FDNeRF: Few-shot Dynamic Neural Radiance Fields for Face Reconstruction and Expression Editing

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Figure 1: FDNeRF, a NeRF-based method for 3D face reconstruction with only few-shot dynamic input frames (e.g., 3 frames), enable novel view synthesis, expression editing, and video-driven reenactment tasks. Input images are from: 1) Knock Knock Behind the Scenes Movie Interview, 2015 (FilmIsNow Movie Bloopers & Extras); 2) YINKA & FRIENDS: EMILY ATACK, 2013 (Rinse FM).

ABSTRACT

We propose a Few-shot Dynamic Neural Radiance Field (FDNeRF), the first NeRF-based method capable of reconstruction and expression editing of 3D faces based on a small number of dynamic images. Unlike existing dynamic NeRFs that require dense images as input and can only be modeled for a single identity, our method enables face reconstruction across different persons with few-shot inputs. Compared to state-of-the-art few-shot NeRFs designed for modeling static scenes, the proposed FDNeRF accepts view-inconsistent dynamic inputs and supports arbitrary facial expression editing, i.e., producing faces with novel expressions beyond the input ones. To handle the inconsistencies between dynamic inputs, we introduce a well-designed conditional feature warping (CFW) module to perform expression conditioned warping in 2D feature space, which is also identity adaptive and 3D constrained. As a result, features of different expressions are transformed into the target ones. We then construct a radiance field based on these view-consistent features and use volumetric rendering to synthesize novel views of the modeled faces. Extensive experiments with quantitative and qualitative evaluation demonstrate that our method outperforms existing dynamic and few-shot NeRFs on both 3D face reconstruction and expression editing tasks. Code is available at https://fdnerf.github.io.

CCS CONCEPTS

• Computing methodologies → Volumetric models.

KEYWORDS

3D face reconstruction, expression editing, NeRF, few-shot and dynamic modeling

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1 INTRODUCTION
Reconstructing and editing a human face from a small number of frames in a monocular video is a highly challenging problem in the field of computer vision and computer graphics [Hong et al. 2022; Sun et al. 2022a,b]. Unlike reconstructing a rigid object, a faithful reconstruction of a dynamic human face is difficult because of complex geometry and appearance variations brought by rich expressions. Moreover, it is even more challenging to capture consistent multi-view frames from a monocular camera for reconstruction, which usually relies on dense synchronized cameras [Gotardo et al. 2018; Tewari et al. 2019; Yang et al. 2020; Zhang et al. 2022].

To simplify the face reconstruction, Blanz and Vetter [1999] proposes to represent the human face with a parametric 3D Morphable Model (3DMM), which decomposes the face attributes into low-dimensional vectors. These vectors can be used to reconstruct 3D textured face mesh using corresponding blend shapes. Based on this model, some methods [Deng et al. 2019; Gecer et al. 2019; Ploumpis et al. 2020] are able to reconstruct 3D facial meshes from single or few-shot images, which facilitates free-view synthesis and expression editing. However, due to the inaccurate mesh model and the limited representation ability of the low-dimensional parameters, these methods struggle to capture fine-scale details of the human face in input images, such as beards and hairs.

Recently, Neural Radiance Field (NeRF) [Mildenhall et al. 2020], which implicitly models the geometries and appearances of static 3D scenes as multilayer perceptrons (MLPs), has attracted widespread attention due to its impressive free-view results in photorealistic rendering. To extend it to dynamic scenes, some dynamic NeRFs [Ma et al. 2022; Park et al. 2021a; Pumarola et al. 2021] introduce a deformation field to handle the inconsistency among different frames. They can be applied to reconstruct a face in a monocular video with different expressions but require hundreds or thousands of input frames for training, which somehow limits practical usage. On the other hand, some few-shot NeRFs [Gao et al. 2020; Hong et al. 2022; Raj et al. 2021] explore how to produce a generalized model that can be used to reconstruct a 3D face with only single or multi-view images. However, they require view-consistent input and cannot handle dynamic frames from a monocular video.

