One Avatar, Any Budget: Robust LoD for Dynamic Gaussian Avatars

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Abstract

Cross-device deployment of a single reconstructed avatar often requires adaptation to varying Gaussian budgets with minimal degradation in visual quality. Motivated by the need for a robust budget-adaptive 3D representation, we propose RobustAvatar, a train-once Level-of-Detail (LoD) adaptation framework for dynamic Gaussian avatars based on sequential selection and compensation. RobustAvatar supports flexible compression-ratio control from a single trained avatar, without requiring ratio-specific fine-tuning or the maintenance of separate LoD models. The framework consists of two coordinated modules: Semantic Distribution-Regularized Selection (SDS) and Canonical Budget-Conditioned Compensation (CBC). SDS performs budget-aware Gaussian selection guided by semantic distribution regularization, preserving the coverage of perceptually salient facial regions in the full avatar under constrained budgets. CBC refines the selected primitives in a canonical, expression- and pose-neutral space by predicting ratio-conditioned attribute residuals, reducing detail loss from Gaussian removal and improving robustness to decreasing Gaussian budgets. Experiments on the NeRSemble dataset show that RobustAvatar achieves more robust budget adaptation than state-of-the-art methods, with slower quality degradation as Gaussian budgets decrease. The code will be made publicly available.

1 Introduction

High-fidelity dynamic head avatars are essential for social VR, telepresence, and multi-user virtual environments. A single reconstructed avatar often needs to adapt to varying memory, compute, bandwidth, and latency constraints across deployment environments. 3D Gaussian Splatting provides an explicit and real-time representation for such avatars Kerbl et al. [2023], and has recently become a common backbone for animatable head modeling Qian et al. [2024], Xu et al. [2024], Chen et al. [2024], Ma et al. [2024], Giebenhain et al. [2024]. The key difficulty is not merely to reduce the number of Gaussian primitives, but to preserve identity appearance, expression-sensitive facial details, and dynamic consistency as the available Gaussian budget decreases. This motivates the need for robust LoD control in dynamic Gaussian avatars, where the representation can adapt to continuous compression ratios. Yet existing methods typically operate at a fixed representation capacity and lack a mechanism to select and compensate Gaussians at reduced budgets. As a result, this can lead to noticeable rendering-quality degradation under tight budgets, making it harder to deploy the same avatar across diverse deployment settings.

Robust LoD control for dynamic Gaussian avatars remains challenging and underexplored. Prior UV-parameterized methods Dongye et al. [2025], Yan et al. [2025] enable continu-

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ous LoD control by resampling a 2D feature field, but this controls capacity through the UV parameterization rather than through the spatial distribution of Gaussian primitives in canonical 3D space. Recent work Song et al. [2026] targets progressive transmission and realizes LoD by monotonically adding Gaussian primitives according to an importance-ordered hierarchy. Although this progressive formulation facilitates reuse of transmitted content, the low-budget representations are determined by prefixes of the learned hierarchy. It does not select a more suitable Gaussian subset for each target budget, nor does it explicitly optimize the attributes of retained Gaussians. These limitations raise a natural question: how can a single reconstructed Gaussian avatar support robust LoD control, keeping visual quality from degrading rapidly as the Gaussian budget decreases?

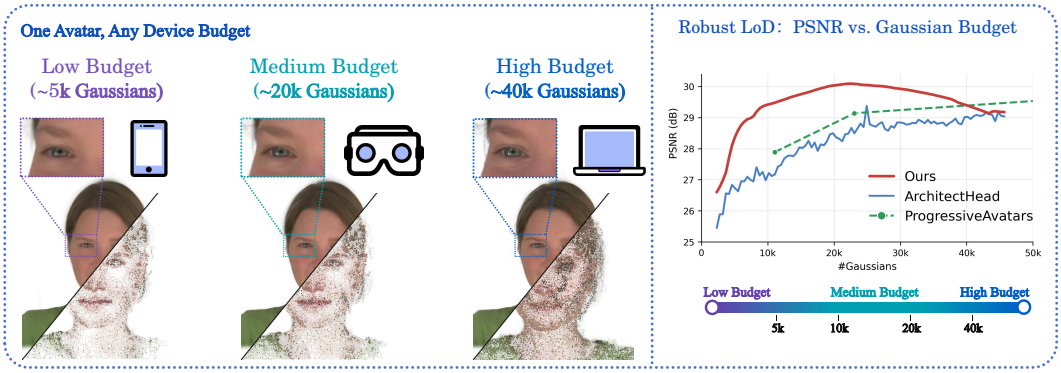


Figure 1: RobustAvatar is motivated by the need to deploy a single dynamic Gaussian avatar across devices with different memory and computation budgets. As shown by the qualitative(left) and quantitative(right) results, RobustAvatar alleviates the rapid visual quality degradation caused by reducing the number of Gaussians.

