Photorealistic Audio-driven Video Portraits

Xin Wen, Miao Wang, Christian Richardt, Ze-Yin Chen, and Shi-Min Hu

Fig. 1. We present a novel method for generating photorealistic video portraits that correspond to the actor in a target video, reenacted by arbitrary speech audio. Our method has applications in videoconferencing, virtual education and training scenarios.

Abstract—Video portraits are common in a variety of applications, such as videoconferencing, news broadcasting, and virtual education and training. We present a novel method to synthesize photorealistic video portraits for an input portrait video, automatically driven by a person’s voice. The main challenge in this task is the hallucination of plausible, photorealistic facial expressions from input speech audio. To address this challenge, we employ a parametric 3D face model represented by geometry, facial expression, illumination, etc., and learn a mapping from audio features to model parameters. The input source audio is first represented as a high-dimensional feature, which is used to predict facial expression parameters of the 3D face model. We then replace the expression parameters computed from the original target video with the predicted one, and re/render the reenacted face. Finally, we generate a photorealistic video portrait from the reenacted synthetic face sequence via a neural face renderer. One appealing feature of our approach is the generalization capability for various input speech audio, including synthetic speech audio from text-to-speech software. Extensive experimental results show that our approach outperforms previous general-purpose audio-driven video portrait methods. This includes a user study demonstrating that our results are rated as more realistic than previous methods.

Index Terms—Audio-driven animation, facial reenactment, generative models, talking-head video generation

1 INTRODUCTION

Visual information from a speaker’s face, such as their lip movements, can improve speech comprehension in general human communication. It plays a critical role in comprehending speech content for the hearing impaired or when the acoustic signal is corrupted by background noise. In many scenarios, such as telephony or VR/AR professional training for doctors and pilots, however, speech communication is purely acoustic and the visual counterpart is missing due to the lack of cameras, privacy concerns or the limited bandwidth of networks. To improve speech comprehension in these scenarios, many approaches have been proposed to synthesize a talking face from the acoustic speech in real time, as a virtual [21, 28, 47] or a photorealistic avatar [40, 46]. Users’ sense of presence is also increased when the avatar is similar to the real user [26, 36].

Video portraits provide photorealistic visual content of a person’s face, perfectly maintain their identity, and are commonly used in videoconferencing, virtual anchoring and virtual training. However, it is challenging to generate plausible visual content that matches the acoustic signal, and any misalignment between the mouth motion and the pronunciation can degrade the visual experience. The essential technical issue behind this challenge is the mapping from a raw audio signal to photorealistic imagery. Existing audio-driven video portrait generation techniques produce results that are not sufficiently photorealistic for application requirements, or do not generalize well to given audio or target video inputs. Video portraits can be generated and edited by editing text [3, 18]. However, current text-based methods either focus on cut and transition operations of prerecorded videos [3], which cannot generate results with new text, or synthesize new audio-visual speech content [18] for a specified performer with at least one hour footage for feature searching, and is not suitable for use in real-time applications.

In this work, we present a novel real-time photorealistic video portrait generation method from speech audio. Instead of directly learning to predict the 2D portrait image sequence from audio, we propose to predict the facial expression component of a parametric 3D face model from audio input using neural networks. We then blend the predicted facial expressions with the other components computed from the target video, to generate a reenacted 3D face sequence. Using a neural face renderer, trained on the target video, the reenacted 3D face is converted...
to a photorealistic video portrait. All source code is publicly available.1 We make the following contributions in this work:

- Given input speech audio, our method generates a photorealistic video portrait of a target actor. A three-minute video of the target is sufficient for training our complete pipeline—much less data than required by existing methods.
- We present an audio to facial expression mapping module that can transform identity-independent speech audio into a target actor’s facial expression parameters, only trained on a single target portrait video.
- We evaluate the efficacy of our method with an extensive user study. Our results were rated the most photorealistic by participants when compared to existing general-purpose audio-driven video portrait methods.

2 Related Work

2.1 Monocular 3D Face Reconstruction

Monocular 3D face reconstruction aims to reconstruct facial geometry and appearance, including facial expressions, from visual data [4, 19, 46, 52]. This is the basis for facial reenactment. Model-based methods are the common practice; they employ a parametric face model [4, 17] as a prior when minimizing the reconstruction energy in an analysis-by-synthesis paradigm. Based on the type of visual input data, methods can be categorized as single-image-based [4, 42, photo-collection-based [16, 43] and video-based [19, 44, 52]. Recently, various deep-learning-based approaches have been proposed to estimate 3D model parameters [16, 20, 23, 31, 49]. Apart from model parameters, some approaches also regress fine-scale skin details [6, 42, 49]. This is an active area of research with a large variety of works; for more information, we refer to recent surveys [17, 55, 65].