To address the challenges of modeling 3D faces with NeRFs based on few-shot dynamic frames, one possible solution is to combine the best of dynamic NeRFs and few-shot NeRFs by integrating the deformation field into an existing few-shot NeRF such as PixelNeRF [Yu et al. 2021]. However, training this 3D deformation field for human faces usually relies on a large number of images with different expressions. Moreover, the deformation fields varying across different persons, even for the same expression, impose additional challenges. Therefore, it is a severe ill-posed problem to learn a 3D deformation field conditioned on expressions and adapted to different identities, with only a small number of dynamic frames as input. To solve this problem, unlike previous dynamic NeRFs performing the 3D deformation, we propose a 2D deformation strategy in the deep feature space with 3D constraints, which is easier to be learned with few-shot frames.

In this paper, we propose a Few-shot Dynamic NeRF (FDNeRF), the first framework to reconstruct and edit 3D faces based on a small number of dynamic frames extracted from a monocular video. Our FDNeRF employs a novel Conditional Feature Warping (CFW) module with 3D constraints to handle the inconsistencies between dynamic frames by warping source expressions to the target one in the 2D feature space. Then, a reconstruction module is adopted to predict the color and density of spatial points in the radiance field based on the warped feature spaces. Finally, the volumetric rendering is used to render the results with the desired expression. Compared to the 3D deformation field adopted in many dynamic NeRFs [Park et al. 2021a,b; Pumarola et al. 2021; Tretschk et al. 2021], our CFW module implemented in the 2D feature space offers two-fold advantages. First, a 2D warping with a lower degree of freedom makes it more friendly to few-shot inputs than a 3D deformation. Second, different from the previous 3D deformation field defined on spatial positions, our 2D warping field defined on whole-image features enables it to better distinguish individuals and thus produce adaptive warping fields for different identities. Moreover, unlike conventional image warping, our feature warping of different frames is constrained by the 3D radiance field, making the 2D warping view consistent. Benefiting from the capability of the CFW module, FDNeRF can not only reconstruct 3D faces from a small number of dynamic frames but also enable editing of facial expressions and rendering of novel views. Extensive experiments demonstrate our superiority over existing methods both qualitatively and quantitatively.

In summary, the main contributions of this work are:
- We propose FDNeRF, the first neural radiance field to reconstruct 3D faces from few-shot dynamic frames.
- We introduce the novel CFW module to perform expression-conditioned warping in 2D feature space, which is also identity adaptive and 3D constrained.
- Our FDNeRF supports free edits of facial expressions, and enables video-driven 3D reenactment.

2 RELATED WORK
Compared with earlier methods that represent 3D faces as parametric textured mesh models [Deng et al. 2019], implicit representation methods have recently received increasing attention for their impressive rendering quality on free-view synthesis [Lombardi et al. 2019; Or-El et al. 2022]. Notably, NeRF [Mildenhall et al. 2020] employs MLP to learn the radiance field of a 3D scene and uses volumetric rendering to visualize the scene. Subsequently, a number of following works are proposed to extend NeRF to different scenarios, which include dynamic NeRFs aimed at alleviating the static input constraint of NeRF, and few-shot works aimed at alleviating the dense input constraint of NeRF. Since our FDNeRF focuses on modeling 3D faces from few-shot dynamic inputs, it is closely related to recent work on dynamic NeRFs and few-shot NeRFs. To clearly distinguish FDNeRF from these methods, we discuss them below.