To address this question, we propose RobustAvatar, a learning framework for LoD adaptation of dynamic Gaussian avatars under varying Gaussian budgets. Unlike existing methods, RobustAvatar directly selects a budget-specific Gaussian subset and compensates the selected Gaussians for each target budget. Specifically, we leverage FLAME to define a canonical space, where Gaussian primitives maintain stable semantic associations and dynamic consistency under expression changes and head motion. To this end, we introduce Semantic Distribution-Regularized Selection (SDS) and Canonical Budget-Conditioned Compensation (CBC): the former learns budget-aware Gaussian selection with semantic distribution constraints, while the latter performs attribute compensation for the selected Gaussian primitives in canonical space. Together, SDS and CBC allow the selected Gaussian primitives to preserve the semantic distribution of the full avatar and compensate for details lost at lower Gaussian budgets, leading to slower quality degradation as the budget decreases. Experiments show that this design improves budget robustness over existing LoD baselines, supporting deployment across settings with different resource constraints, as shown in Figure 1.

In summary, the main contributions of this work are as follows:

- We propose RobustAvatar, a learning framework that enables robust LoD adaptation of dynamic Gaussian avatars through sequential selection and compensation. Given a reconstructed avatar and a target Gaussian budget, RobustAvatar selects an effective subset of Gaussian primitives and compensates the selected subset, enabling flexible budget control without fine-tuning for each ratio or maintaining multiple LoD models.
- We introduce Semantic Distribution-Regularized Selection and Canonical Budget-Conditioned Compensation. SDS preserves facial semantic distributions during budget-aware selection, while CBC performs compensation in canonical 3D Gaussian space to reduce degradation and improve dynamic consistency.

2 Related Work

Animatable Head Avatars. Animatable head avatars have progressed from implicit neural representations to explicit Gaussian-based models. Early methods reconstruct dynamic heads with neural radiance fields or volumetric avatar representations Gafni et al. [2021], Grassal et al. [2022], Bai et al. [2023], while FLAME Li et al. [2017] provides a common scaffold for facial shape, expression, and pose. With 3D Gaussian Splatting Kerbl et al. [2023], GaussianAvatars Qian et al. [2024], Gaussian Head Avatar Xu et al. [2024], MonoGaussianAvatars Chen et al. [2024], 3D Gaussian Blendshapes Ma et al. [2024], NPGA Giebenhain et al. [2024], and GAGA Chu and Harada [2024] show that Gaussian primitives can be rigged, deformed, or generated for high-fidelity and real-time head animation. Recent work further improves projection efficiency Feng et al. [2025], relighting Zhang et al. [2025a], online modeling Li et al. [2025a], mesh-Gaussian editing Wang et al. [2025a], full-head editing Zhang et al. [2025b], statistical head priors Zielonka et al. [2025a], dynamic appearance modeling Wang et al. [2025b], geometry adaptation Moon et al. [2025], hybrid surface-volumetric reconstruction Sun et al. [2025], hair modeling Kim et al. [2025], and generative animation Yu et al. [2025]. A parallel line reduces capture requirements or improves controllability with morphable multi-view diffusion Taubner et al. [2025], zero-shot or few-shot inversion Zhou et al. [2025], Zielonka et al. [2025b], large animatable reconstruction models Kirschstein et al. [2025], personalized or one-shot generation Cha et al. [2025], Chen et al. [2025], Li et al. [2025b], and lifelike audio-driven or talking-head animation Xu et al. [2025], Li et al. [2025c], Zhen et al. [2025], Tan et al. [2025], Hu et al. [2025b], Teotia et al. [2025]. These works advance avatar reconstruction, generation, editing, and animation, but they typically operate at a chosen representation capacity rather than studying how one reconstructed dynamic Gaussian avatar can remain robust under arbitrary Gaussian budgets.

Level of Detail. Level-of-detail methods adapt representation cost to memory, bandwidth, and rendering budgets. For static 3DGS, LightGaussian Fan et al. [2024], Compact 3DGS Lee et al. [2024], and memory-footprint reduction Papantonakis et al. [2024] compress Gaussian parameters, while LP-3DGS Zhang et al. [2024], PUP 3D-GS Hanson et al. [2025b], MaskGaussian Liu et al. [2025c], and Speedy-Splat Hanson et al. [2025a] prune or sparsify primitives; CodecGS Lee et al. [2025], FlexGS Liu et al. [2025b], and LOD-GS Shen et al. [2025] further explore codec-style compression, flexible model-size control, or structured LoD. However, these methods mainly target static or general scenes, where global importance criteria do not need to preserve facial semantics, expression-sensitive details, or deformation consistency. For dynamic Gaussian content, 4DGC Hu et al. [2025a] studies rate-aware 4D Gaussian compression, and HGC-Avatar Tang et al. [2025] builds hierarchical compression for streamable dynamic avatars; however, their emphasis is on bitrate, streaming, or hierarchical coding rather than budget-specific selection and compensation for a reconstructed head avatar. For digital humans, URAvatar Li et al. [2024], LUCAS Liu et al. [2025a], SqueezeMe Iandola et al. [2025], and HRM^{2}Avatar Shi et al. [2025] study codec priors, layered representations, distillation, or mobile-ready deployment, while LoDAvatar Dongye et al. [2025], ArchitectHead Yan et al. [2025], and ProgressiveAvatars Song et al. [2026] provide avatar-specific LoD through UV/template parameterization or additive progressive hierarchies. However, these approaches either redesign the avatar representation, tie budget control to UV/template structures, or rely on nested subsets, leaving open robust selection and compensation of native 3D Gaussian primitives under any target budget.

