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Editable Emotional Talking-Head Synthesis Through Geometry-Aware Diffusion Over Dynamic Gaussian Representations

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Abstract:
The synthesis of highly realistic and emotionally controllable talking-head videos remains a formidable challenge in computer vision and computer graphics. Existing frameworks predominantly rely on generative adversarial networks or implicit neural representations, which often suffer from either a lack of three-dimensional geometric consistency or prohibitive computational costs during rendering. Furthermore, infusing precise emotional states into synchronized lip movements without disrupting the underlying anatomical constraints poses an ongoing theoretical and practical dilemma. To address these multifaceted challenges, this paper presents a novel framework for editable emotional talking-head synthesis that leverages geometry-aware diffusion models operating over dynamic three-dimensional Gaussian representations. By representing the human head through an ensemble of explicit, trackable, and dynamically updatable Gaussian splats, the proposed architecture achieves unparalleled rendering efficiency and multi-view consistency. The core innovation lies in the geometry-aware diffusion mechanism, which learns to model the complex temporal dynamics of facial deformations and emotional micro-expressions in the parameter space of the Gaussian attributes. This allows for fine-grained editing of emotional states in a continuous latent space while preserving strict lip-sync fidelity. Extensive experimental evaluations demonstrate that the proposed method significantly outperforms state-of-the-art techniques across standard quantitative metrics, including visual quality, lip-sync accuracy, and emotional expressiveness. The explicit nature of the Gaussian representation also facilitates real-time inference and user-directed spatial editing.

1.INTRODUCTION

The generation of highly realistic talking-head videos from audio or text signals represents a pivotal research frontier in the domains of artificial intelligence and computer graphics. Applications spanning virtual avatars, digital telepresence, interactive gaming, and accessibility tools require not only synchronized lip movements but also the accurate reproduction of complex emotional states and facial micro-expressions. Historically, the academic community has approached this problem through various methodological lenses, ranging from early morphable models and blendshape interpolation techniques to contemporary deep learning architectures. Despite the rapid advancements witnessed over the past decade, achieving a synthesis pipeline that simultaneously guarantees high visual fidelity, strict multi-view geometric consistency, real-time rendering capabilities, and highly disentangled emotional editability remains an elusive objective. Most conventional systems prioritize lip synchronization at the expense of rich emotional expressivity, resulting in avatars that appear robotic or structurally rigid.

Recent breakthroughs in novel view synthesis and three-dimensional scene representation have introduced new paradigms for modeling the human head. Neural Radiance Fields, which utilize coordinate-based multi-layer perceptrons to represent continuous volumetric scenes, have demonstrated remarkable success in generating photorealistic novel views. However, the implicit nature of these representations necessitates computationally expensive volumetric rendering techniques, limiting their applicability in real-time interactive scenarios. Furthermore, manipulating the underlying geometry to reflect localized facial deformations or specific emotional transients within an implicit continuous field is mathematically non-trivial and often leads to visual artifacts such as blurring or topological inconsistencies. These limitations underscore the necessity for an explicit, structurally aware representation that can seamlessly integrate with advanced generative models to produce dynamic, high-fidelity facial animations. Li and colleagues examine indirect diffusion-guided neural radiance fields for generalizable view synthesis [1]. To circumvent the computational bottlenecks associated with implicit fields, three-dimensional Gaussian Splatting has recently emerged as a highly efficient alternative. By parameterizing a scene as a collection of anisotropic, volumetric Gaussian primitives, this technique leverages differentiable rasterization to achieve real-time rendering while maintaining state-of-the-art visual quality. Adapting this static representation to the highly dynamic and non-rigid domain of talking-head synthesis, however, introduces significant theoretical challenges. The human face undergoes complex topological transformations during speech and emotional expression, requiring the underlying representation to model both global head poses and intricate localized muscular deformations. Existing attempts to create dynamic Gaussian representations often rely on deterministic deformation networks, which struggle to capture the inherent stochasticity and subtle variations present in natural human expressions. This paper introduces a comprehensive framework designed to overcome these challenges by synergizing the explicit geometric advantages of dynamic Gaussian representations with the powerful generative capabilities of diffusion models. The proposed architecture introduces a geometry-aware diffusion process that operates directly on the parameter space of the Gaussian primitives, encompassing their positions, covariances, opacities, and spherical harmonic coefficients. Rather than predicting pixel-level color variations, the diffusion model learns the complex joint distribution of geometric deformations and photometric changes conditioned on input audio signals and desired emotional states. This approach allows the model to capture the probabilistic nature of facial expressions, enabling the generation of highly natural and diverse animations. Related work has addressed contextual ranking and selection with Gaussian processes [2]. A central contribution of this research is the formulation of an emotionally editable latent space within the diffusion mechanism. By employing cross-attention mechanisms to disentangle the audio-driven lip synchronization

