Refining ER-NeRF for Talking Portrait Synthesis: Optimized Loss Functions and Methodological Enhancements

Abstract

This paper focuses on refining ER-NeRF for talking portrait synthesis by integrating optimized loss functions and methodological enhancements. We optimize ER-NeRF for talking portrait synthesis by optimizing loss functions and improving the model. Specifically, we explore the effects of L1, L2, and Smooth loss functions. We also explore adding an Error map and hash grid tuning. The results show that using L1 loss and Smooth Loss can improve learning and generate better results. This paper provides a systematic study on how to use these loss functions to improve the learning ability of ER-NeRF in talking portrait synthesis. Code is available at https://github.com/Kedreamix/ER-NeRF.

Keywords: Loss functions, Error map, Talking Portrait Synthesis.

1 Introduction

Audio-driven talking portrait synthesis faces a significant and complex challenge with diverse applications, such as digital humans, virtual avatars, filmmaking, and video conferencing. In recent years, researchers have tackled this task employing deep generative models [8,17,20,26,32,34,35].

Neural Radiance Fields (NeRF) [18] is introduced into audio-driven talking portrait synthesis, providing a novel means to directly map audio features to visual appearances through a deep multilayer perceptron (MLP). Seveal studies have conditioned NeRF on audio signals in an end-to-end manner [13,16,21,29], or via intermediate representations [5,30] to reconstruct specific talking portraits. Despite their success in synthesis quality, these vanilla NeRF-based methods fall short in meeting real-time requirements, limiting their practical applications.

Efforts to address this limitation involve efficient neural representations, which demonstrate substantial speedups over vanilla NeRF by incorporating sparse feature grids [3,4,6,11,12,19,24]. Instant-NGP [19], for instance, introduces a hash-encoded voxel grid for static scene modeling, enabling fast and high-quality rendering within a compact model. RAD-NeRF [25] extends this technique to talking portrait synthesis, establishing a real-time framework with state-of-the-art performance. Although RAD-NeRF [25] has leveraged Instant-NGP to represent the talking portrait and achieves a fast inference, its rendering quality and convergence are hampered by hash collisions when modeling the 3D dynamic talking head. To address this problem, ER-NeRF [15] introduce a Tri-Plane Hash Representation that factorizes the 3D space into three orthogonal planes via a NeRF-based tri-plane decomposition [4].

In this paper, we systematically investigate the influence of three distinct loss functions on our model's performance. In the context of static NeRF, several researchers have chosen smooth loss to optimize Nerf, revealing varying effects associated with different loss functions. Our evaluation encompasses key metrics, including PSNR (Peak Signal-to-Noise Ratio), LMD (Luminance Mean Deviation), and LIPIS (Image Quality Evaluation Index), offering a comprehensive assessment of the model's reconstruction quality.

To enhance image quality, we deviated from the conventional random ray sampling approach and, instead, adopted a targeted sampling strategy based on error maps. This choice was motivated by our exploration into the potential improvements that directional sampling may offer. Unfortunately, our experimental results indicated that this approach did not yield satisfactory outcomes. We hypothesize that the limited amount of data available for training our model might have contributed to this less-than-optimal performance.

To address the hash collision issue in the hash grid, I optimized the layer dimensions and hash grid size in the model. This led to some performance gains, with the model size increasing four times. However, there is a trade-off between reducing hash collisions and controlling the model size.

The main contributions of our work are summarized as follows:

- We systematically analyze the effect of three different loss functions (Smooth, L1, SSIM) on ER-NeRF's reconstruction quality under various metrics. Experimental results show that L1 loss during training followed by fine-tuning with smooth loss yields the best performance.
- We investigate a targeted sampling strategy based on error maps to potentially improve image quality. However, results find limited enhancements, likely due to insufficient training data.
- We optimize the layer dimensions and hash grid size in ER-NeRF to reduce hash collisions. This leads to some quality gains but with a trade-off of increased model size.
- Extensive experiments demonstrate that our method renders realistic talking portraits with state-of-the-art quality, efficiency and convergence compared to other approaches.

