scoring image tokens. This localizes the reconstruction task, which improves generalization, and keeps the attention context length constant with an increasing number of input images, reducing computation costs for high image counts. After the attention operation, we obtain updated UV tokens, but only sparsely and potentially redundantly updated image tokens, which we address by averaging over all their occurrences.

Grouped attention. This block performs attention separately on the UV tokens and the image tokens of each input image, propagating information to unobserved head regions and enabling image-space feature processing with compute complexity scaling linearly in the number of input images.

UV de-tokenization. The transformer outputs processed UV tokens. We linearly project each token to a texture

patch of Gaussian parameters with shape $p_{\text{uv}} \times p_{\text{uv}} \times C$. These are assembled to the output Gaussian splat texture of shape $H_{\text{uv}} \times W_{\text{uv}} \times C$. For color and location, we follow Avat3r's [27] skip connections and apply the predictions as offsets to the initial values obtained during UV tokenization.

Training. Supervised by multi-view images and ground-truth meshes, MATCH is trained by minimizing:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{photometric}} + w_{\text{geometry}} \cdot \mathcal{L}_{\text{geometry}} + w_{\text{reg}} \cdot \mathcal{L}_{\text{reg}}. \quad (2)$$

The photometric loss $\mathcal{L}_{\text{photometric}}$ matches the predicted appearance against the ground-truth images,

$$\mathcal{L}_{\text{photometric}} = w_{\text{LPIPS}} \cdot \mathcal{L}_{\text{LPIPS}} + w_{\text{L1}} \cdot \mathcal{L}_{\text{L1}} + w_{\text{SSIM}} \cdot \mathcal{L}_{\text{SSIM}} \quad (3)$$

with perceptual loss [64] $\mathcal{L}_{\text{LPIPS}}$ and Structural Similarity Index Measure (SSIM) [58] $\mathcal{L}_{\text{SSIM}}$. We mask out the torso and upper shoulders using a pretrained semantic segmentation model [25]. $\mathcal{L}_{\text{geometry}}$ minimizes the L2-norm between the predicted Gaussian 3D locations and dense target locations from the ground-truth mesh registration. The regularization loss $\mathcal{L}_{\text{reg}}$ applies an L2 loss between the predictions and predefined target values for scale and opacity.

Implementation details: Our training consists of three stages. First, we train solely on the Ava-256 dataset [41], using $\mathcal{L}_{\text{geometry}}$ and $\mathcal{L}_{\text{reg}}$ only. In the second stage, we add $\mathcal{L}_{\text{photometric}}$. In the last stage, we train on a combination of the Ava-256 and the NeRSemble v2 dataset [26]. Since NeRSemble does not provide ground-truth geometry annotations, we deactivate $\mathcal{L}_{\text{geometry}}$ on samples drawn from it.

We adopt Ava-256's mesh topology and UV texture layout. MATCH predicts 64×64 UV tokens, each corresponding to 16×16 texture patches, totalling a 1024×1024 texture with 1M Gaussians that can be rendered at 570 fps [21]. The input images are divided into 8×8 patches.

Each training sample contains 12 head-centered images with a resolution of 640×512, which are used both as model input and rendering target. We train MATCH for 860k iterations on 4 NVIDIA H100 80GB GPUs, with per-GPU batch size 1, taking 11.8 days. See the Sup. Mat. for details.

3.2. Creation of Subject-Specific Head Avatars

Practical applications require animatable avatars. GEM [66] demonstrates the distillation of high-quality 3D head avatars (computationally and memory expensive) into a lightweight representation. We adapt this procedure to obtain controllable head avatars from sequences of Gaussian textures predicted by MATCH.