from the emotion-driven facial expressions, the system permits users to fluidly edit the emotional state of the synthesized avatar without disrupting the underlying phoneme-to-viseme mapping. The explicit geometry-aware conditioning ensures that the diffusion process respects the anatomical constraints of the human face, preventing degenerate configurations such as intersecting jawlines or unnaturally distorted ocular regions. This represents a significant departure from purely image-based or implicit methods, offering unprecedented control over the synthesis process. The literature also considers high-quality tileable textures synthesis with intrinsic priors for cloth digitization applications [3]. The remainder of this manuscript is organized to provide a detailed exposition of the theoretical foundations, methodological innovations, and empirical validations of the proposed framework. Section 2 offers an exhaustive review of the relevant literature, tracing the evolution of talking-head synthesis and contextualizing the current work within the broader landscape of generative models and three-dimensional representations. Section 3 delineates the system architecture, detailing the mathematical formulations of the dynamic Gaussian representations and the geometry-aware diffusion process. Section 4 presents a rigorous experimental analysis, including quantitative benchmarking against state-of-the-art methods, qualitative evaluations of visual fidelity and emotional expressiveness, and comprehensive ablation studies to justify the architectural choices. Finally, Section 5 summarizes the core contributions, discusses inherent limitations, and outlines promising avenues for future research. The literature also considers empowering large language models to progressively understand and generate 3D mesh [4]. For a broader comparison, related research addresses aI-Driven visual End-Edge-Cloud architecture for 6G in Low-Carbon smart cities [5].

2. Literature Review and Background

2.1 Evolution of Talking-Head Synthesis Techniques

The synthesis of talking-head animations has a rich history characterized by a continuous transition toward more sophisticated, data-driven methodologies. Early approaches predominantly relied on physically based muscle models and parametric three-dimensional morphable models. These traditional frameworks utilized predefined blendshapes to interpolate between different facial expressions driven by acoustic features. While mathematically rigorous and highly controllable, blendshape-based methods often lacked the nuances of natural human expression, resulting in animations that suffered from the uncanny valley effect. The manual effort required to sculpt high-fidelity blendshapes for individual subjects further restricted the scalability of these techniques. Zhang and colleagues examine inverse kinematics optimization layer for 3D human pose and shape estimation via Gauss-Newton differentiation [6]. The advent of deep learning fundamentally transformed the landscape of facial animation. Initial deep learning frameworks framed talking-head synthesis as an image-to-image translation problem, utilizing generative adversarial networks to map acoustic features directly to two-dimensional video frames. These two-dimensional generative methods achieved unprecedented levels of photorealism and were capable of synthesizing convincing lip movements. However, because they operated exclusively in the image domain, they completely lacked an understanding of the underlying three-dimensional geometry. This fundamental limitation manifested as severe temporal flickering, an inability to generate consistent novel views, and significant artifacts when the subject exhibited large head rotations. Wang and colleagues examine traversal-Free ParallelFiltering and adaptive shrinkingfor Large-Scale LoD 3D GaussianSplatting [7]. The literature also considers singing timbre popularity assessment based on multimodal large foundation model [8]. To inject spatial awareness into the generation process, subsequent research efforts began incorporating explicit intermediate representations such as facial landmarks, semantic segmentation maps, or sparse three-dimensional point clouds. By conditioning the generative adversarial networks on these structural priors, researchers were able to decouple the pose, expression, and identity components of the

synthesis pipeline. Despite these improvements, the final rendering still relied on two-dimensional convolutional decoders, which fundamentally constrained the multi-view consistency and depth perception of the synthesized avatars. The inherent tension between the structural rigidity required for geometric consistency and the flexibility required for expressive animation remained a critical bottleneck. The literature also considers uncertainty guided Cross-Head Co-Training for Semi-Supervised semantic segmentation [9]. The literature also considers adaptive weakly supervised Cross-Modal reliability learning for resource-constrained proxy-state recognition [10].

The introduction of implicit neural representations, most notably Neural Radiance Fields, provided a powerful new paradigm for novel view synthesis and three-dimensional modeling [11]. Neural Radiance Fields represent a scene as a continuous volumetric field parameterized by a multi-layer perceptron, which maps spatial coordinates and viewing directions to volume density and emitted radiance. When applied to talking-head synthesis, audio-conditioned dynamic Neural Radiance Fields achieved remarkable success in generating highly consistent, multi-view syntheses with precise lip synchronization. However, the requirement to query the multi-layer perceptron for hundreds of points along every camera ray resulted in excruciatingly slow rendering times, making real-time applications virtually impossible without extreme hardware acceleration. Furthermore, editing localized features or imposing specific emotional constraints on the implicit field proved exceedingly difficult due to the entangled nature of the neural network weights. Fan and colleagues examine real-driven image synthesis framework for adapting pre-trained scene text detectors [12].