3 Method

The overview of RobustAvatar is shown in Figure 2. RobustAvatar aims to learn a single ratio-conditioned model on top of an already reconstructed dynamic Gaussian avatar, enabling continuous LoD control over Gaussian budgets at inference time while making the budget-quality curve more robust as the available Gaussian budget decreases. Instead of treating LoD control as a simple primitive removal problem Song et al. [2026], our goal is to slow down the degradation of identity appearance, expression-sensitive facial details, and dynamic consistency under reduced Gaussian budgets.

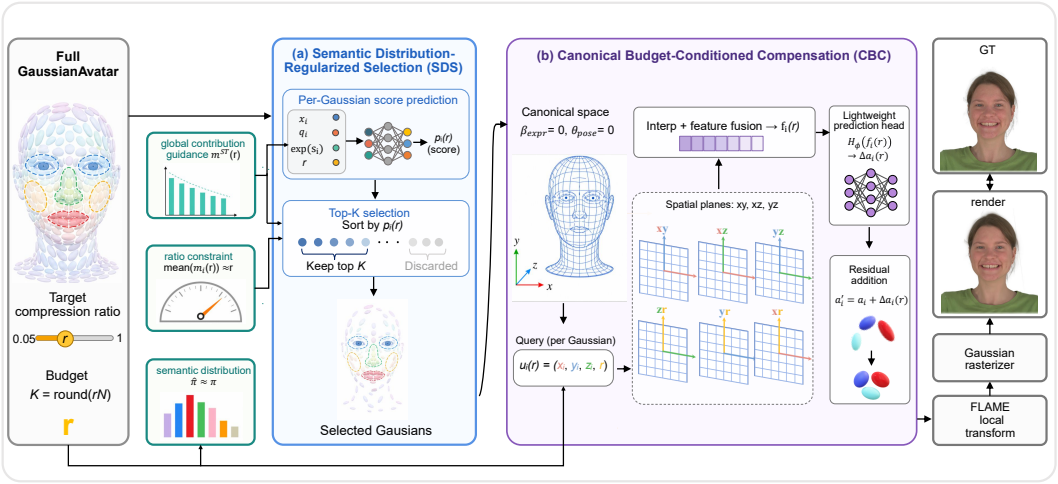


Figure 2: Overview of RobustAvatar. SDS selects a budget-specific Gaussian subset under semantic distribution regularization, while CBC compensates the retained primitives in canonical space with ratio-conditioned attribute residuals. The compensated subset is then transformed to posed avatar space and rasterized, enabling continuous Gaussian-budget control while preserving visual details under low budgets.

Let the Gaussian primitive set of the complete input model, referred to as the full avatar, be

$$\mathcal{G} = \{g_i\}_{i=1}^{N}, \qquad g_i = (\mathbf{x}_i, \mathbf{s}_i, \mathbf{q}_i, o_i, \mathbf{h}_i, b_i), \tag{1}$$

where $\mathbf{x}_i, \mathbf{s}_i, \mathbf{q}_i, o_i, \mathbf{h}_i$ denote the position, log-scale, rotation, opacity logit, and SH/color coefficients of the i-th Gaussian, respectively, and b_i denotes its bound FLAME face. Given a target budget ratio $r \in (0, 1]$, RobustAvatar renders approximately rN Gaussians while preserving visual quality close to that of the full avatar.

To this end, we formulate LoD control as a learning-based budget-conditioned adaptation problem. RobustAvatar consists of two core modules: Semantic Distribution-Regularized Selection (SDS) and Canonical Budget-Conditioned Compensation (CBC). For each ratio r, SDS first learns, through Semantic Distribution-Regularized Selection, to select a more suitable Gaussian subset under the current budget ratio. CBC then applies a budget-conditioned network to adapt the attributes of the retained Gaussians, allowing these retained primitives to compensate for the geometric support and appearance details lost from the removed Gaussians under low budgets. Finally, RobustAvatar learns to adapt the Gaussians available at each budget, thereby slowing down quality degradation as the budget decreases.

3.1 Semantic Distribution-Regularized Selection (SDS)

In a dynamic head avatar, low-budget selection should not be determined only by global rendering contribution. Regions such as the eyes, lips, nose, and eyelids may contain relatively few Gaussians, but they are crucial for identity preservation and expression perception. If only the globally most contributive primitives are retained, the low-budget subset may overconcentrate on a few visually dominant regions, causing rapid degradation of local facial structure and expression-sensitive details.

Therefore, SDS formulates Gaussian selection as a semantic distribution-regularized budgeted subset learning problem. For a target budget ratio r, the model predicts the retention probability of each Gaussian:

$$p_i(r) = S_\theta(\mathbf{x}_i, \mathbf{q}_i, \exp(\mathbf{s}_i), r), \tag{2}$$

where S_θ is a lightweight budgeted subset prediction network. During training, $m^{\mathrm{ST}}(r) \in \{0, 1\}^N$ denotes the straight-through binary keep mask obtained from the keep/drop logits by hard Gumbel-Softmax, while $p_i(r)$ is the corresponding soft keep probability. We constrain the selected Gaussians such that their distribution over facial semantic regions remains

close to the semantic distribution of the full avatar. At inference time, we discard the stochastic mask and sort Gaussians according to $p_i(r)$, retaining the top-K Gaussians, where $K = \max(1, \lfloor rN \rceil)$.