GEM. Given a multi-view video sequence, GEM performs mesh-based head tracking and optimizes a CNN-based head avatar [35], yielding a set of per-frame Gaussian parameter textures $\{\mathcal{G}_1, \ldots, \mathcal{G}_N\}$ in dense correspondence. Principal Component Analysis (PCA) is performed on these textures for each attribute—scale, position, opacity, and rotation—to build a linear Gaussian splat head model. Expressions are described via low-dimensional coefficients $\mathbf{k}_i$, which define linear combinations of the attribute-specific bases $\mathbf{B}_i$:

$$\mathcal{G} = \{\boldsymbol{\mu}_i + \mathbf{B}_i \mathbf{k}_i \mid i \in \{\boldsymbol{\alpha}, \boldsymbol{\phi}, \boldsymbol{\sigma}, \boldsymbol{\theta}\}\}, \quad (4)$$

where the corresponding means are $\boldsymbol{\mu}_{\{\boldsymbol{\alpha},\boldsymbol{\phi},\boldsymbol{\sigma},\boldsymbol{\theta}\}}$. Colors are modeled as expression-independent constants. The bases are refined against the input images using a photometric loss. For image-based animation, two pretrained expression estimators [8, 14] extract features from input images, and a small MLP maps these features to the coefficients $\mathbf{k}_i$.

MATCH-based GEM avatars. The dense correspondence of the Gaussian splat textures predicted by MATCH allows us to bypass GEM's computationally expensive mesh tracking and CNN-based head avatar training. The predicted Gaussians are transformed into a canonical space through inverse linear blend skinning, followed by GEM's PCA decomposition, bases refinement, and MLP training steps. Contrasting GEM, we model dynamic color changes (except for the oral cavity), perform a joint PCA decomposition across all attributes, and optimize the PCA mean $\boldsymbol{\mu}_*$. Please refer to the Sup. Mat. for more details.

Dataset	Method	LPIPS ↓	CSIM ↑	PSNR ↑	SSIM ↑	L1 ↓	L2 ↓
Ava-256 [41]	GPAvatar [7]	0.303	0.507	21.304	0.714	0.046	0.009
	FastAvatar [59]	0.285	0.667	15.880	0.730	0.074	0.032
	LAM [20]	0.273	0.678	15.898	0.734	0.078	0.035
	Avat3r [27]	0.274	0.626	22.722	0.745	0.039	0.007
	FaceLift [40]	0.208	0.868	21.661	0.825	0.038	0.010
	Ours	0.163	0.928	23.680	0.848	0.027	0.008
NeRSemble [26]	GPAvatar [7]	0.259	0.599	25.296	0.801	0.029	0.003
	FastAvatar [59]	0.248	0.725	18.676	0.797	0.050	0.018
	LAM [20]	0.254	0.746	16.996	0.789	0.062	0.027
	FaceLift [40]	0.200	0.866	21.524	0.853	0.040	0.009
	Ours (Ava-256 only)	0.182	0.892	23.182	0.861	0.030	0.005
	Ours (NeRSemble only)	0.168	0.927	24.136	0.870	0.026	0.005
	Ours	0.152	0.944	25.509	0.884	0.024	0.003

Table 1. Novel view synthesis results on Ava-256 and NeRSemble.

4. Experiments

4.1. Datasets

We train and evaluate MATCH on Ava-256 [41] and NeRSemble v2 [26], which contain head-centric, multi-view video sequences of 256/425 subjects performing various facial expressions, captured by 80/16 cameras in a uniformly-lit studio environment. Ava-256 provides a 360° viewpoint coverage, whereas NeRSemble's cameras are restricted to $\pm 50°$ horizontally and $\pm 15°$ vertically. Ava-256 additionally includes registration meshes with hair proxy geometry for all frames. For validation, we held out 11/6 subjects on Ava-256 and NeRSemble.

4.2. Novel View Synthesis

We compare MATCH against single-view and multi-view 3D head reconstruction methods. LAM [20] and FastAvatar [59] employ transformers to predict 3DMM-attached



Figure 4. Novel view synthesis comparison on Ava-256 [41]. MATCH exhibits superior synthesis quality.