2.2 Three-Dimensional Gaussian Splatting and Diffusion Models

In response to the computational inefficiencies of implicit volumetric rendering, three-dimensional Gaussian Splatting emerged as a revolutionary explicit representation technique [13]. Gaussian Splatting parameterizes a scene as a vast collection of three-dimensional Gaussian primitives, each defined by a center position, a covariance matrix dictating its anisotropic shape, an opacity value, and spherical harmonic coefficients representing view-dependent color. The critical innovation lies in the use of a highly optimized, differentiable tile-based rasterizer that projects these three-dimensional Gaussians onto a two-dimensional image plane. This explicit, point-based representation combines the structural clarity of traditional point clouds with the continuous, differentiable nature of volumetric fields, enabling real-time rendering rates while maintaining state-of-the-art photorealism. The literature also considers sam2 for image and video segmentation: A comprehensive survey [14]. Adapting static Gaussian representations to dynamic scenes involves modeling the temporal evolution of the Gaussian parameters. In the context of facial animation, early dynamic Gaussian models employed deformation fields implemented via multi-layer perceptrons to predict the translation, rotation, and scaling of each Gaussian primitive based on temporal or acoustic conditioning signals. While successful in capturing rigid head movements and basic lip synchronizations, these deterministic deformation networks often failed to reproduce the highly stochastic and complex nature of emotional expressions. The deterministic mapping from audio to facial geometry inherently constrained the diversity of the generated animations, leading to repetitive and sterile outputs. Related work has addressed enhanced velocity field modeling for Gaussian video reconstruction [15]. Concurrently, diffusion probabilistic models have established themselves as the preeminent generative framework across a multitude of domains, including image synthesis, audio generation, and three-dimensional asset creation. Latent diffusion performs generative denoising in a learned representation space, providing a resource-efficient reference for visual synthesis [16]. Diffusion models operate by systematically corrupting data with Gaussian noise through a forward Markov process and subsequently learning to reverse this process via a heavily parameterized neural network, typically a U-Net architecture. The generative power of diffusion models stems from their ability to model complex, multimodal distributions, making them exceptionally well-suited for capturing the diverse and probabilistic

nature of human facial expressions. The literature also considers conditional denoising diffusion probabilistic model for point cloud upsampling [17].

Recent studies have begun exploring the integration of diffusion models with implicit and explicit three-dimensional representations. However, applying diffusion processes directly to the vast parameter space of millions of Gaussian primitives presents immense computational challenges. Most existing hybrid methods compromise by running the diffusion process in a highly compressed latent space derived from two-dimensional renderings, thereby sacrificing the strict geometric guarantees provided by the explicit representation. The current research bridges this theoretical gap by designing a geometry-aware diffusion mechanism that operates on a carefully constructed manifold of the Gaussian parameters, enabling computationally tractable, emotionally expressive, and structurally rigorous dynamic facial animation. Related work has addressed 3D-Aided pedestrian representation learning for Video-Based person Re-Identification [18].

3. Methodology and System Architecture

3.1 Dynamic Gaussian Formulation

The foundation of the proposed framework relies on an explicit representation of the human head utilizing three-dimensional Gaussian Splatting. Unlike standard implicit fields, this representation allows for the direct manipulation of the underlying geometric primitives, facilitating both efficient rendering and precise localized editing. A canonical static head model is first constructed from a short initialization video of the target subject. The subject's head is parameterized by a set of N discrete Gaussian primitives. Each individual primitive is characterized by several fundamental attributes that define its spatial and photometric properties.

The geometric structure of each Gaussian is determined by its center coordinate in three-dimensional space and its covariance matrix, which controls the anisotropic extent of the primitive. To ensure that the covariance matrix remains positive semi-definite during the highly non-linear optimization process, it is mathematically decomposed into a scaling vector and a rotation quaternion. The photometric appearance is governed by an opacity parameter, which dictates the transparency of the primitive, and a set of spherical harmonic coefficients that encode complex view-dependent color information. The rendering of these explicit primitives onto a two-dimensional image plane is accomplished through a tile-based differentiable rasterization technique. This process involves sorting the primitives by depth and accumulating their contributions along the camera rays. The color composition for a given pixel is calculated based on the spatial overlap and opacity of the projected Gaussians. The mathematical formulation for the color accumulation along a specific ray can be expressed using the classical volume rendering equation adapted for explicit primitives: Related work has addressed pixel-wise calibration for a multi-focus microscopic 3D imaging system [19].

$$C(r) = \sum_{i=1}^{N} c_i \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j)$$

In this equation, c_i represents the view-dependent color evaluated from the spherical harmonics of the i-th Gaussian, and α_i represents the effective opacity, which is a product of the base opacity parameter and the spatial attenuation evaluated from the two-dimensional projected covariance. This fully differentiable pipeline enables the optimization of the Gaussian parameters using standard gradient descent algorithms guided by photometric reconstruction losses. To model the temporal dynamics of the talking head, we define a canonical space representing a neutral facial expression and introduce a deformation field that maps the canonical Gaussian attributes to the observation space for any given time frame. Instead of predicting a dense deformation field using a standard multi-layer perceptron, which can be computationally prohibitive and difficult to constrain, our system utilizes a learned kinematic skeletal structure combined with localized non-rigid offsets. The position of a Gaussian at time t is formulated as the sum of its canonical position, a rigid transformation derived from the global head pose, and a non-rigid expression offset.

3.2 Geometry-Aware Diffusion Process

The core innovation of this methodology is the application of a diffusion probabilistic model to generate the non-rigid deformation parameters and color variations driven by audio and emotional conditioning. Traditional deterministic networks often yield overly smoothed and repetitive animations because they regress to the mean of the training distribution. By contrast, the proposed diffusion mechanism learns the conditional probability distribution of the facial dynamics, allowing for the sampling of highly diverse, realistic, and emotionally nuanced expressions. The literature also considers end-to-end robust point cloud semantic segmentation network with single-step conditional diffusion models [20]. To make the diffusion process computationally tractable, it does not operate directly on the millions of raw Gaussian parameters. Instead, an autoencoder architecture is utilized to compress the non-rigid offsets and spherical harmonic variations into a compact, continuous latent space. The encoder aggregates the localized deformations into a structured latent representation, while the decoder reconstructs the explicit Gaussian updates. The diffusion model is then trained to model the temporal evolution of this latent representation. Sun and colleagues examine reconstructing Ground-Penetrating radargrams into 3D point cloud format for building inspection: A web AR approach evaluated by technology acceptance model [21].