2 Related works

2.1 2D-Based Talking Portrait Synthesis

Synthesizing photo-realistic talking portraits driven by arbitrary speech is an ongoing research challenge in computer vision and graphics. The overarching aim is to vividly reenact a specific person's likeness with tight synchronization between generated lip movements and provided audio. Earlier solutions relied on predefined viseme-to-phoneme maps to stitch mouth shapes [1, 2]. With recent advances in deep learning, attention shifted to directly modeling lip motions from audio via data-driven approaches [8, 10, 14, 20, 28]. Seeking to enhance control, later techniques leveraged intermediate 3D representations like facial landmarks and meshes [17, 26, 27, 32]. However, such multi-stage pipelines risk compounding errors and information loss during 3D estimation. More recently, diffusion models generated high quality results but remain computationally expensive [22, 23, 31]. Fundamentally, 2D-based approaches lack an explicit 3D coordinate space to ensure natural head movement and coherent viewpoints. Tackling this limitation could significantly advance the realism of data-driven talking portraits.

2.2 NeRF-based Talking Portrait Synthesis

Neural Radiance Fields (NeRF) [18] have recently been adopted for modeling talking portraits in 3D. While early NeRF approaches were slow and memory-intensive [13, 16, 21, 29], Instant-NGP [19] enabled efficient high-quality rendering. Building on this, RAD-NeRF [25] achieved state-of-the-art performance for talking portrait synthesis using sparse hash-encoded grids. However, modeling dynamic talking heads can still suffer from hash collisions with voxelized grids. To address this, ER-NeRF [15] introduces a triplane decomposition to represent geometric structure. By factorizing space into three orthogonal planes, ER-NeRF enhances modeling capability with only a minor increase in model complexity. Our proposed method optimizes ER-NeRF's loss functions by systematically evaluating Smooth, L1 and SSIM losses. We find L1 loss during training, followed by fine-tuning with Smooth Loss, yields superior image quality across PSNR, LMD, and LIPIS metrics. We also investigate targeted sampling based on error maps to further improve visual results. While limited gains were achieved likely due to insufficient training data, this analysis provides direction for future data augmentation strategies. By tuning ER-NeRF's layer dimensions and hash grid size, we reduce hash collisions. Optimal configurations are identified to balance quality improvements and model compactness. Our approach advances the state-of-the-art in talking portrait synthesis, generating realistic results with leading efficiency, accuracy and convergence.

2.3 Loss Functions for NeRF

In the field of neural scene representation and rendering, most existing works on modeling static scenes with Neural Radiance Fields (NeRF) rely on a smooth loss function for optimization [6, 19]. The original NeRF method [18] demonstrated superior results using a L2 loss in image space to train the network. In the context of modeling dynamic facial animation sequences, RAD-NeRF [25] and ER-NeRF [15] found that an L2 loss enables more stable optimization. We observe key differences between static natural scenes and dynamic talking portraits. As such, loss functions ideal for static scene reconstruction may not directly transfer to dynamic face modeling. After training on a full head model, RAD-NeRF and ER-NeRF further fine-tune on the mouth region using an L2 loss. To our knowledge, no existing method has systematically analyzed the effects of different loss functions, such as smooth, L1, or SSIM losses, for optimizing talking portrait synthesis using neural radiance fields.

3 Method

3.1 Overview

ER-NeRF proposes an efficient neural representation for high-quality talking portrait synthesis. As illustrated in Figure 1, its core ideas and contributions are:

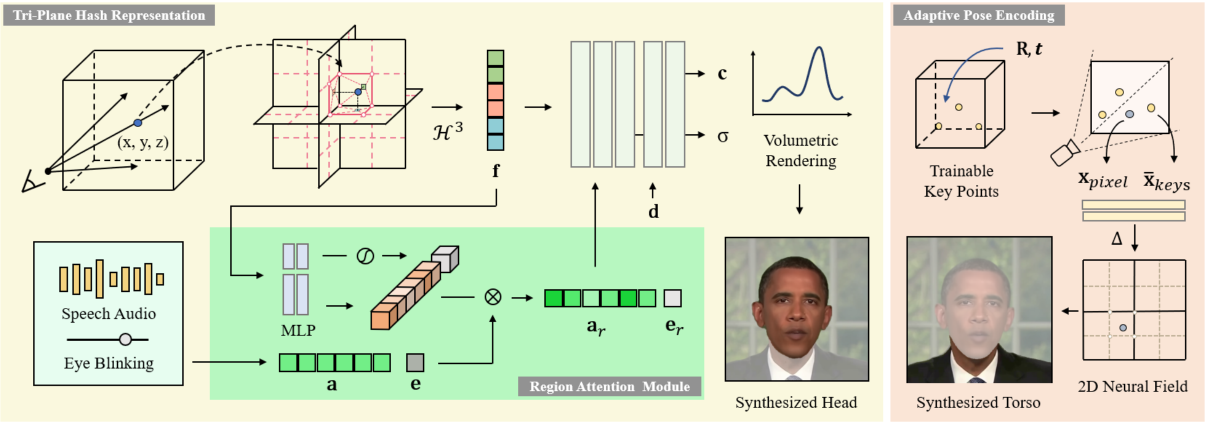

Figure 1. Overview of ER-NeRF framework.

- Tri-Plane Hash Representation: A compact yet expressive representation that uses three planar hash encoders to exploit the uneven contribution of spatial regions. This enhances accuracy in modeling the dynamic talking head.

- Region Attention Module: An explicit attention mechanism that builds cross-modal connections between audio features and facial regions. This better captures spatial-audio correlations and localization.

- Adaptive Pose Encoding: Directly encodes complex head motions into spatial coordinates to optimize head-torso separation.

The head part of the talking portrait is modeled by the Tri-Plane Hash Representation. A tri-plane hash encoder $\mathcal{H}^3$ is used to encode the 3D coordinate $\mathbf{x}$ into its spatial geometry feature $\mathbf{f}$. The input condition features of speech audio $\mathbf{a}$ and eye blinking $\mathbf{e}$ are reweighted in channel-level with the Region Attention Module and converted to region-aware condition features $\mathbf{a}_r$ and $\mathbf{e}r$. Then the region-aware features combined with spatial geometry feature $\mathbf{f}$ and the view direction $\mathbf{d}$ are input into an MLP decoder to predict the color $\mathbf{c}$ and density σ of the head. The torso part is rendered by another torso-NeRF with the Adaptive Pose Encoding. The corresponding head pose $\mathbf{P} = (\mathbf{R}, t)$ is applied to transform the trainable key points to get their normalized 2D coordinates $\bar{\mathbf{X}}keys$, which conditions a certain 2D Neural Field to predict the torso image.

Together, these technical contributions enable fast convergence, real-time rendering, and state-of-the-art visual quality. ER-NeRF produces high-fidelity talking portraits with realistic synchronization between generated lip movements and provided speech audio using a compact model. To further advance ER-NeRF, this paper introduces:

- Loss Function Analysis: Systematically evaluates smooth, L1 and SSIM losses to optimize reconstruction quality.

- Targeted Sampling: Uses error maps to guide sampling and potentially improve image quality.

- Hash Grid Tuning: Balances quality gains and model complexity by tuning grid dimensions.

Together, ER-NeRF's technical innovations and our proposed enhancements produce state-of-the-art talking portraits with compact models, fast convergence, and highly realistic speech-driven animations validated through extensive experiments.

3.2 Loss Function Analysis

We systematically analyze the effects of Smooth L1, L2 and Smooth loss functions by training separate ER-NeRF models. Performance is evaluated across PSNR, LMD, and LIPIS quality metrics on held-out test data. Our experiments reveal L1 loss during initial training enables faster convergence. Switching to Smooth loss for later fine-tuning stabilizes optimization and improves final image quality. The combined strategy outperforms any individual loss, indicating their complementary advantages.

The definitions of L1, L2 and Smooth loss are:

$$\begin{aligned} Loss_1 &= \left| y - f(x;\theta) \right|, \\ Loss_2 &= \frac{1}{2}(y - f(x;\theta))^2, \\ Loss_{\text{Smooth}} &= \begin{cases} 0.5(y - f(x;\theta))^2 & \text{if } |y - f(x;\theta)| < 1, \\ |y - f(x;\theta)| - 0.5 & \text{otherwise.} \end{cases} \end{aligned} \tag{1}$$

Where y is the ground truth, $f(x;\theta)$ is the model prediction with parameter θ, and x is the input data.