2.1 Dynamic NeRFs
The vanilla NeRF assumes that the modeled scene is static and cannot reconstruct dynamic scenes from a set of frames. To solve this problem, methods like NeRFFlow [Du et al. 2021], NeSF [Li et al. 2021], and DynNeRF [Gao et al. 2021] focus on time-varying scenes and learn 3D scene flow between two neighboring frames. VideoNeRF [Xian et al. 2021] learns a spatiotemporal irradiance field
Figure 2: Overview of our FDNeRF. Given few-shot dynamic images, face tracking is implemented to estimate relevant expression parameters $\delta_i$, camera poses $P$, and intrinsic matrix $K$ in the preprocessing stage. In the CFW module, we employ feature encoding network $f_e$ to extract a deep feature volume $F_i$ for each image $I_i$, and semantic mapping network $f_m$ to generate a motion descriptor $\omega_i$ based on source and target expression parameters. The descriptor is then used to guide the conditional warping network $f_w$ to produce warped feature volumes $\hat{F}_i$. During reconstruction, we project the query point $x$ to each image plane and extract aligned feature vectors $v_i$. These vectors, along with the position and direction of the point, are fed into NeRF network to infer color and density. Finally, volumetric rendering is performed to synthesize novel view images. Input images are from Knock Knock Behind the Scenes Movie Interview, 2015 (FilmIsNow Movie Bloopers & Extras).

2.2 Few-shot NeRFs

Simultaneously, there is another line of work that focuses on the 3D reconstruction of static scenes from a small number of input images. For example, Portrait-NeRF [Gao et al. 2020] pretrains a canonical facial NeRF over a set of multi-view face datasets, and reconstructs a 3D face by finetuning the pretrained model on a specific facial image. HeadNeRF [Hong et al. 2022] and MofaNeRF [Zhuang et al. 2021] propose parametric NeRF models conditioned on the 3DMM parameters extracted from input images. Although they enable expression editing by adjusting the associated 3DMM parameters, they cannot recover some facial details in the original frames due to the limited representation of low-dimensional parameters. On the other hand, some few-shot methods condition NeRF on image or feature inputs to learn a scene prior for a sparse set of inputs, like PixelNeRF [Yu et al. 2021], PVA [Raj et al. 2021], and MVSNeRF [Chen et al. 2021]. Here, PixelNeRF and PVA construct radiance fields by using the implicit spatial information in the features of sparse inputs. MVSNeRF employs earlier multi-view stereo methods to produce a geometry-aware feature volume, and deduces radiance fields of target scenes based on the sampled features from this volume. Although these methods allow reconstructing photorealistic 3D scenes from a few static view-consistent images, they cannot handle the dynamic cases. By contrast, our FDNeRF combines the best of both dynamic NeRFs and few-shot NeRFs and thus enables model 3D faces from few-shot dynamic frames.

3 METHOD

Our method enables 3D face reconstruction and expression editing based on few-shot dynamic frames (e.g., 3 frames). To this end,
we propose FDNeRF, a NeRF-based dynamic face reconstruction framework, to handle inconsistencies among different frames.

3.1 Overview

Unlike the previous NeRF-based methods designed for dynamic scenes with dense frames, which require complex optimization for a single scene, our method tries to infer the arbitrary dynamic 3D faces using several inputs only. To accomplish this, the input frames with different facial expressions are first aligned in their 2D feature spaces via a conditional feature warping (CFW) module to eliminate the inconsistency of expressions (Sec. 3.2). Instead of deducing neural radiance fields based solely on positional and directional information of spatial query points like NeRF, we construct radiance fields directly from the aligned features of all input views, which allows us to infer the color and density of query points across identities from the radiance field (Sec. 3.3). The derived density and color along the camera rays are subsequently employed for volumetric rendering to render the final frame under novel views (Sec. 3.4). The optimization procedure is lastly introduced (Sec. 3.5).

3.2 3D Constrained Conditional Warping

Given few-shot dynamic frames captured from a monocular video of a talking human head, it is hard to reconstruct the 3D face by directly using previous few-shot NeRFs designed for static scenes due to the inconsistency of facial expression among different frames. To solve this issue, one potential strategy is to optimize a deformation field to achieve 3D warping between observation and canonical spaces like existing dynamic NeRFs [Park et al. 2021a,b]. Nonetheless, the high freedom of 3D deformation requires abundant inputs of a specific person for training, which limits the construction of deformation fields across identities with few-shot inputs. Another naive strategy is to warp the facial expression of each frame into the same one at the image level by using existing 2D expression warping methods [Meshrey et al. 2021; Ren et al. 2021]. However, without 3D constraints, the per-frame warped images lack view consistency, which would critically tamper with the following 3D reconstruction.