To learn selection strategies under different budgets, we estimate the contribution of each Gaussian from the rendering process of the full avatar. This full-avatar contribution is determined by the Gaussian's visibility, opacity, and screen-space footprint in full-avatar rendering, and is accumulated across training views. For a given budget ratio r, the top-K Gaussians with the highest full-avatar contribution form a binary global importance guidance mask $m^{\text{full}}(r) \in \{0,1\}^N$.

Each Gaussian inherits a FLAME semantic region label $\ell_i \in \{1, \dots, R\}$ through its bound face b_i. Let w_i^{full} denote the full-avatar contribution of the i-th Gaussian. We normalize the average contribution of the full avatar in the k-th semantic region into a target region distribution:

$$\pi_k = \frac{\frac{1}{n_k} \sum_{i:\ell_i=k} w_i^{\text{full}}}{\sum_{j=1}^{R} \frac{1}{n_j} \sum_{i:\ell_i=j} w_i^{\text{full}}}, \tag{3}$$

where n_k is the number of Gaussians in the k-th region. This distribution characterizes the relative importance of different facial regions in the full avatar.

Given the retention probabilities $p_i(r)$ under the current budget ratio, the soft selected region distribution is defined as

$$\hat{\pi}_k(r) = \frac{\sum_{i:\ell_i=k} p_i(r)}{\sum_{j=1}^{R} \sum_{i:\ell_i=j} p_i(r)}. \tag{4}$$

The budgeted subset learning objective is

$$\mathcal{L}_{\text{sub}} = \lambda_{\text{imp}} \| m^{\text{ST}}(r) - m^{\text{full}}(r) \|_1 + \lambda_{\text{ratio}} \left| \frac{1}{N} \sum_i m_i^{\text{ST}}(r) - r \right| + \lambda_{\text{sem}} \| \hat{\pi}(r) - \pi \|_1. \tag{5}$$

This objective imposes three constraints simultaneously: retaining high-contribution Gaussians from the full avatar, satisfying the target budget ratio, and preserving the semantic-region importance distribution of the full avatar.

3.2 Canonical Budget-Conditioned Compensation (CBC)

Primitives in a dynamic Gaussian avatar move across frames under expression changes, head pose, and FLAME-driven deformation. We refer to the frame-dependent coordinate domain after applying expression coefficients, pose coefficients, and head motion as the posed avatar space. In this space, the world-space position and orientation of the same Gaussian change with the expression and pose of each frame. Therefore, directly learning budget compensation in posed avatar space would entangle budget adaptation with frame-dependent motion, weakening dynamic consistency and causing temporal flickering.

We therefore define a canonical space. Specifically, we set both the FLAME expression coefficients and pose coefficients to 0, obtaining the canonical FLAME state. This state removes frame-dependent motion factors introduced by expression deformation and pose-driven motion. We refer to the coordinate domain that represents Gaussian attributes in the FLAME face-local frame under this canonical state as the canonical space, denoted by Ω_c. When rendering an arbitrary frame, the canonical local attributes are transformed to posed avatar space through the local coordinate transform of the corresponding FLAME face under the current expression and pose, and are then passed to the Gaussian rasterizer.

Under low-budget settings, removing unselected Gaussians can cause insufficient local geometric support, broken boundaries, blurred expression-sensitive regions, and appearance drift. Thus, after obtaining a suitable Gaussian subset under the current budget, CBC further adapts the attributes of the retained Gaussians in Ω_c, allowing retained primitives to compensate for the local representation capacity originally carried by the removed Gaussians. Specifically, we define a canonical-ratio field:

$$\Psi_\phi : \Omega_c \times [r_{\min}, 1] \to \mathbb{R}^C, \qquad f_i(r) = \Psi_\phi(\mathbf{x}_i, r), \tag{6}$$

where $\mathbf{x}_i = (x_i, y_i, z_i)$ is the position of the Gaussian in the canonical space.

Directly storing a dense four-dimensional field is expensive. We factorize Ψ_ϕ into six two-dimensional feature planes:

$$\mathcal{P} = \{xy, xz, yz, xr, yr, zr\}. \tag{7}$$

Given a query point $u_i(r) = (x_i, y_i, z_i, r)$, we perform bilinear interpolation on each plane and fuse the resulting features to obtain a budget-conditioned feature:

$$f_i(r) = F_{\text{fuse}}\left(\{\text{Interp}\left(P_{ab}, u_{i,a}, u_{i,b}\right)\}_{(a,b)\in\mathcal{P}}\right). \tag{8}$$

The spatial planes $\{xy, xz, yz\}$ capture the canonical geometric structure, while the ratio planes $\{xr, yr, zr\}$ capture how the compensation at the same canonical location changes with the target budget. A lightweight prediction head then predicts full-attribute residuals from $f_i(r)$:

$$\Delta a_i(r) = H_\phi\big(f_i(r)\big), \qquad \Delta a_i(r) = (\Delta\mathbf{x}_i, \Delta\mathbf{s}_i, \Delta\mathbf{q}_i, \Delta o_i, \Delta\mathbf{h}_i). \tag{9}$$