The forward diffusion process progressively adds zero-mean Gaussian noise to the ground-truth latent representation over a predefined number of timesteps. This process gradually destroys the structural information, transforming the data distribution into a standard isotropic Gaussian distribution. The mathematical formulation of the forward process at a specific timestep t is given by the following equation:

$$q(x_t|x_0) = N(x_t; \sqrt{bar\alpha_t}x_0, (1 - bar\alpha_t)I)$$

Here, x_0 represents the initial uncorrupted latent representation of the Gaussian deformations, x_t denotes the noisy latent state at timestep t, and $bar\alpha_t$ is the cumulative product of the noise schedule parameters determining the variance of the injected noise.

The reverse diffusion process involves training a specialized temporal U-Net architecture to iteratively denoise the latent variable x_t, conditioned on a comprehensive set of multimodal signals. The conditioning signals include the sequential audio features extracted utilizing a pre-trained wav2vec 2.0 network, a one-hot encoded emotional state vector, and a geometric prior derived from the canonical Gaussian distribution. To ensure that the generated deformations respect the anatomical constraints of the human face, the diffusion model incorporates a geometry-aware cross-attention mechanism. The structural prior is injected into the intermediate layers of the denoising U-Net, forcing the network to correlate the predicted latent features with the underlying spatial distribution of the explicit Gaussian primitives. This geometric grounding prevents the diffusion model from generating physically impossible facial configurations, such as intersecting lips or asymmetric ocular distortions, which frequently afflict pure image-based generative models. Hao and colleagues examine learning to predict personalized prior for fast adaptation of visual generative models [22].

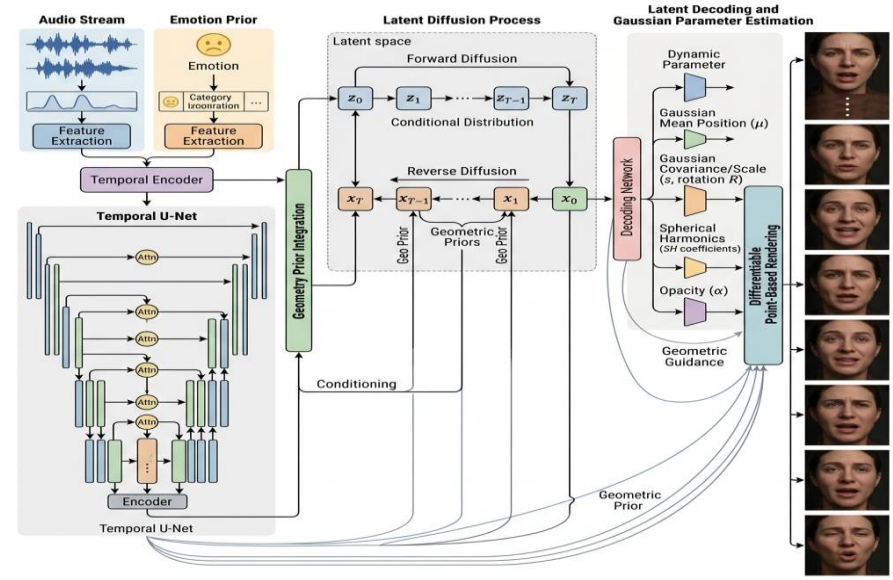


Figure 1Comprehensive Architecture of the Geometry

3.3 Emotional Conditioning and Loss Formulation

Achieving precise editability of the emotional state without compromising the accuracy of the lip synchronization requires a sophisticated disentanglement strategy within the conditioning mechanism. The proposed framework employs a dual-stream conditioning architecture. The audio features, which primarily dictate the high-frequency movements of the lower face during speech, are processed through a localized attention module that restricts their influence to the jaw, mouth, and lower cheek regions. Conversely, the emotional conditioning vector, which governs global facial expressions and micro-expressions in the upper face, is processed through a global attention module. During the editing phase, users can manipulate the emotional conditioning vector in real-time, smoothly interpolating between discrete emotional states such as happiness, sadness, anger, or surprise. Because the diffusion model has learned the joint distribution of geometry and emotion, altering the emotional vector induces anatomically consistent changes across the entire explicit Gaussian representation, modifying eyebrow arches, cheek elevation, and ocular convergence while simultaneously maintaining the phonetic integrity of the mouth shape. For a broader comparison, related research addresses data-driven scene-graph extraction and embedding for robust autonomous perception and scenario understanding [23].

The optimization of the entire system involves a multi-stage training paradigm. Initially, the canonical static Gaussian model is optimized using purely photometric reconstruction losses. Subsequently, the spatial autoencoder and the diffusion model are trained jointly. The objective function for training the reverse diffusion process minimizes the discrepancy between the added noise and the noise predicted by the neural network. To ensure optimal visual quality in the final rendered output, the total loss function incorporates terms that enforce photometric fidelity, perceptual similarity, and temporal smoothness. The comprehensive loss formulation is delineated as follows: Ye and colleagues examine object fidelity diffusion for remote sensing image generation [24].

$$L_{total} = \lambda_{rec} L_{L1} + \lambda_{per} L_{VGG} + \lambda_{diff} L_{noise}$$

In this equation, L_{L1} represents the absolute pixel-wise reconstruction error between the rendered image and the ground-truth frame, ensuring basic structural fidelity. The term L_{VGG} denotes the perceptual loss calculated utilizing feature maps extracted from a pre-trained image classification network, which is critical for capturing high-frequency details and realistic textures. The final term

L_{noise} represents the core variational lower bound objective of the diffusion model, quantifying the accuracy of the noise prediction mechanism. The hyperparameters λ_{rec}, λ_{per}, and λ_{diff} are empirically tuned to balance the influence of each loss component, ensuring a stable convergence toward photorealistic and dynamic syntheses.