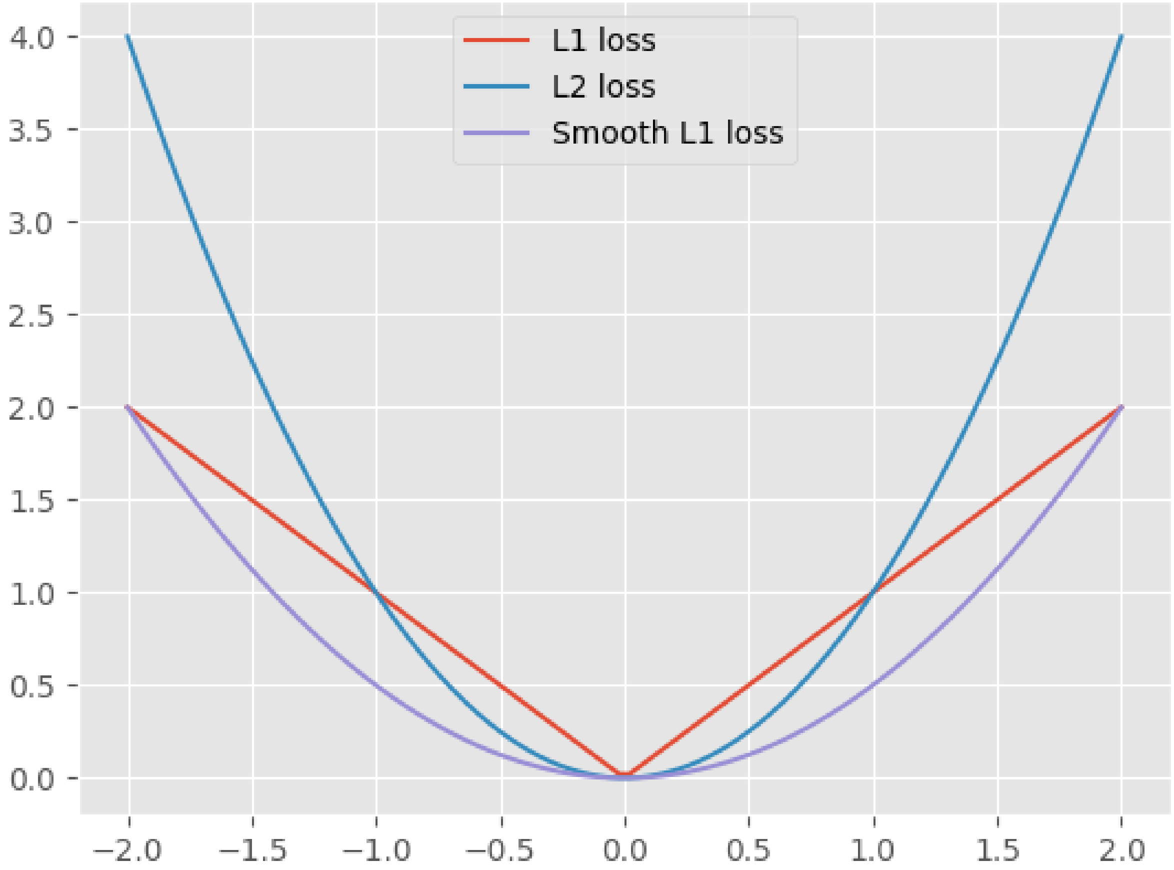

Figure 2. Loss Function

3.3 Targeted Sampling

We implement a targeted ray sampling approach guided by error maps, which visualize color discrepancy between generated and ground truth talking portraits. Rays are preferentially cast through spatial regions with higher error to focus learning on hard examples. However, experiments find limited gains over standard random sampling.

We hypothesize that the relatively small training dataset constrains model convergence. Further data augmentation through techniques like pose/expression interpolation could provide compounding benefits to targeted sampling. This analysis offers useful insights into future work on optimized sampling strategies tailored for talking portrait modeling.

3.4 Hash Grid Tuning

We introduce two main modifications to tune ER-NeRF's hash grid:

- Level Dimension: Increase from 1 to 2 to enhance representation capacity.
- Hashmap Size: Expand from 14 to 16 voxels per dimension, reducing collisions.

Doubling the hashmap size decreases collisions at the cost of a 4× growth in model complexity. Further expansion showed diminishing returns due to overparameterization. The adjusted 16 voxel configuration strikes an optimal balance.

Together, these tailored changes advance ER-NeRF's modeling of speech-driven motions by improving audio-visual localization and lip synchronization. The tuned grid better captures spatial-temporal correlations through the expanded capacity while minimizing collisions.