The compensated Gaussian attributes are

$$(\mathbf{x}_i', \mathbf{s}_i', \mathbf{q}_i', o_i', \mathbf{h}_i') = (\mathbf{x}_i + \Delta\mathbf{x}_i,\ \mathbf{s}_i + \Delta\mathbf{s}_i,\ \text{normalize}(\mathbf{q}_i + \Delta\mathbf{q}_i),\ o_i + \Delta o_i,\ \mathbf{h}_i + \Delta\mathbf{h}_i). \tag{10}$$

CBC is the key to the robustness of RobustAvatar. As the budget decreases, the retained Gaussians learn to provide additional geometric support and appearance compensation for missing regions, thereby reducing the impact of removed primitives on the final rendering quality.

3.3 Training Objective and Inference

During training, we sample a target budget ratio r from a predefined budget set. The full avatar renders the reference image I^{full}. RobustAvatar first selects the Gaussian subset under the current budget, then applies budget-conditioned compensation to the retained Gaussians, and finally renders the image I^r. The reconstruction loss is

$$\mathcal{L}_{\text{rec}} = (1 - \lambda_{\text{ssim}})\|I^r - I^{\text{full}}\|_1 + \lambda_{\text{ssim}}(1 - \text{SSIM}(I^r, I^{\text{full}})). \tag{11}$$

To prevent low-budget adaptation from overly altering the identity structure of the avatar, we introduce preservation and regularization terms. The final training objective is

$$\mathcal{L} = \mathcal{L}_{\text{rec}} + \mathcal{L}_{\text{sub}} + \lambda_{\text{pres}}\mathcal{L}_{\text{pres}} + \lambda_{\text{reg}}\mathcal{L}_{\text{reg}}. \tag{12}$$

Here, $\mathcal{L}_{\text{pres}}$ constrains full-avatar rendering and the local attributes of compensated Gaussians from deviating from the full avatar, while $\mathcal{L}_{\text{reg}}$ includes geometric range constraints and smoothness regularization for the budget-conditioned feature field.

At inference time, given an arbitrary target budget ratio r, RobustAvatar first selects the top-K Gaussians under the current budget and directly discards the remaining primitives. It then applies budget-conditioned compensation and rasterization only to the retained subset. Therefore, the same avatar representation can be deployed continuously under different budgets, while the actual number of rendered primitives is strictly controlled by r.

4 Experiments

4.1 Experiment Settings

Implementation Details. We use the Adam optimizer Kingma and Ba [2015] for all parameter updates. The full avatar is initialized from a 60k-iteration GaussianAvatars Qian et al. [2024] model. For each scene, we train our model for 60k iterations on a single NVIDIA RTX 4090 GPU. Learning rates are set to 5×10^{-4} for Gaussian positions, 2.5×10^{-3} for SH features, 5×10^{-2} for opacity, 1×10^{-2} for scales, and 1×10^{-3} for rotations. Both the budget-conditioned compensation field in CBC and the subset prediction network in SDS are optimized with a learning rate of 1×10^{-4}.

We set $\lambda_{\text{imp}} = 0.5$, $\lambda_{\text{ratio}} = 0.01$, $\lambda_{\text{sem}} = 0.2$, and $\lambda_{\text{pres}} = 1.0$. During training, the budget condition is randomly sampled from $\{10\%, 30\%, 60\%, 90\%\}$ at each iteration, and at inference time the same trained model is queried at deployment ratios of $\{5\%, 10\%, 20\%, 50\%\}$ through top-K Gaussian selection.

Datasets. We evaluate our method under the preprocessed GaussianAvatars Qian et al. [2024]/NeRSemble Kirschstein et al. [2023] setting. For each subject, we use the calibrated camera parameters, white-background preprocessing, foreground masks, and train/validation/test splits provided by the GaussianAvatars data pipeline. A GaussianAvatars model trained for 60k iterations is used as the full avatar for each subject.

Baselines and Metrics. We compare RobustAvatar with ArchitectHead and ProgressiveAvatars. ArchitectHead is evaluated under the same input setting as ours, where both methods use the full GaussianAvatars trained for 60k iterations. Since ProgressiveAvatars does not release its code, we cite its reported results and align the comparison by the actual number of rendered Gaussians. As the ratio definitions differ across methods, we report both the method-specific ratio and the rendered Gaussian count: ours denotes the retained proportion relative to the full avatar, ArchitectHead uses its own LoD control parameter, and ProgressiveAvatars reports the progressive transmission ratio. We evaluate Novel View Synthesis (NVS) and Novel Expression Synthesis (NES) quality using PSNR, SSIM, and LPIPS, and assess temporal stability with optical-flow-based TWE, warped tLPIPS, and rTWE, computed on valid foreground regions after forward–backward flow consistency filtering.

4.2 Reconstruction and Animation Results

Comparison with ArchitectHead Across all tested budgets, RobustAvatar achieves better reconstruction and animation quality than ArchitectHead under comparable numbers of rendered Gaussians. As shown in Table 1, RobustAvatar improves NVS PSNR by approximately 2 dB and NES PSNR by approximately 7 dB on average, while using a similar number of Gaussians.