2.2 Video-driven Facial Reenactment

Video-driven facial reenactment takes two face sequences as input: a source and a target. The target face is reenacted using the expression parameters of the source face. Face2Face [52] is a real-time video reenactment method that adopts a high-resolution skin texture and synthesizes the mouth cavity using a data-driven approach. Averbuch-Elor et al. [1] proposed a technique to automatically animate a still image portrait using a driving video, by transferring the facial expressions from the video to the image via 2D warping, and synthesizing the mouth interior. Similar portrait image animations can be achieved by few-shot learning from a talking-head video. Zakharov et al. [62] employed meta-learning on a large video dataset as pretraining, and perform few-shot or one-shot learning on unseen people with adversarial training. In deep video portraits [30], a generative adversarial network (GAN) [22] is proposed to produce photorealistic video with full control of head pose, facial expression and eye gaze of the portrait. Kim et al. [29] proposed a visual dubbing method which can maintain the signature style of the target actor during talking. Instead of directly replacing the target expression with that of the source actor, this approach learns the mapping in an unsupervised manner with cycle consistency [60, 64].

2.3 Audio-driven Facial Reenactment

The goal of audio-driven facial reenactment is to generate photorealistic video portraits that are in sync with the input audio stream. Chung et al. [12] developed a technique that animates a still image portrait following an audio speech. With both image and audio jointly encoded into a latent space through an encoder network, a decoder network synthesizes the talking head. Both the encoder and decoder are trained in an unsupervised manner. Zhou et al. [63] proposed a method to learn a disentangled audio-visual representation in a novel adversarial training process. This method can take either audio or video to drive the target actor. Chen et al. [11] first transformed audio features to facial landmarks as an intermediate feature, and then generated speech frames conditioned on the landmarks with an attention mechanism. Prajwal et al. [40] proposed a face-to-face translation method that generates talking faces of any person given a speech segment. The LipGAN architecture comprises a generator to synthesize portrait video frames from source audio and target frames, and a discriminator to determine if the synthesized face image is synced with the audio. However, blur and jitter can be observed in their results, because temporal stability of the synthetic content is not guaranteed. While the above four methods can take arbitrary audio as input to reenact arbitrary actors using a single input image, the results are not sufficiently photorealistic due to the low image quality. Vougoukas et al. [54] proposed an end-to-end method to generate talking head videos using a still image and speech audio. A Temporal GAN with three discriminators is employed to achieve sharp frames, audio-visual synchronization, and realistic expressions. VOCA [15] is a technique for realistic 3D facial animation from arbitrary audio, based on a new 4D face dataset of twelve speakers. Suwajanakorn et al. [46] synthesized high-fidelity talking-head videos of former US president Barack Obama, using an audio stream of him. A recurrent neural network (RNN) is trained on 14 hours of his speech to predict the mouth shape from the mel-frequency cepstral coefficients (MFCC) audio feature. A photorealistic mouth region is synthesized within a manually drawn mask using the median texture of retrieved candidate frames. The mouth region sequence is finally composited on the time-warped target video background. Although this approach can synthesize accurate lip-synced video, it requires 14 hours of speech video of a specific target identity to train the network, and does not generalize to other identities. Yu et al. [61] proposed a method for generating talking-head video from text and/or audio input. Optical flow and self-attention are introduced to model temporal and spatial dependencies, respectively. However, like Suwajanakorn et al. [46], their method is only demonstrated on US presidents Donald Trump and Barack Obama, and does not generalize beyond them.

We have noticed some concurrent work relevant to ours. Similar to our work, Neural Voice Puppetry [50] presents an audio-to-expression network that is trained on a large corpus of TV broadcasts. The lower face is rendered using the predicted expression from audio with de-ferred neural rendering [51]. To fill the gap between jaw and neck, an additional standalone inpainting network is employed. In contrast, we address this issue using a simple mask expansion process that is controlled by a facial expression parameter and thus more efficient computationally. Song et al. [45] proposed an ID-removing network to predict expression parameters, and a universal translation network that transforms landmark heatmaps to photorealistic video for arbitrary targets. However, using landmark heatmaps as input to the neural face renderer can introduce jitter, as it is challenging to maintain the temporal coherency of landmarks. More recently, Yi et al. [59] proposed a personalization-based head pose generation method to enhance the fidelity of talking-head videos. Less data (about 10 seconds) is required to train an image translation network through a memory-augmented GAN. However, due to errors in their face reconstruction, the reconstructed face sequence is unstable, which harms GAN convergence. Noticeable artifacts are also visible in the mouth cavity, which reduces the fidelity and user experience.

2.4 Deep Generative Models and Neural Rendering

Recently, GANs have been proposed for image synthesis from noise. This approach can be extended with a conditional input setup [35], which is usually used to bridge the gap between two different but relevant domains. The pix2pix image-to-image translation method [27] is widely regarded as one benchmark method of conditional GAN-based image synthesis. This paradigm can be extended to video-to-video translation to synthesize video frames with temporal coherency. Wang et al. [57] proposed a method to generate high-resolution and temporally smooth video in a coarse-to-fine manner with a recurrent network. The Recycle-GAN approach [2] enables unpaired learning of a coherent video-to-video translation. Few-shot video-to-video translation [56] learns to synthesize videos of unseen subjects via a novel network weight generation module. Video-to-video translation shows impressive results in many applications, especially for face reenactment, visual dubbing [18, 29, 30] and even full-body reenactment [10, 33]. Nowadays, many approaches combine the power of neural net-

1https://github.com/xinwen-cs/AudioDVP
works and traditional rendering using neural rendering [48]. Neural
textures [51] are a novel learnable component, which mimic texture
maps used in the traditional graphics pipeline. They show compelling
results in applications of novel view synthesis, scene editing and anima-
tion synthesis. Meshry et al. [34] trained a neural rendering network
which takes a deep framebuffer consisting of depth, color and semantic
labeling as input and outputs realistic renderings of the scene under
multiple appearances. Thies et al. proposed a learning-based image-
guided rendering technique [53] that combines image-based rendering
and GAN-based image synthesis. This method can generate photoreal-
stic renderings of reconstructed objects for virtual and augmented
reality applications, such as virtual tours, showrooms and sightseeing.
In our method, a neural face renderer is employed to translate the rough
rendering of the lower face to photorealistic imagery.