Gaussians while GPAvatar [7] generates animatable triplanes. Avat3r [27] and FaceLift [40] predict pixel-aligned Gaussian splats from the multi-view input images. We provide 12 input images at 640×512 resolution and render a random disjoint target view. For the single-image method LAM, the one with the smallest Euclidean distance to the target camera center is selected.

As shown in Figure 4, GPAvatar's reconstructions are blurry. FastAvatar and LAM achieve higher synthesis quality, but struggle with extreme expressions and exhibit identity shift. FaceLift and Avat3r produce more plausible results, yet FaceLift suffers from oversaturation artifacts and blurry textures, while Avat3r exhibits a loss of identity, especially in the mouth (top) and eye region (bottom). Overall, MATCH reconstructs the target subjects most faithfully, even for extreme expressions such as tongue protrusion. As CAP4D [54] only held out two Ava-256 subjects for testing, we only qualitatively compare to it on the single overlapping test subject in the Sup. Mat. We find that MATCH reconstructs extreme expressions better than CAP4D.

Table 1 quantitatively compares MATCH on 1,000 samples from Ava-256 using standard metrics such as perceptual similarity (LPIPS), Peak Signal to Noise Ratio (PSNR), Structural Similarity Metric (SSIM), pixel-wise L1 and L2 errors, and the cosine similarity between identity vectors extracted by a face recognition network [9] (CSIM). We find that MATCH consistently outperforms all baselines.

Application to datasets w/o geometry. We train MATCH using the 3D head registrations available in Ava-256 as supervision. Although public datasets with larger subject counts exist [26, 43, 62], they lack registered meshes. This raises two questions: i) What is the impact of incorporating NeRSemble during training, despite the absence of ground-truth registrations? and ii) How well does MATCH generalize across datasets? To answer these questions, Figure 5 and Table 1 compare MATCH (trained jointly on Ava-256 and NeRSemble) against two model variants: one trained exclusively on Ava-256, and one trained exclusively on NeRSemble using pseudo-ground-truth meshes obtained via VHAP [48]. Note that the NeRSemble-only variant uses the FLAME mesh topology provided by VHAP, whereas the other versions utilize the Ava-256 topology. We evaluate these variants, alongside other baselines, on 1,000 NeRSemble samples. Even when trained solely on Ava-256, MATCH generates plausible synthesis results on the unseen NeRSemble dataset, outperforming all baselines. While training on NeRSemble alone improves performance, joint training on both datasets yields the best results, despite lacking geometry supervision for the NeRSemble samples. MATCH circumvents the need for expensive head registration on NeRSemble (estimated 216k GPU-hours for 65M frames) by enabling direct training on the images.

	LPIPS ↓	CSIM ↑	PSNR ↑	SSIM ↑	L1 ↓	L2 ↓
Dense Attention	0.221	0.849	20.364	0.794	0.041	0.013
w/o Sapiens	0.202	0.907	22.104	0.819	0.034	0.010
w/o Skipconn.	0.192	0.913	23.075	0.816	0.032	0.009
Orig. TEMPEH	0.190	0.909	22.775	0.823	0.033	0.009
$H_{\text{uv}} = W_{\text{uv}} = 256$	0.194	0.907	22.830	0.817	0.033	0.009
$H_{\text{uv}} = W_{\text{uv}} = 512$	0.190	0.914	22.829	0.822	0.032	0.009
Ours	0.187	0.918	23.032	0.825	0.032	0.009

Table 2. Ablation experiments on Ava-256.

Ablations. Table 2 evaluates the impact of individual model design choices and Figure 6 provides visualizations for the most influential components. All models are trained for 300k iterations on Ava-256. We find that the registration-guided attention yields the biggest performance gain; performing dense attention across all UV and image tokens ('Dense Attention') instead gives the worst scores. Qualitatively, we observe less fine detail in face accessories and worse hair textures with the dense attention approach. The pretrained Sapiens [25] feature extractor has the second-biggest impact. Disabling it ('w/o Sapiens') worsens generalization and reduces the synthesis quality.