Comparison with GaussianAvatars As shown in Table 1, at the 50% retained-Gaussian budget, RobustAvatar matches or slightly exceeds the full GaussianAvatars on several metrics while rendering only half of the primitives. This does not indicate that primitive removal alone improves the original avatar; rather, the gains come from budget-conditioned adaptation. SDS selects a high-utility subset whose semantic coverage better matches the 50% budget, reducing the loss of expression-sensitive regions under naive pruning. CBC further adjusts the retained primitives in canonical space, allowing them to compensate for part of the geometric and appearance capacity carried by the removed Gaussians. Since 50% remains a moderate-capacity regime, the selected subset still provides enough support for CBC to refine geometry and appearance. The resulting compact avatar can therefore slightly outperform the unadapted full GaussianAvatars under the evaluation protocol. This effect is most visible at moderate budgets; under very low budgets, reduced representation capacity still leads to inevitable degradation.

Table 1: Quantitative comparison under different Gaussian budgets. Different methods use different ratio definitions; therefore, we report the method-specific setting together with the actual number of rendered Gaussians. The missing entries are marked with "/" because ProgressiveAvatars is not publicly available and the corresponding temporal metrics are not reported in its paper.

Method / Setting	NVS			NES			Temporal			#Gaussians
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	TWE↓	tLPIPS↓	rTWE↓	
Ours (5%)	26.36	0.912	0.197	24.17	0.900	0.188	0.0413	0.0968	0.0366	2,307
Ours (10%)	**28.42**	**0.923**	**0.182**	**25.05**	**0.906**	**0.177**	**0.0381**	**0.0905**	**0.0317**	4,615
ArchitectHead (0.90)	26.18	0.881	0.201	17.83	0.799	0.284	0.0583	0.1453	0.0663	4,871
Ours (20%)	**29.47**	**0.929**	**0.164**	**25.54**	**0.910**	**0.164**	**0.0374**	**0.0872**	**0.0295**	9,230
ArchitectHead (0.75)	26.62	0.886	0.191	18.75	0.813	0.257	0.0579	0.1432	0.0658	8,788
ProgressiveAvatars (5%)	27.89	0.851	0.186	25.13	0.804	0.176	/	/	/	10,144
Ours (50%)	**29.72**	**0.930**	0.152	**25.67**	**0.910**	0.155	**0.0379**	**0.0877**	**0.0292**	23,076
ArchitectHead (0.45)	27.72	0.897	0.159	18.72	0.811	0.241	0.0590	0.1409	0.0668	23,133
ProgressiveAvatars (25%)	29.14	0.892	**0.080**	25.58	0.846	**0.124**	/	/	/	37,302
GaussianAvatars (100%)	29.19	0.927	0.153	25.55	0.909	0.154	0.0382	0.0887	0.0296	46,152

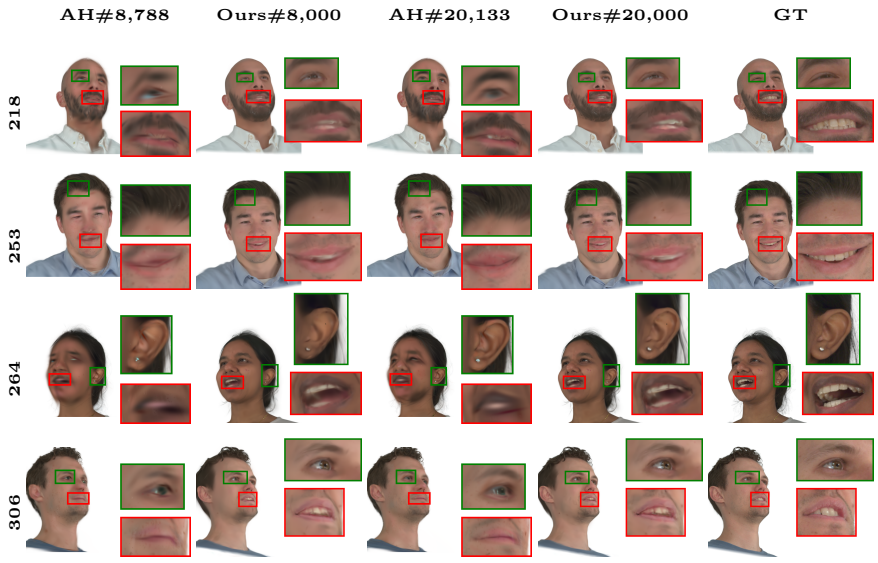


Figure 3: Qualitative comparison with ArchitectHead (AH) under comparable Gaussian budgets. RobustAvatar preserves sharper local details, especially around expression-sensitive regions such as eyes, lips, teeth, and ears, while using a similar number of rendered Gaussians.

Comparison with ProgressiveAvatars. ProgressiveAvatars is designed for monotonic progressive transmission, where low-budget representations are formed by accumulating Gaussian prefixes from a fixed hierarchy. As shown in Table 1, RobustAvatar achieves better NVS and NES quality under comparable Gaussian counts, and in some settings reaches comparable or better quality with fewer Gaussians. For example, RobustAvatar at 20% uses fewer Gaussians than ProgressiveAvatars at 5% while improving all reported NVS and NES metrics. This suggests that a fixed progressive hierarchy does not necessarily provide the most effective representation for each target budget, whereas budget-conditioned selection and compensation make more effective use of limited Gaussian budgets.