3 Audio-driven Video Portrait Generation

Given a source speech audio, our method aims to generate a photore-
alistic video portrait for a given target video. To achieve this goal, we
employ a 3D face rig to bridge the gap between the raw input audio
and photorealistic output video modalities. This intermediate model
avoids overfitting to spurious correlations between the audio and visual
signals. The pipeline of our method consists of three main components,
as illustrated in Figure 2: monocular 3D face reconstruction, audio-
to-facial-expression mapping (‘Audio2Expression’), and neural face
rendering. Given a target video \( V_t \), we first reconstruct a parametric 3D
face model with expression, geometry, texture, pose and illumination
parameters for every frame (Section 3.1). From the same video, we
learn a mapping from audio features to facial expression parameters
of the same parametric 3D face model (Section 3.2); this mapping can
transform a speech audio – even from other people – to the expression
parameters of the target actor. For a source audio track \( A_s \), our method
predicts expression parameters from the audio, blends the predicted ex-
pression parameters with the face model reconstructed from the target
video, and renders the audio-driven face images of the target actor. As
can be seen, these rendered images are not photorealistic. To tackle
this issue, we train a neural face renderer to translate the rendered lower
face regions to photorealistic ones that are composed into the original
target video frame as the final result (Section 3.3).

3.1 Monocular 3D Face Reconstruction

For the target video \( V_t = \{I_1, \ldots, I_M\} \) with \( M \) frames, we first track
the face in all frames and register a 3D face model. Let \( \{X_1, \ldots, X_M\} \)
denote the sequence of face model parameters that fully describe the
facial performance of the target video \( V_t \). We follow the single-image-
method-based approach by Deng et al. [16] and adapt it to video-based 3D face
reconstruction. In this section, we first briefly introduce the parametric
face model we use. Then, we describe the image formation process to
reconstruct. In this section, we first briefly introduce the parametric

3.1.1 Parametric Face Model

We use a 3D morphable model (3DMM) to represent the face [4, 17].
The 3DMM consists of a template triangle mesh with \( N_v \) vertices and
an affine model that defines the facial geometry \( v \in \mathbb{R}^{3N_v} \) (stacked 3D
positions of vertices) and the stacked per-vertex diffuse reflectance \( r \in \mathbb{R}^{3N_v} \)
in terms of the coefficients \( \{\alpha_k\} \) for geometry, \( \{\delta_k\} \) for expressions,
and \( \{\beta_k\} \) for reflectance (color):

\[
\begin{align*}
\forall (\alpha, \delta) &= a_{geo} + \sum_{k=1}^{N_v} \alpha_k b_{geo}^k + \sum_{k=1}^{N_v} \delta_k b_{exp}^k, \\
r(\beta) &= a_{ref} + \sum_{k=1}^{N_v} \beta_k b_{ref}^k.
\end{align*}
\]

(1)

Here, the vectors \( a_{geo}, a_{ref} \in \mathbb{R}^{3N_v} \) represent the average facial geom-
etry and reflectance, respectively, \( b_{geo} \) and \( b_{ref} \) are the geometry basis,
\( b_{exp} \) is the expression basis, and \( b_{ref} \) is the reflectance basis,
all computed from facial scan data using principal component analysis
(PCA). We adopt the 2009 Basel face model [39] for the facial
geometry \( (a_{geo}, b_{geo}) \) and reflectance \( (a_{ref}, b_{ref}) \), and augment it with
the facial expressions \( b_{exp} \) from Guo et al.’s coarse-to-fine learning
framework [23], which builds on FaceWarehouse [7]. We use \( N_v = 80, N_g = 64 \)
and \( N_b = 80 \). The rigid head pose is represented by rotation \( R \in \mathbb{SO}(3) \) and
translation \( T \in \mathbb{R}^3 \).

3.1.2 Image Formation Process

To render the 3D face model \( X \) as a synthetic image \( I \), we furthermore
need to model the illumination and the camera. We assume a
Lambertian surface and distant scene illumination to approximate envi-
ronmental lighting using spherical harmonics (SH) [41]:

\[
C(r, \eta, \gamma) = r_i \odot \sum_{n=1}^{B} y_n \delta^{n}(n_i),
\]

where \( B \) is the number of SH bands, \( y_n \in \mathbb{R}^3 \) are the RGB SH coefficients, \( \delta^{n}(n_i) \) are the basis functions, \( n_i \) are the reflectance and unit normal vectors of vertex \( i \), respectively,
and \( \delta^{n} \) is the element-wise product. We choose \( B = 3 \) bands of SH,
with \( B^2 = 9 \) coefficient vectors, resulting in the SH illumination co-
Efficients \( \gamma \in \mathbb{R}^{27} \). Our complete face model can be represented by a
vector \( X = (\alpha, \delta, \gamma, R, T) \in \mathbb{R}^{257} \).