Figure 5. Novel view synthesis on NeRSemble. Ours (Ava) / Ours (NeRSemble) are trained on Ava-256 and NeRSemble only, respectively.

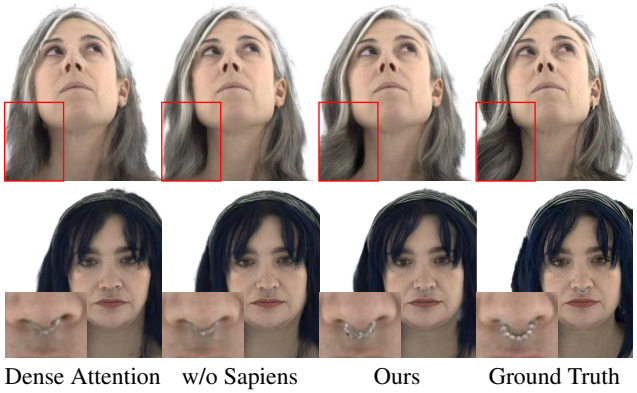


Figure 6. Ablation experiment on Ava-256.



Figure 7. Interpolation between Gaussian textures by factor γ.

Further, the reconstruction quality improves as we increase the UV texture resolution. Additionally, both removing the skip connections ('w/o Skipconn.') and using the original global TEMPEH model for geometry initialization instead of our adapted version ('Orig. TEMPEH'), produce slightly worse reconstructions. The Sup. Mat. provides additional ablations on the number of input images and the number of image tokens $k_{\mathcal{T},\text{img}}$ to attend to in the registration-guided attention blocks. We find that MATCH produces plausible reconstructions from only four input images and that smaller $k_{\mathcal{T},\text{img}}$ improve performance.



Figure 8. (Top) Semantic editing: Replacing a source's nose with that of a target. (Bottom) Expression transfer: Jaw articulation and mouth interior are transferred from a target to a source identity.

4.3. Interpolation, Editing & Expression Transfer

The dense semantic correspondence predicted by MATCH enables diverse applications, including cross-identity and cross-expression interpolation, part-based editing, and expression transfer. Figure 7 shows that simple interpolation between two subjects with different expressions gives smooth and plausible intermediate results. Figure 8 (top) demonstrates semantic editing, where Gaussian splat attributes in the nose region of a source identity are replaced with the ones from a target subject, resulting in a seamless blend. Additionally, Figure 8 (bottom) illustrates an arithmetic expression transfer approach, where the residual of Gaussian maps for an expressive and a neutral frame of a target subject is added to the neutral reconstruction of a source identity, resulting in a plausible expression transfer. Please refer to the Sup. Mat. for more results.

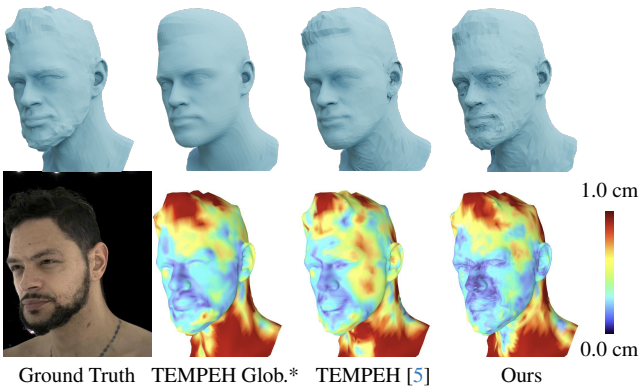


Figure 9. Geometry reconstruction comparison. The heatmaps visualize the Euclidean distance between the predicted and ground truth vertices. 'TEMPEH Glob.*' is the adapted version of TEMPEH's global stage that we use for the coarse mesh registration.