Visual Quality Comparison Figure 3 compares RobustAvatar with ArchitectHead under comparable Gaussian budgets. Although ArchitectHead renders a similar number of Gaussians, it often produces over-smoothed facial regions and loses expression-sensitive details around the eyes, lips, and teeth. In contrast, RobustAvatar better preserves local structures such as eye contours, mouth interiors, and tooth boundaries under novel expressions. These visual results are consistent with the NVS and NES gains in Table 1, indicating that budget-conditioned selection and compensation more effectively preserve reconstruction- and animation-critical Gaussians. Figure 4 further shows RobustAvatar under different budget ratios.

4.3 Ablations and Analysis

For compactness, Table 2 denotes three ablated variants as a, b, and c. Variant a removes the canonical-space formulation, variant b disables the deformation branch of CBC, and variant c removes the semantic regularization in SDS. The full model achieves the best or comparable performance in most settings, with the clearest gains at 10% and 20% budgets, where Gaussian removal most strongly affects local facial structures. This indicates that robust LoD adaptation benefits from joint canonical-space compensation and semantic-aware selection.

At the 50% budget, the variant without semantic regularization can match or slightly outperform the full model on some PSNR, SSIM, and LPIPS entries. This does not contradict the purpose of semantic regularization, which is to preserve the facial-region distribution of retained Gaussians rather than directly maximize image-level metrics. Since PSNR, SSIM,

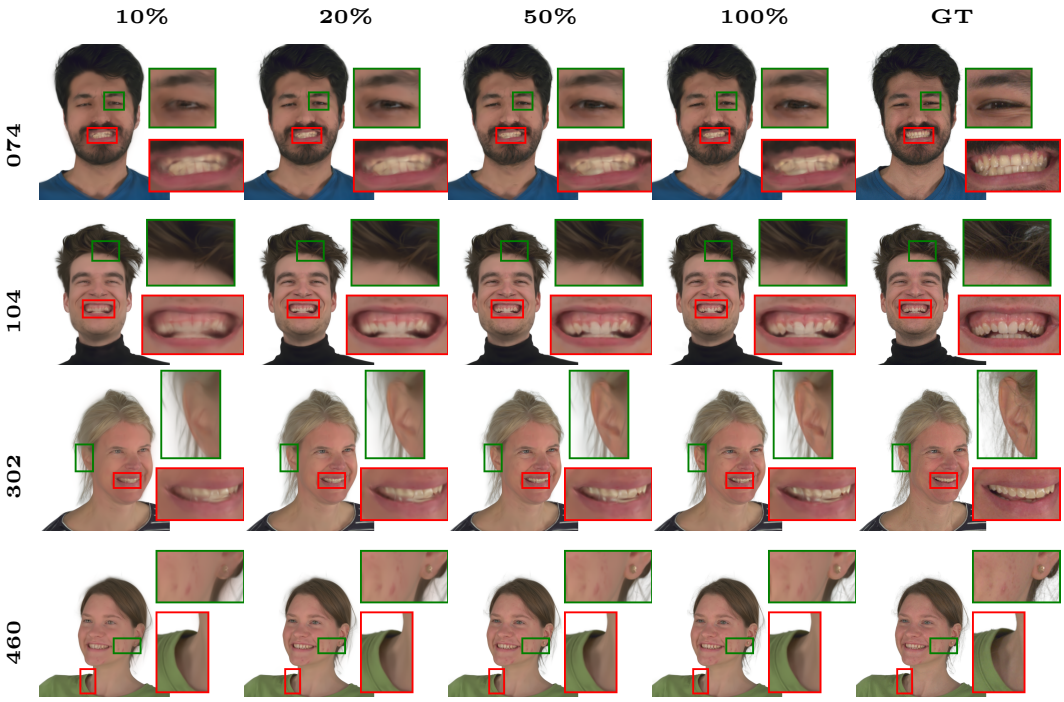


Figure 4: Qualitative results of RobustAvatar under different budget ratios. As the Gaussian budget increases from 10% to 100%, local facial details are progressively recovered and the rendering approaches the ground truth.

Table 2: Ablation results on the validation and test datasets, reporting average PSNR, SSIM, and LPIPS over all avatar subjects.

Dataset	Ratio	10%				20%				50%			
	Strategy	a	b	c	Full	a	b	c	Full	a	b	c	Full
NVS	PSNR↑	27.51	28.02	28.09	28.42	28.40	27.92	28.83	29.47	29.15	29.01	29.68	29.72
	SSIM↑	0.87	0.88	0.87	0.88	0.90	0.90	0.91	0.93	0.92	0.92	0.93	0.93
	LPIPS↓	0.24	0.23	0.23	0.20	0.22	0.20	0.20	0.16	0.16	0.16	0.15	0.15
NES	PSNR↑	24.67	24.57	24.93	25.05	25.39	24.98	25.03	25.54	24.21	25.04	25.82	25.67
	SSIM↑	0.89	0.80	0.90	0.91	0.90	0.91	0.91	0.91	0.90	0.91	0.92	0.91
	LPIPS↓	0.22	0.22	0.21	0.18	0.20	0.19	0.19	0.16	0.18	0.19	0.15	0.16

and LPIPS do not explicitly measure whether expression-sensitive regions are proportionally preserved, the semantic module should be viewed as a structural constraint for robust budgeted selection.