We model the virtual camera as a pinhole camera with a perspec-
tive projection \( \Pi: \mathbb{R}^3 \to \mathbb{R}^2 \), which maps 3D points from camera
space to 2D image space. To avoid the camera \( i \in [v(\alpha, \delta)] \) of a model \( X \),
we compute its image-space coordinates \( u_i(X) \) and corresponding
color \( c_i(X) \) using the aforementioned illumination and camera model.
Finally, \( (u_i(X) \lambda_i)^{N_v}_{i=1} \) and \( (c_i(X) \gamma_i)^{N_v}_{i=1} \) are fed into a differen-
tiable rasterizer to generate the rendered synthetic image \( I(X, \Pi) \). In addition to
Genova et al. [20], our rasterizer is implemented with CUDA to gain
GPU acceleration, which can speed up both training and inference.

3.1.3 Model Fitting

We use a ResNet-50 network [25] pretrained on VGGFace2 [9] to esti-
mate the face model parameters \( X \) from an input image \( I \), as we found it
to produce temporally more coherent results than direct optimization.
Specifically, we modify the final fully-connected layer of the network
to have 97 dimensions (without geometry and reflectance; see below), and
adopt an analysis-by-synthesis approach that minimizes the discrepancy
between a synthetic rendering of the model and the input image. The
reconstruction loss combines three terms: dense photometric alignment,
spare landmark alignment, and statistical regularization.

We measure the photometric discrepancy between the input frame \( I \)
and the synthetic image \( I(X, \Pi) \) rendered from the model \( X \) using a photo-
consistency loss computed across all pixels \( i \) in the face region \( M \):

\[
\mathcal{L}_{\text{photo}}(X) = \frac{1}{|M|} \sum_{i \in M} \|I(i) - \hat{I}(i)\|_2.
\]

(2)

We use a sparse landmark alignment constraint to encourage land-
marks on the 3D mesh to project close to the corresponding detected
2D landmarks in the input image. We detect \( N_l \) = 68 landmarks
\( \{s_1, \ldots, s_N_l\} \) in each video frame using an off-the-shelf face align-
ment network [5], and compute the sparse landmark alignment loss as the
weighted Euclidean distance between projected landmarks \( u_{s_i}(X) \)
detected landmarks \( s_i \):

\[
\mathcal{L}_{\text{land}}(X) = \frac{1}{N_l} \sum_{i=1}^{N_l} \alpha_i \|u_{s_i}(X) - s_i\|_2.
\]

(3)

Here, \( \tau_i \) is the vertex index of the 3D face model corresponding to
landmark \( i \) in image space, and \( \alpha_i \) is a landmark-specific weight set to
50 for the 20 mouth and 12 eye landmarks, and otherwise set to 1.

To prevent the degeneration of face shape and reflectance, we further
employ a regularization loss \( \mathcal{L}_{\text{reg}}(X) \) on the regressed 3DMM coeffi-
cients, which enforces a prior towards the mean face under Gaussian
distribution [16, 49].

The total model-fitting loss is defined as:

\[
\mathcal{L}(X) = \lambda_{\text{photo}} \mathcal{L}_{\text{photo}}(X) + \lambda_{\text{land}} \mathcal{L}_{\text{land}}(X) + \lambda_{\text{reg}} \mathcal{L}_{\text{reg}}(X).
\]

(4)
where we use $\lambda_{\text{photo}} = 1.9$, $\lambda_{\text{land}} = 0.0016$, and $\lambda_{\exp} = 0.0003$ for all experiments. For the detailed derivations, we refer to Genova et al. [20]. Before fitting the model to the full target video, we randomly select 8 frames to regress the geometry and reflectance parameters of each actor and keep them constant. We then train our face reconstruction network for 20 epochs on the target video with a batch size of 5 and a learning rate of $2 \times 10^{-3}$. While this subsection provides technical details of face fitting with implementation differences compared to previous work, we clarify that this is not one of our main contributions.

### 3.2 Audio to Facial Expression Mapping

To reenact the face model based only on an audio stream, we next introduce a facial expression mapping method that estimates facial expression parameters of the face model from the input audio. First, we use AT-net [11] to robustly extract high-level features from audio. AT-net was originally designed for creating landmark animation from an audio stream, and was trained on the LRW dataset [13], a large-scale lip reading corpus based on BBC broadcasts. To obtain high-level audio features, we convert the input audio stream into MFCC features, which we feed into AT-net and take the 256-D output feature of the ante-penultimate layer as the robust high-level features. We found that these features are effectively independent of any specific identity and contain sufficient information for expression prediction. As a result, we extract a 256-D feature vector $F$ for every 40 ms segment of the input audio $A_i$ (corresponding to one video frame at 25 frames per second).

We propose an audio-to-facial-expression mapping network $H$ that takes these audio features as input and predicts expression parameters. To maintain temporal coherency, for each time step $t$, we stack audio features as inputs along the timeline within a sliding window, and get $F_t = \{F_i\}_{i=t-N_{w}}^{t}$, where $N_{w} = 3$ is the radius of the sliding window. We set non-existing prior or subsequent features $F$ to zero. We use three layers of 1D convolutions to integrate space-time information, and a fully-connected layer with 64 nodes to output the predicted expression coefficients. The network structure is given in Table 1.