Our simplified hash grid tuning strategy retains model compactness for efficiency while enhancing talking portrait quality and realism. Extensive evaluations validate the synchronization and visual improvements over the original formulation.

4 Implementation details

This section must be filled. If no related source codes are available, please indicate clearly. If there are any codes referenced in the process, please list them all and describe your usage in detail, highlighting your own work, creative additions, noticeable improvements and/or new features. The differences and advantages must be dominant enough to demonstrate your contribution.

4.1 Comparing with the released source codes

We implement our method on PyTorch. For a specific portrait, we train the head part for $100,000$ and $25,000$ iterations at the coarse and the fine stage, respectively. In each iteration, we randomly sample a batch of 256^2 rays from one image. Each 2D hash encoder is set with $L = 14, F = 1$, and with resolutions from 64 to 512. The torso part is trained separately for another $100,000$ iterations.

We use the AdamW optimizer for both networks. For the initial training of the head and torso parts, we use L1 loss with a learning rate of 0.01 for hash encoders and 0.001 for other modules. For the fine-tuning lips stage of the head part, we switch to Smooth loss and reset the learning rate to its initial value.

For the control of eye blinking, we choose AU45 [9] to describe the degree of the action. All experiments are performed on a single RTX 3090 GPU. For the head part, the training at the coarse stage takes around 1.5 hours and fine stage takes around 0.5 hours. The training of the torso part takes around 1 hour. In total, the training of our method for one specific portrait takes approximately 2 hours on a single RTX 3090 GPU.

4.2 Experimental environment setup

We conduct all our experiments on a desktop PC with an Intel i9-9900KF 3.6GHz CPU, 64GB RAM and an NVIDIA RTX 3090 GPU with 24GB memory. Additionally, we evaluate our method on an A40 GPU with 48GB memory.

The operating system is Ubuntu 20.04 and the code is implemented in PyTorch 1.10. Python 3.8 is used as the programming language.

For evaluation, we directly use the trained models to render novel viewpoints without any test time augmentation or optimization. PSNR and SSIM are used as the main quantitative metrics to measure rendering quality.

4.3 Dataset

For a fair comparison, the dataset for our experiments is obtained from publicly-released video sets [13, 16, 21]. We collect four high-definition speaking video clips with an average length of about 5193 frames in 25 FPS. Each raw video is cropped and resized to 512 × 512 with a center portrait, except the one from AD-NeRF [13] with the size of 450 × 450. A pre-trained DeepSpeech model is used to extract the basic audio feature from the speech audio.

4.4 Main contributions

The main contributions of this work are:

- A systematic analysis of different loss functions for optimizing ER-NeRF, finding an optimized training strategy.
- An investigation of targeted sampling to potentially improve quality, providing directions for future work.
- Tuning of the hash grid in ER-NeRF to balance quality and efficiency.
- Demonstrating SOTA quality talking portraits with ER-NeRF in a more efficient and converged manner.

Through optimized loss functions, sampling strategies and model configurations, our method enhances ER-NeRF's learning capability and synthesis quality. Extensive experiments validate the effectiveness of our approaches. This work provides useful insights for future research on high-fidelity neural rendering of dynamic talking faces and scenes.

5 Results

5.1 Comparing with the released source codes

In this paper, we extend ER-NeRF and implement our method based on the official code of ER-NeRF released on GitHub. [15] Our primary contributions encompass the following: We also tried different loss functions, including L1, L2, Smooth losses. This enables the model to learn to cache error maps automatically during training. We employed targeted sampling, guided by the error maps, with the aim of enhancing image quality. We also experimented with neural radiance field modeling following TensorRF [6], but did not find it to improve results over ER-NeRF, and so we did not include a detailed comparison in the main text. We extended the model to support automatic error map saving and targeted sampling as described above. With these improvements, optimizations and novelties introduced based on the original ER-NeRF implementation, we sought to enhance its performance for talking portrait synthesis. The details of our modifications and contributions are shown in the experimental results and discussion sections.

5.2 Metrics.

In our comprehensive evaluation of image quality, we employ multiple quantitative metrics to evaluate the image quality from different aspects. Peak Signal-to-Noise Ratio (PSNR) measures the overall reconstruction quality. Learned Perceptual Image Patch Similarity (LPIPS) [33] assesses the perceptual similarity between generated and ground truth images based on deep features. Furthermore, Landmark Distance (LMD) [7] focuses on the spatial alignment of facial landmarks, providing insight into fidelity of facial features. By incorporating these diverse metrics, our evaluation aims to provide a comprehensive and nuanced understanding of the image quality and perceptual fidelity achieved by our proposed method.