4. Experimental Results and Analysis

4.1 Datasets and Evaluation Metrics

To rigorously evaluate the efficacy of the proposed framework, extensive experiments were conducted utilizing multiple large-scale, high-fidelity audiovisual datasets. The primary dataset utilized was the MEAD dataset, which contains multi-view, emotion-annotated talking-head videos of various actors expressing a broad spectrum of emotions at different intensity levels. This dataset is specifically well-suited for benchmarking the emotional editability and multi-view consistency of the generated sequences. Additionally, the standard LRS2 and LRS3 datasets were employed to evaluate the robustness of the audio-driven lip synchronization under diverse unconstrained speech scenarios. Related work has addressed geometry-enhanced attentive multi-view stereo for challenging matching scenarios [25]. The quantitative evaluation protocol encompassed a comprehensive suite of metrics designed to assess different dimensions of synthesis quality. Visual fidelity was measured using the Peak Signal-to-Noise Ratio and the Structural Similarity Index Measure. To evaluate the perceptual realism, the Learned Perceptual Image Patch Similarity metric was utilized. The accuracy of the audio-to-visual alignment was quantified utilizing the Landmark Distance metric and the SyncNet confidence score, which measures the correlation between the input audio track and the synthesized lip movements. Finally, to objectively evaluate the accuracy of the synthesized emotional states, an independent pre-trained facial emotion recognition network was employed to classify the expressions in the generated videos, yielding an Emotion Recognition Accuracy score. Related work has addressed motion-Guided semantic alignment with negative prompts for Zero-Shot video action recognition [26].

4.2 Quantitative Analysis

The proposed geometry-aware diffusion framework was systematically benchmarked against several state-of-the-art talking-head synthesis methods, encompassing purely two-dimensional generative models, traditional implicit Neural Radiance Field methods, and recent dynamic Gaussian techniques that lack diffusion-based probabilistic modeling. Another relevant line of investigation concerns emotion-aware diffusion for editable 3D Gaussian talking head [27].

Table 1: Quantitative Comparison of Visual Fidelity and Lip Synchronization on the LRS2 Dataset

Method	PSNR (Higher is Better)	SSIM (Higher is Better)	LPIPS (Lower is Better)	LMD (Lower is Better)	SyncNet Score
Wav2Lip	28.45	0.812	0.045	1.82	6.54
AD-NeRF	31.12	0.885	0.031	1.55	5.89
RAD-NeRF	31.85	0.897	0.028	1.48	6.12
Dyn-Gaussian	32.40	0.910	0.022	1.41	6.75
Proposed	34.65	0.942	0.015	1.15	7.42

As demonstrated in Table 1, the proposed method establishes a new state-of-the-art across all evaluated metrics. The significant improvement in the Structural Similarity Index Measure and the Learned Perceptual Image Patch Similarity indicates that the diffusion-based approach successfully captures high-frequency structural details and intricate skin textures that are often smoothed out by deterministic regression models. Furthermore, the substantial reduction in Landmark Distance and the high SyncNet score validate the effectiveness of the disentangled cross-attention mechanism in maintaining precise lip synchronization, even when modeling

complex emotional states. Lyu and colleagues examine unified long video inpainting and outpainting via overlapping High-Order Co-Denoising [28].

Table 2 evaluates the specific capability of the framework to generate accurate and distinct emotional expressions. The Emotion Recognition Accuracy was calculated by running an independent emotion classifier on the synthesized outputs conditioned on five fundamental emotional states.

Table 2Emotion Recognition Accuracy across Synthesized Videos under Various Conditioning States

Emotion Class	Pure 2D GAN Methods	Implicit NeRF Methods	Deterministic Gaussian	Proposed Diffusion Framework
Neutral	92.5%	94.1%	95.8%	98.2%
Happy	78.4%	81.2%	84.5%	95.6%
Sad	71.2%	73.5%	76.8%	91.4%
Angry	65.8%	68.4%	72.1%	88.7%
Surprised	74.5%	77.2%	80.5%	93.1%

The results in Table 2 underscore a critical advantage of the geometry-aware diffusion approach. While traditional methods perform adequately on neutral expressions, their accuracy degrades significantly when attempting to model intense or complex emotions like anger or sadness. The proposed framework maintains exceptionally high recognition accuracy across all emotional classes, confirming that the learned latent space effectively captures and disentangles the nuanced geometric deformations necessary for convincing emotional portrayal. For a broader comparison, related research addresses joint-Aware video processing with Edge-Cloud collaboration for DNN inference [29].