5 Conclusion

We presented RobustAvatar, a budget-robust LoD framework for dynamic Gaussian avatars. Starting from a single full avatar, RobustAvatar enables continuous Gaussian-budget control through budget-conditioned selection and compensation, without ratio-specific fine-tuning or separate LoD models. SDS selects budget-specific Gaussian subsets under semantic distribution constraints, while CBC compensates the retained primitives in canonical space to reduce geometric and appearance loss from Gaussian removal. Experiments show that RobustAvatar better preserves identity appearance, expression-sensitive details, and dynamic consistency, especially in low- and mid-budget regimes. These results demonstrate that selection followed by compensation is an effective paradigm for deploying one reconstructed avatar across diverse resource constraints.

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Supplementary Material

A Overview

This supplementary material provides additional information to support the main paper. We first discuss the limitations of RobustAvatar, including its dependence on controlled multi-view capture, accurate FLAME tracking, and the inevitable loss of fine details under very low Gaussian budgets. We then provide a reproducibility statement that details the experimental protocol, data preprocessing assumptions, training setup, evaluation procedure, and the artifacts required to verify the reported results.

In addition to this document, we submit **two supplementary videos**, `demo-render-only.mp4` and `demo-render-gaussian.mp4`. These videos present multi-scene novel-view rendering results under a continuous compression-ratio sweep, showing how RobustAvatar adapts smoothly across different Gaussian budgets. The videos are intended to complement the quantitative results in the main paper by providing a direct visual demonstration of budget-controllable rendering quality across continuous LoD settings.

B Limitations

Similar to existing Gaussian avatar methods, our approach mainly targets controlled multi-view capture settings and relies on accurate calibration, segmentation, and face tracking. Its quality may degrade under in-the-wild videos, severe occlusions, extreme illumination, or large appearance changes caused by hair and accessories. Since we use FLAME as the underlying facial prior, details that are difficult to represent with the FLAME topology, such as complex hairstyles, glasses, teeth, or non-rigid accessories, may also remain challenging.

Although our ratio-conditioned model supports multiple LoD levels, very low retention ratios inevitably lose some high-frequency appearance and subtle expression details, reflecting the trade-off between compression and rendering quality. Moreover, the compression ratio mainly controls the number of retained Gaussians and does not directly correspond to hardware latency or frame rate, which may vary across rasterizers, GPU architectures, and batching strategies.

C Reproducibility Statement

We provide a detailed and self-contained description of the method and experimental protocol to make the reported results reproducible and verifiable. The paper and supplementary material specify the proposed representation, the ratio-conditioned level-of-detail mechanism, the canonical FLAME-local coordinate system, the ratio-conditioned residual deformation field, the selector architecture, the rendering pipeline, all training losses, and the complete evaluation protocol. We also provide the training and evaluation settings used to produce the reported results, including the scene IDs, data splits, training ratios, evaluation ratios, optimization schedule, loss weights, and metrics.

Method specification. The method is described at the level needed for an independent implementation. In particular, we specify the inputs and outputs of each model component: the hierarchical Gaussian selector, the ratio-conditioned local residual deformation field, the FLAME-local to world-space composition, the opacity and spherical-harmonic residual parameterization, and the final differentiable Gaussian rendering step. We also describe how the compression ratio is injected into the selector and deformation modules, how the selected Gaussian subset is constructed, and how the model behaves at different target ratios. The supplementary material includes the mathematical form of the objective terms and the role of each regularization term.

Data and split protocol. For each scene, we use the same train/validation/test split across all variants. The data follow the standard GaussianAvatars-style preprocessing format, including calibrated cameras, per-frame FLAME parameters, mesh bindings, masks,

and RGB images. If redistribution of the original images or subject data is restricted by the dataset license, we provide the exact scene identifiers, directory structure, preprocessing assumptions, and split definitions so that users with authorized access to the data can reconstruct the same experimental setting.

Training protocol. All reported models are initialized from the corresponding full-resolution GaussianAvatars teacher model and trained for 60,000 iterations. The teacher checkpoint is taken at iteration 60,000. Unless otherwise stated, the same optimizer settings, learning-rate schedule, loss weights, rendering settings, and data split are used for all scenes and ablations. The supplementary material lists the full set of hyperparameters required to reproduce the reported runs, including the selector loss weight, ratio regularization weight, semantic distribution loss weight, preservation loss weights, deformation-field regularization weights, and rendering settings. All experiments use a white background and evaluate the same validation and test views.

Model and result verification. To support verification, we provide the full numerical results in the supplementary material, including PSNR, SSIM, and LPIPS for every scene, ratio, split, and ablation setting. We also report the averaged tables used in the main paper. When permitted by the dataset and model licenses, we will provide trained model checkpoints or intermediate artifacts that allow direct verification of the reported evaluation numbers without retraining. If such artifacts cannot be redistributed, the supplementary material still provides the complete training recipe and evaluation protocol required for independent reproduction by researchers with access to the same data.

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