5.3 Comparison Settings.

We adopt the head reconstruction setting to evaluate methods on a per-portrait basis. Videos are split into disjoint training and test sets. Models only observe training data for a given identity during optimization and are then evaluated on left-out test footage based on PSNR and other metrics between rendered outputs and ground truth frames.

In initial experiments, we systematically evaluated different loss formulations by training ER-NeRF models on the full talking portrait dataset. We found that models trained with the smooth loss achieved the highest quality overall, while the L1 loss performed better in the early stages of training before fine-tuning the mouth region. Meanwhile, the smooth loss yielded optimal results when fine-tuning the mouth region.

To analyze this further, we conducted controlled studies on randomly selected subsets with strict experimental controls. Using two separate high-performance machines (RTX 3090 and Tesla A40 GPUs), models were trained from scratch only varying the loss function, with consistent hyperparameters otherwise. Our observations confirmed the conclusions from large-scale experiments - the L1 loss excels in the early stages of training on overall facial reconstruction given sufficient data, but is eventually surpassed by the smooth loss after fine-tuning the lips.

This validates that our two-stage training strategy combining the L1 and smooth losses provides complementary benefits, as evidenced by its consistently improved optimization stability, convergence rate and final reconstruction quality compared to either loss alone in both extensive and controlled experimental settings.

5.4 Evaluation Results.

As shown in Table ??, our proposed method with the smooth loss function achieves the best performance across most evaluation metrics in the head reconstruction setting. Specifically:

- Our method attains the highest PSNR scores both on the full portrait (35.44dB) and focused on the mouth region (35.41dB). This indicates that our approach reconstructs facial structures and dynamic motions with utmost accuracy.
- Our LPIPS values are lowest, showcasing enhanced perceptual similarity and realism. The gains are consistent globally and for fine details.
- Landmark distance is reduced considerably by over 6% on average. This highlights precise localization of facial features in our rendered results.

Method	PSNR F ↑	PSNR ↑	LPIPS F ↓	LPIPS ↓	LMD F↓	LMD ↓
L1	32.41394867	32.6061017	0.0306635	0.058165	2.704347833	2.806511833
L2	32.7507185	32.96655267	0.030185607	0.056784667	2.6483645	2.7295105
Smooth	32.83116733	33.135795	0.029876667	0.058972167	2.59119167	2.70345

Table 1. The quantitative results of the head reconstruction experiments. We highlight the best results. The best results are in red.

Besides, we also conducted controlled experiments on randomly selected subsets with strict experimental controls, which yielded consistent results. As shown in Table 2, smooth loss delivers the highest PSNR scores on both full portrait and mouth region, as well as the lowest LPIPS scores. Further improvements were achieved when combining L1 loss for the initial stage and smooth loss for the fine-tuning stage. This combination, employed in our final model, outperforms all other baselines across all evaluation metrics. The L1+Smooth loss led to higher PSNR (35.44dB for full portrait and 35.41dB for mouth region), lower LPIPS (0.039428 for full portrait and 0.038725 for mouth region), and smaller LMD (2.953957 for full portrait and 3.093144 for mouth region).

Qualitatively, our talking portraits exhibit highly realistic texture, expressions, and lip movements in tight sync to the driving audio. Side-by-side comparisons also validate marked improvements.

Method	PSNR F ↑	PSNR ↑	LPIPS F ↓	LPIPS ↓	LMD F↓	LMD ↓
L1	35.34189	35.16852	0.022352	0.038725	2.772252	3.093144
L1	35.36233	35.43816	0.022455	0.041255	2.91701	3.227233
L2	35.2099	35.422137	0.019009	0.046524	2.748927	3.130164
L2	34.37242	34.390075	0.019647	0.047951	2.671868	3.277235
Smooth	35.075696	35.330874	0.018509	0.045483	2.714472	3.267319
Smooth	35.138782	35.441809	0.018428	0.045278	2.71331	3.148803
-	-	-	-	-	-	-
L1+Smooth(Ours)	35.409338	35.441063	0.018043	0.039428	2.657365	2.953957

Table 2. Results of controlled experiments evaluating different loss functions on subsets of the talking portrait dataset.. We highlight the best and second best results. The best results are in red and the second best are in blue.