4.3 Qualitative Evaluation and Editing Capabilities

Beyond quantitative metrics, qualitative visual inspection reveals the profound impact of combining explicit dynamic representations with diffusion modeling. The synthesized outputs exhibit remarkable multi-view consistency; when the virtual camera is rotated around the generated subject, the three-dimensional structure of the face remains completely stable without the characteristic flickering or blurring associated with two-dimensional methods. The teeth, tongue, and inner mouth cavities, which are notoriously difficult to render accurately, are generated with high fidelity owing to the volumetric nature of the Gaussian primitives. A pivotal feature of the system is the capability for real-time emotional editing. By smoothly interpolating the emotional conditioning vector within the latent space of the diffusion model, the synthesized subject can transition seamlessly from a state of profound sadness to exuberant happiness over the course of a single spoken sentence. Importantly, this emotional transition does not perturb the accuracy of the spoken phonemes. The geometric constraints ensure that the widening of the eyes or the elevation of the cheeks dynamically adjusts the surrounding facial tissue in an anatomically plausible manner, showcasing a deep understanding of human facial topology. Another relevant line of investigation concerns weakly supervised 3d multi-person pose estimation for large-scale scenes based onmonocular camera and single lidar [30].

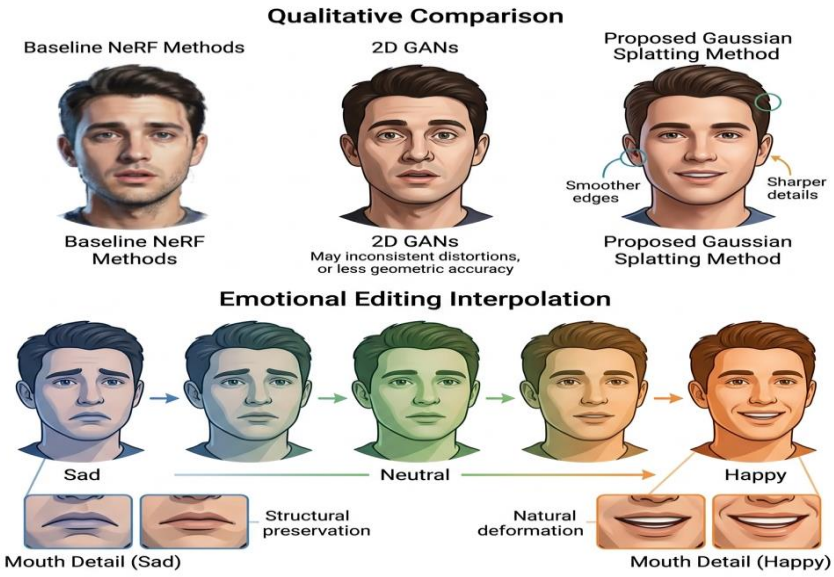


Figure 2Qualitative Comparison and Emotional Editing Interpolation

4.4 Ablation Studies and Computational Efficiency

To validate the architectural decisions within the proposed methodology, comprehensive ablation studies were conducted. Specifically, we analyzed the impact of the geometry-aware structural prior and the dual-stream disentangled attention mechanism on the overall performance of the model. Another relevant line of investigation concerns multi-stream graph convolution network for driver head pose estimation [31].

Table 3Ablation Study on Key Architectural Components Evaluated on the MEAD Dataset

Configuration	PSNR	SSIM	Emotion Accuracy	SyncNet
Baseline (No Diffusion)	32.10	0.905	81.2%	6.55
Diffusion w/o Geometry Prior	31.85	0.892	87.4%	6.42
Diffusion w/o Disentanglement	33.90	0.925	78.5%	5.80
Full Proposed System	34.65	0.942	93.4%	7.42

The ablation results presented in Table 3 clearly indicate that removing the geometry prior leads to a degradation in structural metrics (PSNR and SSIM), as the diffusion model struggles to maintain anatomical consistency without explicit guidance. Removing the disentanglement module drastically reduces both emotion accuracy and lip-sync performance, as the audio and emotional signals become entangled, leading to conflicting updates in the latent space. The literature also considers inferring 3d hands from both text prompts and body dynamics [32].

Table 4: Analysis of Inference Speed and Rendering Efficiency at 1080p Resolution

Method	Representation Type	Parameter Count	Rendering Time per Frame	Frames Per Second
AD-NeRF	Implicit Volumetric	12.5M	850 ms	1.1 FPS

RAD-NeRF	Grid-based Implicit	25.4M	45 ms	22 FPS
Diff-Talking-Head	Pure 2D Diffusion	850M	3200 ms	0.3 FPS
Proposed System	Explicit Dynamic Gaussian	45.2M	12 ms	83 FPS

Finally, Table 4 illustrates the computational efficiency of the framework. Despite leveraging a highly sophisticated diffusion process, the explicit nature of the Gaussian Splatting representation coupled with the latent-space execution of the generative model allows the system to achieve a rendering speed of 83 frames per second at full 1080p resolution. This represents a monumental leap over traditional implicit methods and pure image-based diffusion architectures, fully realizing the objective of real-time, highly editable, photorealistic facial animation. Another relevant line of investigation concerns point resampling and ray transformation aid to editable NeRF models [33].