To avoid the inconsistency of facial details among warped frames, we design a 2D feature warping module conditioned on expression and at the same time constrained by the 3D geometry. As shown in Fig. 2, the conditioned feature warping (CFW) module consists of three sub-networks: a ResNet-like feature encoding network $f_e$, a semantic mapping network $f_m$, and a conditional warping network $f_w$. More specifically, the encoding network $f_e$ is employed to get a deep feature volume $F_i$ for each input frame $I_i$, which encodes the identity and expression information in $I_i$.

$$F_i = f_e(I_i), \quad \text{(1)}$$

where $F_i$ is composed of feature maps extracted from the first four layers of $f_e$.

Semantic conditions to guide the warping of feature volume $F_i$ are extracted by the semantic mapping network $f_m$. Specifically, we first leverage off-the-shelf face tracking method [Thies et al. 2016] to estimate the expression parameters $\delta$, face pose $P$, and intrinsic matrix $K$ for each input frames. Subsequently, $f_m$ transfers the original parameters into latent codes $f_m(\delta_i)$ and $f_m(\delta_{tar})$ for extracting more discriminative representations to achieve a fine-grained guidance in the warping network. Here, the target semantic indicates the desired expression in reconstructed face model. For each unaligned frame, we concatenate its latent code $f_m(\delta_i)$ with the target expression code $f_m(\delta_{tar})$ to form the high-dimensional motion descriptor $\omega_i$ to guide the warping network:

$$\omega_i = f_m(\delta_i) \oplus f_m(\delta_{tar}). \quad \text{(2)}$$

We implement the conditional warping network $f_w$ with an encoder-decoder like architecture. To more adequately guide the warping network, we inject the motion descriptor $\omega_i$ into all convolutional layers of $f_w$ by the adaptive instance normalization (AdaIN) operator. More specifically, a light-weight mapping network will transfer the motion descriptor $\omega_i$ into affine parameters $\gamma^\omega_i$ and $\beta^\omega_i$ respectively. The intermediate feature $z$ of each convolutional layer is modulated as follows:

$$\text{AdaIN}(z, \omega_i) = \gamma^\omega_i \left( \frac{z - \mu(z)}{\sigma(z)} \right) + \beta^\omega_i, \quad \text{(3)}$$

where $\mu(\cdot)$ and $\sigma(\cdot)$ calculate the average and variance statistics regarding $z$. Based on the feature volume $F_i$ and the descriptor $\omega_i$, the warping network $f_w$ will estimate a deformation flow field, which indicates the coordinate offsets between the input feature volume $F_i$ and the desired target feature volume $\hat{F}_i$. Ultimately we obtain the aligned feature volumes through bilinear interpolation sampling:

$$\hat{F}_i = \text{Sample}(F_i, f_w(F_i, \omega_i)), \quad \text{(4)}$$

where $f_w(F_i, \omega_i)$ indicates the deformation flow field estimated by the warping network, $\text{Sample}(a, b)$ represents the interpolated sampling operation on $a$ according to the flow field $b$.

It is noteworthy that although the warping fields are established in individual frames, they are actually constrained by the 3D geometry represented in the jointly trained neural radiance field, which would effectively enhance the consistency of warping across different views. We will introduce more details about the radiance fields in the following section.

3.3 Radiance Field Reconstruction

To reconstruct the 3D face with desired expression from the target feature volumes $\hat{F}_i$, we adopt a framework similar to [Yu et al. 2021] as our reconstruction module to deduce the color and density of each spacial point, and then use volumetric rendering to produce the final geometry and appearance.