	Full		Face		Mouth		Eyes	
	P2P ↓	P2S ↓	P2P ↓	P2S ↓	P2P ↓	P2S ↓	P2P ↓	P2S ↓
TEMPEH Glob.*	7.34	2.76	3.84	1.50	2.69	1.15	2.27	1.09
TEMPEH [5]	7.84	2.18	4.04	0.97	2.99	0.69	2.66	0.62
Ours	6.69	2.10	3.18	0.88	2.14	0.72	1.54	0.61

Table 3. Quantitative geometry reconstruction comparison on Ava-256. Scores are reported in mm. P2P: Point-to-Point distance. P2S: Point-to-Surface distance. 'TEMPEH Glob.*' is the adapted version of TEMPEH's global stage that we use for the coarse mesh registration. 'Face' is the facial area w/o mouth, eyes, and ears.

4.4. Geometry Reconstruction

MATCH predicts texture maps of Gaussian splat attributes, including a map of 3D positions. Given vertex UV coordinates, these location textures can be converted into a mesh, making MATCH an inference-based head tracker. We compare our geometry reconstruction against TEMPEH [5], a state-of-the-art tracker that estimates registered meshes from multi-view images in a single inference step. For a fair comparison, we retrain TEMPEH on the Ava-256 dataset using the provided mesh topology. We also include the adapted TEMPEH global stage, which generates the coarse mesh registrations $\mathcal{M}$ used as input to our method. Table 3 reports the Euclidean vertex-to-vertex distance (P2P) and the Point-to-Surface (P2S) distance between the predicted and ground-truth meshes on 1,000 Ava-256 samples, while a qualitative comparison can be found in Figure 9. We observe that our method outperforms both baselines on both metrics when averaged over the entire head. In the mouth and eye regions, our method performs comparably to or slightly worse than TEMPEH. This is expected, as the ground truth meshes approximate the oral cavity and eyes with planar faces, while MATCH deviates from this coarse approximation to reconstruct the appearance necessary for a photorealistic rendering.

	Reconstr.	Self-Reenactment			Cross-Reenactment	
	Time ↓	LPIPS ↓	SSIM ↑	PSNR ↑	CSIM ↑	EmoL1 ↓
GA [49]	15.5h	0.233	0.755	21.248	0.629	10.618
RGBAvatar [30]	11.4h	0.233	0.782	22.185	0.657	10.333
GEM [66]	45.3h	0.214	0.778	21.761	0.800	9.866
Ours	4.6h	0.174	0.809	24.122	0.813	9.837

Table 4. Quantitative comparison of subject-specific head avatars.

4.5. Subject-Specific Head Avatars

We compare MATCH-based GEM avatars (Section 3.2) with GEM [66], GaussianAvatars (GA) [49], and RGBAvatar [30]. All methods are optimized per-subject on Ava-256 multi-view videos, captured by 12 cameras with an average sequence length of 3,300 frames. We evaluate the self- and cross-reenactment performances for five subjects on held-out sequences in Table 4 and Figure 10. For image-based animation, we drive GaussianAvatars and RGBAvatar with EMOCA's [8] parameters, which is also used as a pretrained feature extractor to drive GEM and our MATCH-based GEM avatar. Please refer to the Sup. Mat. for more details. We measure standard image metrics for self-reenactment. For cross-reenactment, we evaluate the cosine similarity between features extracted with a pretrained face recognition network [9] (CSIM), and follow GEM [66] in evaluating the L1 distance between features of the emotion recognition network EmoNet [1] (EmoL1).

We find that our method consistently outperforms all baselines in the self-reenactment scenario and performs slightly better or on par with GEM for cross-reenactment. As we adapt GEM's image-based encoder, a similar cross-reenactment performance is plausible. RGBAvatar exhibits noticeable artifacts for subjects with long hair and produces blurry results for unseen expressions. GaussianAvatars generally handles unseen expressions more robustly, but is inferior to GEM and MATCH in terms of synthesis fidelity.