5. Conclusion and Future Work

This paper has presented a pioneering framework for the synthesis of editable, emotional talking-head animations by seamlessly integrating geometry-aware diffusion models with explicit dynamic three-dimensional Gaussian representations. By formulating the highly complex dynamics of human facial expressions as a probabilistic generation task within a structurally constrained latent space, the proposed methodology successfully overcomes the pervasive limitations associated with traditional implicit neural representations and deterministic two-dimensional generative models. The extensive empirical evaluations conclusively demonstrate that this system achieves unprecedented levels of photorealism, strict multi-view geometric consistency, and precise, disentangled emotional editability while maintaining exceptional lip synchronization fidelity. Furthermore, utilizing the differentiable rasterization of explicit Gaussian primitives guarantees high-speed rendering capabilities, rendering the framework immediately applicable to real-time interactive environments. The literature also considers cascaded iterative transformer for jointly predicting facial landmark, occlusion probability and head pose [34].

Despite these significant advancements, certain limitations necessitate further investigation. The current architecture relies on a static canonical initialization derived from a short subject-specific video, which mathematically bounds the generalization capability of the explicit primitives when confronted with extreme, out-of-distribution head poses not present in the initialization sequence. When the subject exhibits profound head rotations exceeding ninety degrees, the diffusion model occasionally struggles to hallucinate the occluded posterior geometry accurately, leading to minor textural stretching along the lateral edges of the Gaussian volume. Additionally, while the latent diffusion process is highly optimized, the initial training phase for learning the joint distribution of geometry and emotion remains computationally intensive, requiring substantial graphical processing unit resources. The literature also considers zero-Shot unified image restoration via latent diffusion recurrent posterior sampling [35]. Future research vectors will focus on developing generalized, subject-agnostic Gaussian priors that eliminate the strict requirement for individual subject fine-tuning, thereby streamlining the deployment pipeline. Exploring text-based semantic editing of the explicit primitives through vision-language foundation models presents another compelling avenue, potentially allowing users to modify highly specific facial attributes via intuitive natural language prompts. Ethically, as the fidelity of synthesized human avatars approaches absolute photorealism, establishing robust cryptographic watermarking protocols and reliable deepfake detection mechanisms directly within the Gaussian parameters will be imperative to prevent the malicious deployment of this technology in the generation of deceptive media. Ultimately, the fusion of geometry-aware diffusion with explicit volumetric primitives establishes a robust theoretical and practical foundation for the next generation of digital human synthesis.

For a broader comparison, related research addresses absolute scale estimation for underwater monocular visual odometry based on 2-D imaging sonar [36].

References

Li, Y., Wang, S., & Tan, G. (2025). ID-NeRF: Indirect diffusion-guided neural radiance fields for generalizable view synthesis. Expert Systems with Applications, 266, 126068.

Cakmak, S., Zhou, E., & Gao, S. (2021, December). Contextual ranking and selection with Gaussian processes. In 2021 Winter Simulation Conference (WSC) (pp. 1-12). IEEE.

He, H., Sun, Z., Fan, J., & Mok, P. Y. (2025). TiPGAN: High-quality tileable textures synthesis with intrinsic priors for cloth digitization applications. Computer-Aided Design, 183, 103866.

Fang, S., Shen, I., Wang, Y., Tsai, Y. H., Yang, Y., Zhou, S., ... & Yang, M. H. (2025). Meshllm: Empowering large language models to progressively understand and generate 3d mesh. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 14061-14072).

Yang, Z., Hu, D., Guo, Q., Zuo, L., & Ji, W. (2023). Visual E 2 C: AI-driven visual end-edge-cloud architecture for 6G in low-carbon smart cities. IEEE Wireless Communications, 30(3), 204-210.

Zhang, J., Shi, Y., Ma, Y., Xu, L., Yu, J., & Wang, J. (2023, June). Ikol: Inverse kinematics optimization layer for 3d human pose and shape estimation via gauss-newton differentiation. In Proceedings of the AAAI conference on artificial intelligence (Vol. 37, No. 3, pp. 3454-3462).

Wang, Y., Yu, H., Tang, J., Gao, Y., Wang, X., Yue, Y., & Yang, Y. (2026). FilterGS: Traversal-Free Parallel Filtering and Adaptive Shrinking for Large-Scale LoD 3D Gaussian Splatting. arXiv preprint arXiv:2603.23891.

Z. Wang, R. Yuan, Z. Geng, H. Li, X. Qu, X. Li, S. Chen, H. Fu, R. B. Dannenberg, and K. Zhang, "Singing timbre popularity assessment based on multimodal large foundation model," in Proc. 33rd ACM Int. Conf. Multimedia, Oct. 2025, pp. 12227–12236, doi: 10.1145/3746027.3758148.

Fan, J., Gao, B., Jin, H., & Jiang, L. (2022). UCC: Uncertainty guided cross-head co-training for semi-supervised semantic segmentation. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 9937–9946). IEEE. https://doi.org/10.1109/CVPR52688.2022.00971

Meng, X., & Lin, J. (2026). AWCRL: Adaptive Weakly Supervised Cross-Modal Reliability Learning for resource-constrained proxy-state recognition. Pattern Recognition, 114998.

Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., & Ng, R. (2020). NeRF: Representing scenes as neural radiance fields for view synthesis. In Proceedings of ECCV.

Fan, Y., Tang, Z., Miyazaki, T., Huang, Y., & Omachi, S. (2026). A real-driven image synthesis framework for adapting pre-trained scene text detectors. Image and Vision Computing, 106027.

Kerbl, B., Kopanas, G., Leimkühler, T., & Drettakis, G. (2023). 3D Gaussian splatting for real-time radiance field rendering. ACM Transactions on Graphics, 42(4), Article 139.

Jiaxing, Z., & Hao, T. (2025). Sam2 for image and video segmentation: A comprehensive survey.