Specifically, we first cast camera rays through each pixel of the target view and sample $N$ points along each ray for volumetric rendering [Mildenhall et al. 2020]. Then, we project each sampled point $p$ on the rays to each frame coordinate using known intrinsic matrix $K$ and corresponding pose $P_i$, and extract the associated aligned feature vectors $v_i$ from the target feature volumes $\hat{F}_i$ via bilinear interpolation.

$$v_i = \Pi(F_i, K \cdot P^{-1}_i \cdot \overline{x}), \quad \text{(5)}$$

where $\Pi$ represents the extraction procedure, and $K \cdot P_i^{-1} \cdot \overline{x}$ indicates the coordinate on the $i$-th frame plane. Note that, $\overline{x}$ is the homogeneous coordinate of the point $p$. 
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The feature vectors, as well as the position $x$ and direction $d$ of the query point $p$, are fed into the reconstruction module to estimate the color $c$ and density $\sigma$ values:

$$(c, \sigma) = f_\theta (\gamma(d), G(\gamma(x), v_1, \ldots, v_M)),$$  \hspace{1cm} (6)

where $\gamma(\cdot)$ is the positional encoding introduced by [Mildenhall et al. 2020] that maps the input into a higher dimensional Fourier space, and $G(\cdot)$ is the averaging function formed by a neural network to gather all available information. $M$ indicates the number of input frames, which is not fixed and can be set flexibly by the user. Note that, to eliminate the geometric discrepancy between views, we do not feed the direction component $\gamma(d)$ at the beginning of the NeRF network like [Yu et al. 2021] to affect the density-related parameters. Instead, we input it into the last several layers to adjust color-related parameters only.

### 3.4 Volumetric Rendering

Since our reconstruction module acts as a radiance field, we employ volumetric rendering to visualize the geometry and appearance of the implicit 3D face in a desired view. Like previous NeRF works, the expected color $\hat{C}$ of each pixel in the rendered image can be calculated by accumulating the estimated color $c$ and density $\sigma$ of all sampled points along the camera ray $r$:

$$\hat{C}(r) = \int_{t_n}^{t_f} T(t) \cdot \sigma(r(t)) \cdot c(r(t), d) \, dt,$$  \hspace{1cm} (7)

where $r(t) = o + td$ indicates the point positions of the ray from camera center $o$, $t_n$ and $t_f$ are near and far bounds of the ray, respectively. $T(t) = \exp \left[-\int_{t_n}^{t} \sigma(r(s)) \, ds \right]$ is the accumulated transmittance along the ray. Here, a hierarchical sampling strategy similar to [Mildenhall et al. 2020] is adopted for efficient rendering in practice. Specifically, there are two NeRF network for coarse and fine reconstructions. The densities estimated by the coarse one are used for important sampling of query points in the fine one.

### 3.5 Optimization

We jointly optimize the network weights of our CFW module and reconstruction module based on the photometric reconstruction loss:

$$\mathcal{L} = \sum_{r \in \mathcal{R}(P)} \| \hat{C}(r) - C(r) \|_2^2,$$  \hspace{1cm} (8)

where $\mathcal{R}(P)$ indicates the set of camera rays in pose $P$ and $C(r)$ represents the pixel color in the target image. During optimization, we randomly select $M$ frames from one of the training videos as input frames and one frame from the rest frames as the target. Then, the expression parameters of input and target frames are used to guide the feature warping process in the CFW module. Note that, to adapt our model to the modeling of flexible input frames, we randomly set $M$ in the range of 1 to 12 at each optimization iteration. Besides, in order to make the optimization converge effectively, we initialize the feature encoding network in our CFW module with the weights of ImageNet pre-trained ResNet34. Apart from that, other networks in our framework are trained from scratch.

### 4 EXPERIMENTS

In this section, we first give the implementation details, baselines, and metrics of our work (Sec. 4.1 and Sec. 4.2), and then we compare our method with state-of-the-art NeRF-based methods for 3D face reconstruction and expression editing (Sec. 4.3 and Sec. 4.4). Furthermore, we extend our method to implement video-driven...
Table 1: Quantitative evaluation.

| Methods       | NeRF | NeRF_{30} | NeRFace | NeRFace_{30} | HyperNeRF | HyperNeRF_{30} | PixelNeRF | FDNeRF |
|---------------|------|-----------|---------|--------------|-----------|----------------|-----------|-------|
| PSNR ↑        | 17.368 | 21.963 | 13.212 | 19.454 | 10.422 | 15.521 | 24.149 | 24.847 |
| SSIM ↑        | 0.537 | 0.704 | 0.281 | 0.585 | 0.252 | 0.432 | 0.792 | 0.821 |
| LPIPS ↓       | 0.320 | 0.167 | 0.566 | 0.307 | 0.687 | 0.501 | 0.190 | 0.142 |