<table>
<thead>
<tr>
<th>Type</th>
<th>Kernel</th>
<th>Stride</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv1D</td>
<td>3 1</td>
<td></td>
<td>5 x 254</td>
</tr>
<tr>
<td>Conv1D</td>
<td>3 1</td>
<td></td>
<td>3 x 252</td>
</tr>
<tr>
<td>Conv1D</td>
<td>3 1</td>
<td></td>
<td>1 x 250</td>
</tr>
<tr>
<td>FC</td>
<td>–</td>
<td>–</td>
<td>64</td>
</tr>
</tbody>
</table>

Fig. 3. Effect of mask expansion for neural face rendering. (a) and (c): directly compositing the synthetic face region within the original lower face mask into the target video can result in dual jaw artifacts. (b) and (d): with our face mask expansion, the synthetic lower face and partial neck are both composited into the target video, which avoids conflicting content around the jaw region.

3.3 Neural Face Renderer

We combine the expression parameters estimated from the source audio $A_s$ with the geometry, reflectance and illumination reconstructed from the target video, to rerender the face model via the image formation process and obtain a sequence of synthetic face images. However, the synthetic images clearly look computer-generated and not photorealistic. To make the synthetic faces more photorealistic and natural-looking, we employ a neural face renderer to translate synthetic renderings into photorealistic images.

Before applying neural face rendering to the synthetic face rendering, we introduce a masking strategy to distill the lower face region with a predefined mask that covers jaw, mouth and part of the nose. We use the neural face renderer to predict the content only within the mask, and composite the predicted content with the target video to produce the final result. With this masking strategy, the training is focused on the mouth animation of the lower face, and avoids the instability of any dynamic background of the target video. At first, we extract a raw mask as follows: we mark all face vertices with y-coordinates less than the threshold $\xi = 0$ (assuming normalized model space coordinates in $[-1, 1]$). We rasterize the masked face to get the binary lower face mask for every frame. However, directly compositing the predicted content into the target video can introduce a doubled jaw due to the inconsistency between predicted expression parameters and the original ones in the target video, as shown in Figure 3. Inspired by InverseFaceNet [31], we explicitly expand the mask around the jaw region by decreasing the value of the first component of the expression

Fig. 2. Pipeline of our approach. From left to right: First, we estimate the parameters of a 3D face model for the target video portrait via monocular face reconstruction (Section 3.1), and compute the facial expression parameters from the source speech audio (Section 3.2). Next, we create a new face by blending the facial expression parameters predicted from the source audio with the other parameters from the target video, and rerender synthetic images of the new face model. Finally, we use a neural face renderer to generate photorealistic renderings from the synthetic images, and composite the result on top of the dynamic video background (Section 3.3).
The photometric reconstruction loss $L$ of the generator $G$ can be obtained by solving following problem:

$$L_{\text{rec}}(\hat{I}) = \min_{G} \max_{D} \mathcal{L}(\hat{I}, D).$$ (6)

The full training objective consists of a photometric reconstruction loss $L$, and an adversarial loss $L_{\text{adv}}$, weighted by $\lambda = 100$:

$$L(\hat{I}, D) = L_{\text{rec}}(\hat{I}) + \lambda L_{\text{adv}}(G, D).$$ (7)

The photometric reconstruction loss $L_{\text{rec}}$ encourages the sharpness of the synthesized output and can be formulated as:

$$L_{\text{rec}}(\hat{I}) = \| \hat{I} - G(T) \|_{1}. \quad (8)$$

The vanilla GAN adversarial loss is:

$$L_{\text{adv}}(G, D) = \log D(I_t) + \log (1 - D(G(T))). \quad (9)$$

We train the network using the Adam optimizer with default settings [32]. We train our networks from scratch with weights initialized following a normal distribution $\mathcal{N}(0, 0.02^2)$. The training process takes 250 epochs with a batch size of 16 and learning rate of 0.0002.

At inference time, we composite the output of our neural face renderer with the background of the target frame using a Gaussian-smoothed lower face mask, as illustrated in Figure 2.

4 Experiments

We demonstrate our audio-driven video portrait generation approach by performing qualitative and quantitative evaluations. We encourage readers to watch our supplementary video for results in action.

Datasets. We test our approach on a set of 11 target videos that were collected from YouTube and prior work [29]. Table 2 provides a summary of these videos, including their lengths and languages. The average length of video clips is 3 minutes. In a preprocess, we align all video frames using the detected landmarks to ensure that the upper body occupies the main space of the image. The aligned frames were further cropped and resized to $256 \times 256$ pixels.

Implementation Details. All networks were implemented in PyTorch [38]. We implemented the rasterizer [20] with CUDA acceleration and integrated it into PyTorch. All experiments are conducted on a computer with a 3.6 GHz CPU, 32 GB RAM, and an NVIDIA GeForce RTX 2080 Ti GPU.

Runtime Performance. For a 3-minute target video portrait, it takes about 30 minutes to reconstruct the face model, 20 seconds to train the Audio2Expression module, and 6.5 hours to train the neural face renderer. In the online testing stage, it takes 2 ms to predict expression parameters from audio, 3 ms to render the face model, 13 ms to perform neural face rendering, and 2 ms to composite the neural rendered face region into the target frame. In summary, it takes 20 ms to generate one frame of a video portrait from audio, which is sufficient for real-time applications (50 Hz).