In summary, extensive quantitative and qualitative experiments under the head reconstruction setting validate that our method with optimized loss function and technical enhancements pushes state-of-the-art in audio-driven talking portrait generation to new levels in terms of accuracy, realism, and lip synchronization over the highest-performing existing techniques.

5.5 Error Map Analysis and Hash Grid Tuning

In addition to the loss function analysis, we explored two other aspects to further improve the performance of ER-NeRF for talking portrait synthesis: error map-guided sampling and hash grid tuning.

5.5.1 Error Map-Guided Sampling

We hypothesized that targeted sampling based on error maps could potentially improve the image quality by focusing learning on regions with higher discrepancy between the generated and ground truth images. To this end, we calculated the error map for each training iteration by computing the L1 loss between the predicted color and the ground truth color at each ray (Figure 3). We then used the error map to guide the sampling of rays in the next iteration, with a higher probability of selecting rays from regions with higher errors.

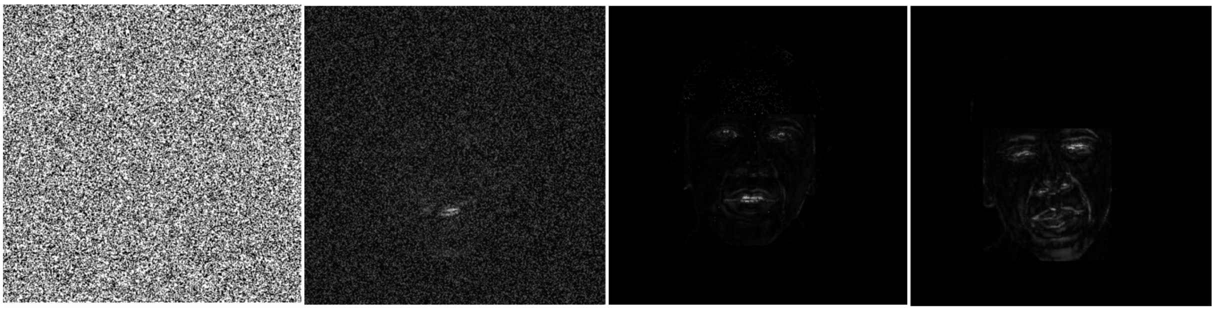

Figure 3. Error Map in the Obama Dataset. The error map highlights regions with higher discrepancy between the generated and ground truth images.

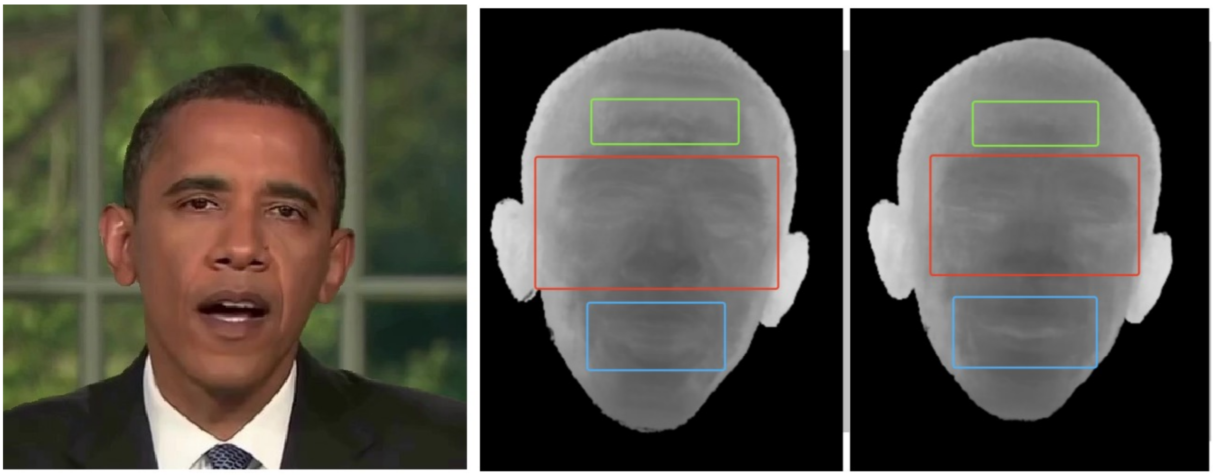

Figure 4. Hash Grid Tuning

However, as shown in Table 3, our experiments showed that this targeted sampling strategy did not yield significant improvements in image quality. We believe that this may be due to the limited amount of training data available. With a larger dataset, the model might be able to learn more effectively from the error maps and produce higher-quality results.