Our method not only improves synthesis quality but also drastically cuts reconstruction time. We achieve a $10\times$ reduction relative to GEM (the baseline with the closest synthesis quality) and are $2.5\times$ faster than the fastest baseline, RGBAvatar, which exhibits inferior visual fidelity. Please refer to the Sup. Mat. for detailed timings and ablation experiments on the changes compared to GEM.

5. Discussion

Registration dependency. MATCH uses Ava-256 mesh registrations as training supervision. While Section 4.2 shows cross-dataset training with mesh supervision on only one dataset, training entirely without it is subject to future work. This could potentially be achieved by training MATCH's geometry part solely on synthetic data.

Expression transfer. The direct transfer of extreme expressions between MATCH's predicted Gaussian textures



Figure 10. Qualitative comparison for image-based self-reenactment (top) and cross-reenactment (bottom) of the subject-specific avatars.

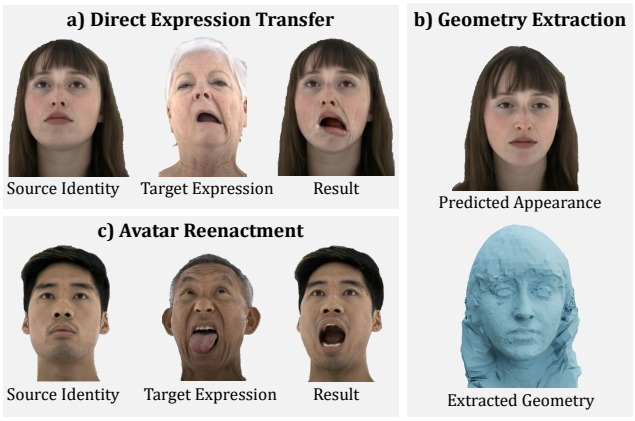


Figure 11. Limitations. a) Direct expression transfer (Section 4.3) may incur identity leakage for dissimilar identities. b) The meshes extracted from the predicted Gaussian 3D location textures (Section 4.4) can exhibit self-intersecting surfaces. c) The subject-specific head avatars (Section 3.2) are bound to interpolations of the training expressions and do not track eye movement.

sometimes results in appearance leakage (Figure 11a). A less simplistic, learning-based method for expression transfer would likely be a more suitable choice.

Geometry reconstruction. Converting the predicted Gaussian 3D location textures into registered meshes occasionally results in self-intersecting surfaces (Section 4.4). While providing perfectly smooth registration meshes is not a primary goal of MATCH, adding additional surface regularization during training could mitigate such artifacts.

Avatar quality. By following GEM's [66] avatar formulation, the resulting avatars inherit its limitations of only generating expressions similar to those in the training data. Moving forward, an interesting direction is to leverage MATCH's cross-subject and cross-expression correspondence by learning a prior across identities and expressions, and then adapting it for per-subject avatars to achieve stronger generalization to unseen expressions.

6. Conclusion

We have presented MATCH, a framework that unifies geometry registration and radiance field reconstruction by predicting Gaussian splats in dense semantic correspondence. Central to this approach is our novel registration-guided attention mechanism, which enhances both computational efficiency and synthesis quality. By bypassing the bottleneck of traditional optimization-based tracking, MATCH reduces the total avatar creation time from 45 hours to just 4.6 hours, a $10\times$ speedup over the qualitatively closest baseline, while simultaneously improving visual fidelity. Beyond efficiency, the learned intra- and inter-subject correspondence unlocks diverse applications, including semantic editing, robust geometry registration, and identity interpolation. Overall, MATCH represents a clear step toward scalable, high-fidelity avatar creation and the structured Gaussian registration representation provides a solid basis for future work on learning priors across different subjects.

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