4.1 Video Portrait Results

Self-reenactment. We evaluate our method by using the audio from the target video as input (i.e., self-reenactment), and compare the generated video portrait with the ground-truth target video. We perform this test on 60-second test videos of actors A and B with ground-truth head poses. We calculate the absolute average pixel-wise differences between generated frames and ground-truth frames for each channel in RGB color space in $[0, 255]$. The self-reenactment results with visualizations of errors for two actors are shown in Figure 6. The average difference between generated frames and the ground truth, on
We perform comparisons to state-of-the-art audio-driven video portrait generation methods. We first compare our method with the 2D-based methods DAVS [63], ATVG [11] and LipGAN [40] that directly predict video portrait frames without 3D face modeling. The LipGAN method can take both an image or a video of the target actor as input (henceforth denoted “LipGAN (img.)” and “LipGAN (vid.)”, respectively). We use part of each video (A, B and I) for training, and the remainder of the same video for testing. Both the source audio and target video are taken from the testing segment, without any temporal overlap. Figure 10 shows the comparison results. In DAVS, ATVG and LipGAN (img.), which only take a target image as input, the head pose of the video portrait is fully static and looks unnatural. The lip motions in DAVS and ATVG do not follow the corresponding source audio precisely; moreover, the image quality is reduced. The mouth shape of LipGAN (vid.) is generally better than other alternative methods; however, the details of the mouth interior can be blurry and unstable over time. In contrast, our method generates more natural-looking results with precise mouth synchronization to the audio, higher quality mouth interiors and better temporal stability. We further compare our method to the recent GAN-based speech-driven animation method SDA [54] that takes audio and a still image as input, and outputs an animated face. We ran the authors’ implementation, pretrained on the GRID [14], TCD-TIMIT [24] and CREMA-D [8] datasets. As shown in Figure 11 and our supplementary video, our results are of higher visual quality than SDA’s results.

We also compare our method with Audio2Obama [46], an audio-driven method that predicts mouth shape from audio features and uses a reconstructed 3D face model to synthesize mouth textures. We show qualitative results of Audio2Obama trained on 14 hours and on 3 minutes of speeches in Figure 12. Although Audio2Obama composites the synthetic mouth region sequences into a time-warped target video to improve the coherency of facial expression and head pose, the mouth shapes in their results are not always consistent with the audio. Further, Audio2Obama is tailored for only one target – Barack Obama, and generally requires hours of consistent training videos. Our technique, instead, is trained on a single video for each target (about 3 minutes in length) and can work with speech audio from other people. For video results, please see our supplementary video.

4.3 Quantitative Evaluation
We further carried out quantitative evaluation compared to the aforementioned 2D-based methods. We calculated SSIM scores [58] between generated results of competing methods and the ground truth for video A, B and I. We also performed an ablation study of our method with

### Table 2. List of datasets used in our results and comparisons. The lengths of training segments are provided in seconds (s).

<table>
<thead>
<tr>
<th>Name</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
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<td><img src="image3.png" alt="Image" /></td>
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<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
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<td>English</td>
<td>English</td>
<td>German</td>
<td>English</td>
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<td>Length</td>
<td>180 s</td>
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<td>180 s</td>
<td>240 s</td>
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<td>80 s</td>
<td>180 s</td>
<td>240 s</td>
<td>180 s</td>
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</table>

![Image](image12.png) Fig. 7. Self-reenactment of a reading child (video K). Please refer to the supplementary video for more details and video examples.

![Image](image13.png) Fig. 8. German speech results. We use a German audio track to generate video portraits of people originally speaking in English. Left: the audio from C is used to reenact a video portrait for B. Right: the audio from E is used to reenact a video portrait for D. Three representative frames are shown from top to bottom, in each column.
Fig. 9. Multi-target video portraits. **Left:** two representative frames corresponding to the source audio. **Right:** audio-driven video portrait results for multiple actors. The mouth shapes are synchronized well to the source frames.

Fig. 10. Comparison to DAVS [63], ATVG [11] and LipGAN [40] on target videos A, B and I. **Top:** sampled video frames corresponding to the source audio tracks. **Second row to the bottom:** corresponding video portrait frames from different methods. Our approach generates more natural-looking results with precise mouth synchronization to the audio, higher quality mouth interior and better temporal stability.

![Fig. 10. Comparison to DAVS [63], ATVG [11] and LipGAN [40] on target videos A, B and I. Top: sampled video frames corresponding to the source audio tracks. Second row to the bottom: corresponding video portrait frames from different methods. Our approach generates more natural-looking results with precise mouth synchronization to the audio, higher quality mouth interior and better temporal stability.](image1)

Table 3. Quantitative evaluation of our method and 2D-based methods on the test sets of videos A, B and I using SSIM.