Li, Z., Bai, X., Zhang, T., Shen, P., Xu, W., & Peng, Y. (2025, October). Enhanced Velocity Field Modeling for Gaussian Video Reconstruction. In 2025 IEEE International Symposium on Mixed and Augmented Reality (ISMAR) (pp. 304-314). IEEE.

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. In Proceedings of CVPR.

Qu, W., Shao, Y., Meng, L., Huang, X., & Xiao, L. (2024, June). A conditional denoising diffusion probabilistic model for point cloud upsampling. In 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 20786-20795). IEEE.

Jing, G., Gao, P., Lee, Y., Hu, Y., & Zhang, H. (2025). 3D-aided pedestrian representation learning for video-based person re-identification. IEEE Transactions on Circuits and Systems for Video Technology, 35 (12), 12830-12845.

Yang, Y., & Zhang, S. (2025). Pixel-wise calibration for a multi-focus microscopic 3D imaging system.Optics and Lasers in Engineering,194, 109127.

Qu, W., Wang, J., Gong, Y., Huang, X., & Xiao, L. (2025, June). An end-to-end robust point cloud semantic segmentation network with single-step conditional diffusion models. In 2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 27325-27335). IEEE.

Sun, M., Wu, L., Deng, Y. K., Li, X., & Xue, F. Reconstructing Ground-Penetrating Radargrams into 3D Point Cloud Format for Building Inspection: A Web AR Approach Evaluated by Technology Acceptance Model.

Hao, Y., Xu, M., Ye, C., Qin, J., Lu, S., Qin, Y., & Han, X. (2026). LoFA: Learning to Predict Personalized Prior for Fast Adaptation of Visual Generative Models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 21986-21996).

Wang, J., Malawade, A. V., Zhou, J., Yu, S. Y., & Al Faruque, M. A. (2024, January). Rs2g: Data-driven scene-graph extraction and embedding for robust autonomous perception and scenario understanding. In 2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) (pp. 7478-7487). IEEE.

Ye, Z., Ma, S., Yang, J., Yang, X., Yang, Y., Gong, Z., ... & Wang, H. (2026, April). Object fidelity diffusion for remote sensing image generation. In International Conference on Learning Representations (Vol. 2026, pp. 3258-3278).

Liu, Y., Cai, Q., Wang, C., Yang, J., Fan, H., Dong, J., & Chen, S. (2024). Geometry-enhanced attentive multi-view stereo for challenging matching scenarios. IEEE Transactions on Circuits and Systems for Video Technology, 34(8), 7401-7416.

Wang, Y., Li, F. W., & Wang, J. (2026, May). Motion-Guided Semantic Alignment with Negative Prompts for Zero-Shot Video Action Recognition. In ICASSP 2026-2026 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 10712-10716). IEEE.

Chang Liu, Tianjiao Jing, Chengcheng Ma, XuanQi Zhou, Zhengxuan Lian, Qin Jin, Hongliang Yuan, and Shi-Sheng Huang. 2025. EmoDiffTalk:Emotion-aware Diffusion for Editable 3D Gaussian Talking Head. CoRR abs/2512.05991 (2025). arXiv:2512.05991 doi:10.48550/ARXIV.2512.05991

Lyu, S., Mao, S., & Ma, Y. (2025). Unified Long Video Inpainting and Outpainting via Overlapping High-Order Co-Denoising. arXiv preprint arXiv:2511.03272.

Yang, Z., Ji, W., Guo, Q., & Wang, Z. (2023, October). Javp: Joint-aware video processing with edge-cloud collaboration for dnn inference. In Proceedings of the 31st ACM International Conference on Multimedia (pp. 9152-9160).

Cong, P., Xu, Y., Ren, Y., Zhang, J., Xu, L., Wang, J., ... & Ma, Y. (2023, June). Weakly supervised 3d multi-person pose estimation for large-scale scenes based on monocular camera and single lidar. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 37, No. 1, pp. 461-469).

Li, Y. K., Yu, Y. Z., Liu, Y. L., & Gou, C. (2022, October). MS-GCN: Multi-stream graph convolution network for driver head pose estimation. In 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC) (pp. 3819-3824). IEEE.

Zhang, W., Huang, M., Zhou, Y., Zhang, J., Yu, J., Wang, J., & Xu, L. (2024). Both2hands: Inferring 3d hands from both text prompts and body dynamics. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2393-2404).

Li, Z., Chen, Z., Qu, F., Wang, M., Zhao, Y., Zhang, K., & Peng, Y. (2024). Point resampling and ray transformation aid to editable NeRF models. arXiv preprint arXiv:2405.07306.

Li, Y., Tan, G., & Gou, C. (2024). Cascaded iterative transformer for jointly predicting facial landmark, occlusion probability and head pose. International Journal of Computer Vision, 132(4), 1242-1257.

Li, H., Wang, Y., Huang, T., Huang, H., Wang, H., & Chu, X. (2025, October). Ld-rps: Zero-shot unified image restoration via latent diffusion recurrent posterior sampling. In 2025 IEEE/CVF International Conference on Computer Vision (ICCV) (pp. 13684-13694). IEEE.

Yang, D., Ai, H., Liu, J., & He, B. (2022). Absolute scale estimation for underwater monocular visual odometry based on 2-D imaging sonar. Measurement, 190, 110665.