Figure 4: Comparison on expression editing. Input images are from: 1) Actor Eli Wallach on why he always plays the bad guy, 2010 (CBC Archives); 2) Emily Atack Interview - Theatre, New Films & Butterfly Ball, 2016 (Red Carpet News TV); 3) Emily Atack Interview - Dad’s Army, West End & 2016 Plans, 2016 (Red Carpet News TV); 4) Exclusive Interview: Susan Sarandon, Elle Fanning And Naomi Watts Talk About Ray, 2015 (We Got This Covered).

3D reenactment task (Sec. 4.5). For more experiments and ablation studies please refer to the supplementary material.

4.1 Implementation Details

We leverage Pytorch framework [Paszke et al. 2019] to implement FDNeRF and use Adam [Kingma and Ba 2014] optimizer with default hyperparameters and a learning rate of 0.0001 to update network parameters. Our training data involves 213 talking videos which are selected from the VoxCeleb dataset [Nagrani et al. 2017]. To process these videos, we adopt the monocular face tracking method [Thies et al. 2016] to estimate the expression semantic, face pose, and intrinsic matrix for each frame. Here, the estimated face pose is used as the camera pose of the image in our implementation.

4.2 Setup

Baseline methods. For 3D face reconstruction and free-view synthesis, we compare with the vanilla NeRF [Mildenhall et al. 2020], two dynamic NeRFs (NeRFace [Gafni et al. 2021] and HyperNeRF [Park et al. 2021b]), and two few-shot NeRFs (MoFaNeRF [Zhuang et al. 2021] and PixelNeRF [Yu et al. 2021]). Here, NeRFace and HyperNeRF are two methods for modeling dynamic scenes with dense inputs, while MoFaNeRF and PixelNeRF are designed for few-shot modeling of static scenes. We do not compare to PVA [Raj et al. 2021] (a few-shot NeRF for face modeling) as their code is unavailable. Instead, we compare with PixelNeRF, which has a similar framework and performance to PVA.

Evaluation metrics. For the quantitative comparisons, we employ peak-signal-to-noise ratio (PSNR), structural similarity index measure (SSIM) [Wang et al. 2004], and learned perceptual image patch similarity (LPIPS) [Zhang et al. 2018] to evaluate the visual quality of rendered frames. We do not involve the quantitative scores of MoFaNeRF, considering the rendered 3D faces of MoFaNeRF significantly differ from the video frames.

4.3 Reconstruction and Novel View Synthesis

We first evaluate our FDNeRF and baseline methods on the task of 3D face reconstruction and novel view synthesis based on few-shot dynamic frames. Specifically, only three dynamic frames extracted from a monocular talking video are used for 3D face modeling. Then, three novel views (frontal, left and right sides) with facial expression same as the first input frame are synthesized (if suitable). Moreover, since NeRF, NeRFace, and HyperNeRF require dense input views for 3D modeling, we add additional 27 frames uniformly extracted from the video to improve their performance and denote them as NeRF_{30}, NeRFace_{30}, and HyperNeRF_{30}, respectively.

As shown in Fig. 3 and Table 1, compared to these baselines, our FDNeRF achieves more realistic 3D face reconstruction with view-consistent facial expressions. Specifically, NeRF with three dynamic frames as input fails to produce clear 3D faces. With more
inputs, NeRF\textsubscript{30} enables inference of rough facial contours but cannot capture the misaligned facial details since NeRF is proposed for modeling static scenes. Compared to the vanilla NeRF, NeRFFace and HyperNeRF are more sensitive to the number of input frames due to their complex designs for dynamic modeling. They cannot estimate reasonable 3D facial structures with only three dynamic frames since they require abundant inputs to generalize the facial expression space or the 3D deformation field. Even if we try to increase the input frames as in NeRF\textsubscript{Face30} and HyperNeRF\textsubscript{30}, such collapse still happens. PixelNeRF produces more plausible 3D faces than the previous methods. Nonetheless, as it is designed to reconstruct static scenes, PixelNeRF fails to distinguish the expression misalignment between frames, resulting in blurred textures and inaccurate facial expressions. For MoFaNeRF, we observe that it strongly overfits the property of training data in terms of occlusion, lighting, and facial shapes, which could not generalize to the video data well. By contrast, with the well-designed CFW module, our FDNeRF eliminates inconsistencies among input frames and reconstructs 3D faces with the desired expression and realistic facial details.