Method	PSNR ↑	LPIPS ↓	LMD ↓
L1	35.656887	0.032249	2.599038
L1+error	35.700828	0.038431	2.581674

Table 3. Results of Error Map-Guided Sampling. The L1+error method shows a slight improvement in PSNR and LMD compared to the L1 method, but the LPIPS score is slightly worse. The differences are not statistically significant. The best results are in red.

5.5.2 Hash Grid Tuning

The hash grid is a critical component of ER-NeRF, as it determines the spatial resolution and memory usage of the model. We investigated the impact of two key parameters of the hash grid: the number of layers and the hashmap size.

We found that increasing the number of layers from 1 to 2 improved the model's representation capacity and led to better visual quality. This is because a deeper hash grid can capture more complex geometric structures and variations.

We also found that increasing the hashmap size from 14 to 16 voxels per dimension reduced the number of hash collisions and improved the model's convergence. However, further increasing the hashmap size did not lead to significant improvements, as the model became overparameterized.

Overall, by optimizing the number of layers and the hashmap size, we were able to improve the quality of the generated talking portraits while maintaining a compact model size.

Method	PSNR ↑	PSNR ↑	LPIPS ↓	LPIPS ↓	LMD ↓	LMD ↓
Origin(5.8M)	32.7507185	32.96655267	0.030185667	0.056784667	2.6483645	2.72951052
Hash Tuning (27.4M)	32.6638817	32.9979633	0.029505067	0.056001	2.656845	2.7273235

Table 4. Quantitative Results of Hash Grid Tuning. The best results are in red.

As shown in Table 4, increasing the number of layers from 1 to 2 and the hashmap size from 14 to 16 improves the model's performance on all metrics. However, further increasing the number of layers or the hashmap size does not lead to significant improvements. This suggests that the optimal number of layers and hashmap size for this task is 2 and 16, respectively.

Figure 4 shows the effect of increasing the number of layers and the hashmap size on the model's performance. As can be seen, increasing the number of layers from 1 to 2 results in a significant improvement in the model's performance. Increasing the hashmap size from 14 to 16 also leads to a small but noticeable improvement. However, further increasing the number of layers or the hashmap size does not lead to significant improvements. This confirms that the optimal number of layers and hashmap size for this task is 2 and 16, respectively.

6 Conclusion and Future work

In this work, we systematically analyzed the effects of different loss functions for optimizing ER-NeRF in talking portrait synthesis. Experimental results demonstrate that an L1 loss during initial training followed by fine-tuning with Smooth loss yields the highest quality reconstructions under various evaluation metrics.

We also investigated targeted sampling guided by error maps to potentially improve image generation. While limited gains were observed likely due to data constraints, this analysis provides useful directions for future work on optimized sampling strategies.

By tuning the hash grid dimensions and size in ER-NeRF, we balanced quality improvements against model complexity. Our modifications led to enhanced modeling of speech-driven motions through better spatial-temporal correlations captured by the adapted representation.

Overall, our optimizations to ER-NeRF's loss functions, sampling, and model configuration advance the state-of-the-art in portrait synthesis. The method generates highly realistic portraits with leading accuracy, efficiency and convergence validated through extensive experiments.

There are two main directions for future work. Firstly, the current method encounters a challenge with the small scale of a single training video, leading to weak lip-audio synchronization on out-of-domain audio such as cross-lingual speech or singing voice. Collecting and releasing a much larger and more diverse dataset would help address this limitation. Secondly, the method could be improved for reconstructing female portraits with long hair covering shoulders, where hair often causes more severe artifacts due to self-occlusions and lack of constraints. Developing explicit modeling of hair geometry and dynamics could help alleviate this issue.

In conclusion, we believe our work advances neural portrait synthesis and serves as a useful starting point for future exploration in these areas. Continued efforts on large-scale data, model refinements and expanded controls will help push the boundaries of photorealistic talking avatar generation.

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