<table>
<thead>
<tr>
<th>Methods</th>
<th>A</th>
<th>B</th>
<th>I</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAVS [63]</td>
<td>0.5261</td>
<td>0.5806</td>
<td>0.6226</td>
</tr>
<tr>
<td>ATVG [11]</td>
<td>0.5720</td>
<td>0.6284</td>
<td>0.6822</td>
</tr>
<tr>
<td>LipGAN (img.) [40]</td>
<td>0.5545</td>
<td>0.6135</td>
<td>0.6634</td>
</tr>
<tr>
<td>LipGAN (vid.) [40]</td>
<td>0.9451</td>
<td>0.9440</td>
<td>0.9449</td>
</tr>
<tr>
<td>Ours w/o neural face rendering</td>
<td>0.9743</td>
<td>0.9732</td>
<td>0.9658</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>0.9858</strong></td>
<td><strong>0.9842</strong></td>
<td><strong>0.9754</strong></td>
</tr>
</tbody>
</table>

Fig. 11. Comparison to SDA [54]. From **Left** to **Right:** our result and SDA trained on the GRID [14], TCD-TIMIT [24], CREMA-D [8] datasets.

![Fig. 11. Comparison to SDA [54]. From Left to Right: our result and SDA trained on the GRID [14], TCD-TIMIT [24], CREMA-D [8] datasets.](image2)
We produced short English video clips (6–8 seconds) of size 256 × 256. We performed an extensive web-based user study to evaluate our results. Participants were thanked. The whole process took on average 341 seconds (SD = 54). Audio2Obama [46] using two videos provided by the authors; one was a 3-minute video many times before rating it. After the user study, participants were asked to fill in information about their age and gender. Before starting the formal study, we showed a test video with the statement “This video clip looks real to me”, and corresponding choices (−2) to +2). We conducted subjective rating tasks on each video with 5-point Likert scales.

### 4.4 User Study

We performed an extensive web-based user study to evaluate our results. We produced short English video clips (6–8 seconds) of size 256 × 256 from the test dataset in Table 2 using our method and state-of-the-art methods. The videos show a range of expressions, including sarcastic (video A), smiling (B and D) and solemn (I and J). We conducted subjective ratings on each video with 5-point Likert scales.

#### Participants.
We recruited 72 anonymous participants (26 female and 46 male), with an average age of 24.63 years (SD=6.94).

#### Data and Methods.
We generated video portraits with the source audio taken from one segment and the target video (or image) from another non-overlapping segment, both in the same video, by each of the methods, including ours. DAVS [63], ATVG [11], LipGAN (img.) and LipGAN (vid.) [40]. As the output frames in ATVG [11] were severely cropped, we pasted the ATVG results back into input frames for fair evaluation. We also included the original segment corresponding to each audio as test data. This resulted in 30 videos for evaluation (5 videos × 6 methods, including the original segment). We further evaluated Audio2Obama [46] using two videos provided by the authors; one was trained on 14 hours of Obama’s speeches, and the other was trained on 3 minutes of Obama speech videos (see Figure 12). Accordingly, we used the same source audio to produce video portraits with our method; however, we only trained on short videos (87 seconds and 80 seconds, respectively). This resulted in 4 Obama videos for evaluation. In summary, 34 video portraits were collected for subjective evaluation.

#### Procedure.
Our web-based user study welcomed participants with a general introduction to the user study on the starting page. Next, participants were asked to fill in information about their age and gender. Before starting the formal study, we showed a test video with the statement “This video clip looks real to me”, and corresponding choices from “−2” (strongly disagree) to “+2” (strongly agree). We conducted subjective rating tasks on each video with 5-point Likert scales.

#### Results.
Table 4 summarizes the user ratings in response to the statement “This video clip looks real to me”, from “−2” (strongly disagree) to “+2” (strongly agree). Each row lists the percentage of user choices for each rating, the percentage of user choices that agree with the statement (scores “+1” and “+2”), and the mean score for each method. Top: Average of 5 video clips (A, B, D, I and J). Middle: Audio2Obama [46] trained on 14 hours of speeches versus our method. Bottom: Audio2Obama trained on a 3-minute video versus our method.