4.4 Expression Editing

Thanks to the well-designed CFW module, our FDNeRF enables editing 3D faces to novel expressions beyond those in input frames. Since most NeRF-based methods cannot accomplish the expression editing task, we only compare with NeRF\textsubscript{Face} and MoFaNeRF in this section. Both approaches are conditioned on explicit 3DMM expression semantics and theoretically support expression editing of 3D faces. Considering that NeRF\textsubscript{Face} fails to reconstruct a basic facial contour based on three dynamic frames, we adopt faces generated by NeRF\textsubscript{Face30} on the editing task. As shown in Fig. 4, we use five specific expressions as the target to drive the 3D faces. NeRF\textsubscript{Face} fails to perform expression editing since it cannot to generalize the facial expression space and perceive expression changes without enough input frames. Although MoFaNeRF fails to fit reasonable 3D faces, it allows editing facial expressions to a certain extent. By contrast, our FDNeRF could faithfully edit the expression and render realistic results based on both general priors learned from the training stage and personal information extracted from three input frames. As a result, our expression edit, like “mouth open” in Fig. 4, is not with the same deformation for all persons but adaptive to different individuals.

4.5 Extension to Video-driven Reenactment

Since our FDNeRF supports expression editing, it could be applied to video-driven 3D reenactment by using the expression parameters of a video sequence. However, in practice, we find that slight inconsistencies between the estimated parameters of adjacent frames may cause the discontinuity artifacts in the reenactment results (shown in Fig. 6), although the frame-to-frame tracking method [Thies et al. 2016] can reduce the temporal jitter to some extent. To alleviate this issue, we modify the semantic mapping network to receive a set of parameters instead of a per-frame one to output a latent code. With this modification, we input parameters of a window with continuous frames as the target expression semantic, where the parameter window is set to the forward and backward $L$ frames centered on the target frame. $L$ is set to 13 in our video-driven experiments. The effectiveness of the parameter window is shown in Fig. 6, and Fig. 5 gives more reenactment results driven by a video of the same person or a different person.

5 CONCLUSION

In this paper, we propose the FDNeRF for 3D face reconstruction and expression editing based on a small number of dynamic frames extracted from a talking head video. We design the expression-conditioned feature warping module to eliminate inconsistencies between dynamic frames and a radiance field reconstruction module to perform accurate 3D reconstruction with aligned features. Consisting of these well-designed modules, the proposed FDNeRF demonstrates superior performance on novel view synthesis and arbitrary expression editing tasks. We further extend the FDNeRF...
with a window-based strategy for temporal coherent video-driven reenactment.

Limitation. Although our FDNerf can effectively handle the expression inconsistencies between input frames and reconstruct realistic 3D faces, there are still some limitations. For example, inconsistencies in the non-face region (e.g., hair and torso), which are not conditioned on expressions, will cause some blurriness in the result, as shown in the third example of Fig. 4. It might be alleviated by introducing separate warping fields for different parts, such as a body warping field conditioned on skeleton pose [Su et al. 2021]. Besides, the lighting inconsistency among input frames may also cause reconstruction to fail. To overcome this issue, a reflectance field [Srinivasan et al. 2021] may be employed to decompose the illumination and achieve relighting. We seek to solve these challenges in the following works.

Potential Social Impact. Although not the purpose of this work, our expression editing technology could be misused in some deep-fake applications like fake talking video generation. The risk can be effectively relieved by existing forgery detection methods like [Wang et al. 2020; Zhao et al. 2021].

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