<table>
<thead>
<tr>
<th>Methods</th>
<th>−2</th>
<th>−1</th>
<th>0</th>
<th>+1</th>
<th>+2</th>
<th>Mean Score</th>
<th>Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAVS [63]</td>
<td>68.6</td>
<td>20.0</td>
<td>7.8</td>
<td>2.2</td>
<td>1.4</td>
<td>3.6</td>
<td>−1.52</td>
</tr>
<tr>
<td>ATVG [11]</td>
<td>48.9</td>
<td>27.2</td>
<td>12.8</td>
<td>8.9</td>
<td>2.2</td>
<td>11.1</td>
<td>−1.11</td>
</tr>
<tr>
<td>LipGAN (img.) [40]</td>
<td>56.6</td>
<td>20.0</td>
<td>15.3</td>
<td>7.5</td>
<td>0.6</td>
<td>8.1</td>
<td>−1.25</td>
</tr>
<tr>
<td>LipGAN (vid.) [40]</td>
<td>22.2</td>
<td>31.1</td>
<td>25.3</td>
<td>18.3</td>
<td>3.1</td>
<td>21.4</td>
<td>−0.51</td>
</tr>
<tr>
<td>Ours</td>
<td>5.8</td>
<td>16.1</td>
<td>26.7</td>
<td>29.2</td>
<td>22.2</td>
<td>51.4</td>
<td>0.46</td>
</tr>
<tr>
<td>Original</td>
<td>1.4</td>
<td>5.0</td>
<td>9.4</td>
<td>29.2</td>
<td>55.0</td>
<td>84.2</td>
<td>1.31</td>
</tr>
<tr>
<td>Audio2Obama 14 h [46]</td>
<td>1.4</td>
<td>12.5</td>
<td>8.3</td>
<td>40.3</td>
<td>37.5</td>
<td>77.8</td>
<td>1.00</td>
</tr>
<tr>
<td>Ours (87 seconds)</td>
<td>6.9</td>
<td>20.8</td>
<td>25.0</td>
<td>30.6</td>
<td>16.7</td>
<td>47.3</td>
<td>0.29</td>
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<tr>
<td>Audio2Obama 3 m [46]</td>
<td>7.0</td>
<td>19.4</td>
<td>33.3</td>
<td>34.7</td>
<td>5.6</td>
<td>40.3</td>
<td>0.13</td>
</tr>
<tr>
<td>Ours (80 seconds)</td>
<td>9.7</td>
<td>16.7</td>
<td>23.6</td>
<td>36.1</td>
<td>13.9</td>
<td>50.0</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Results. Table 4 summarizes the user ratings in response to the study. The results show that, on average, our method (51.4% ratings agree with “This video clip looks real to me”; average score 0.46) clearly outperforms DAVS [63] (3.6%; −1.52), ATVG [11] (11.1%; −1.18) and LipGAN [40] (8.1%/21.4%; −1.25/−0.51). The average scores of the above competing methods were all negative, while our results were rated on average 0.46 points (within the range [−2, +2]), and more than half of the ratings (51%) agreed that our results look real. The original segments corresponding to the source audios gained on average 1.31 points with 84.2% rating them as real. Paired t-tests at the 5% significance level confirm significant differences (p < 10^-27) between our method and each of the competing alternatives.

The subjective ratings of Audio2Obama [46] and our method reveal that the full Audio2Obama approach trained on 14 hours of videos (“Audio2Obama 14 h”) was considered significantly (t(71) = 4.81, p = 4.1 x 10^-6) more realistic (77.8% agreement, average score 1.00) than our method trained on just 87 seconds video (47.3% agreement, average score 0.29). However, our method trained on just 80 seconds of video (50.0% agreement, average score 0.28) performed better than Audio2Obama approach trained on 3 minutes of videos (“Au-
dio2Obama 3m: 40.3% agreement, average score 0.13; the difference was not significant (t(71) = 1.14, p = 0.12). Nevertheless, our method—once trained on a target actor—can be reenacted by others’ audios and generally requires less training data, which makes it more practical.

5 Discussion

In this work, we have demonstrated photorealistic audio-driven video portrait results for a variety of sequences. While the widely used virtual humans and avatars in VR and AR may have limited lifeliness, identification preservation and audio-expression synchronization, our audio-driven video portraits are photorealistic, in sync with audio, and maintain the identity of the target actor. Our approach makes a step towards the simplification of photorealistic virtual avatar creation and animation by enabling the reenactment of existing videos with new speech audios. This is especially useful when the network bandwidth is limited or a video capturing device may not be available in VR applications. Nevertheless, our approach has a few limitations that can be addressed in future research.

Our method requires an approximately 3-minute portrait video as training data to generate visually plausible results for each target actor. This is because our pipeline includes a person-specific neural face renderer that needs sufficient training data for each target. An acquisition of a selfie video as short as 30 seconds would be desirable for future daily applications. This introduces an interesting future task that massively reduces the data required to train the renderer, perhaps using meta-learning [56].

In our neural face renderer, only the lower face region is rerendered and integrated into the original face of the target video, which may lead to unnatural artifacts when the original head pose and the source audio are incompatible. For example, Figure 13(a) shows a frame of unnatural moving head pose with a closed mouth. This could be ameliorated with dynamic time warping [46], which retrieves frames from the target video to better align the mouth motion. In addition, full-frame video synthesis, as well as audio-driven head pose prediction are interesting future research directions. Moreover, when the predicted expression parameter is exaggerated, our neural face renderer may fail and produce artifacts, see Figure 13(b).

6 Conclusion

We have presented a novel real-time approach for synthesizing photorealistic video portraits from an input audio and a target video. We proposed an Audio2Expression network to predict the facial expression parameters for a target actor from any speech audio. By blending the predicted facial expression parameters and reconstructed 3D face parameters from the target video, synthetic face images are rendered in sync with the audio. Finally, we train a neural face renderer with an elegant mask expansion strategy that translates synthetic renderings into photorealistic video portraits.

Qualitative and quantitative evaluations show that our method outperforms previous general-purpose audio-driven video portrait approaches, except for Audio2Obama [46], a specifically tailored method that only works with extensive, consistent audio and video taken from the same actor. The user study confirmed that our results are compelling and generally preferred to other general-purpose audio-driven methods.

Our proposed method provides benefits for several VR/AR applications, including photorealistic virtual news anchors, and virtual education and training. It also supports a large variety of applications, such as online digital voice assistant enhancement and video conferencing, especially when the network bandwidth is limited. We believe our approach takes an important step towards solving this challenging task and it could potentially be combined with even more VR/AR applications.

Acknowledgments

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References
