Head2Head++: Deep Facial Attributes Re-Targeting

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Abstract—Facial video re-targeting is a challenging problem aiming to modify the facial attributes of a target subject in a seamless manner by driving a monocular sequence. We leverage the 3D geometry of faces and Generative Adversarial Networks (GANs) to design a novel deep learning architecture for the task of facial and head reenactment. Our method is different to purely 3D model-based approaches, or recent image-based methods that use Deep Convolutional Neural Networks (DCNNs) to generate individual frames. We manage to capture the complex non-rigid facial motion from the driving monocular performances and synthesise temporally consistent videos, with the aid of a sequential Generator and an ad-hoc Dynamics Discriminator network. We conduct a comprehensive set of quantitative and qualitative tests and demonstrate experimentally that our proposed method can successfully transfer facial expressions, head pose and eye gaze from a source video to a target subject, in a photo-realistic and faithful fashion, better than other state-of-the-art methods. Most importantly, our system performs end-to-end reenactment in nearly real-time speed (18 fps).

Index Terms—face reenactment, full head reenactment, neural rendering, video renderer, 3DMM, 3D reconstruction, gaze tracking, temporal discriminator, facial flow.

1 INTRODUCTION

Image and video synthesis receives a rapidly increasing amount of attention in Computer Vision and Deep Learning research, as “synthetic” data appear more and more realistic, as well as especially promising for real-world applications. Video editing, film dubbing, social media content creation, teleconference and virtual assistance are some indicative examples. However, generating artificial human faces indistinguishable from real ones is a very challenging task, particularly when it comes to video data. Adding the extra dimension of time, might give rise to the so-called problem of temporal incoherence. As the uncanny valley effect suggests, people are extremely perceptible in unnatural facial and head movements, thus even small discontinuities can expose a synthetic video.

Over the past years, various methods that target human faces have emerged, taking advantage of different modalities, such as audio \cite{1, 2} and video \cite{3, 4, 5} to drive synthesis and dictate the movements of the generated subject. Facial reenactment is a widely-studied approach \cite{3, 6, 7}, which aims to transfer the facial expressions from a source to a target subject, by conditioning the generative process on the driving video of the source. In most cases \cite{3, 7}, this is done by modifying the deformations solely within the internal facial region of the target identity and placing the manipulated face back to the original target frames, using an image interpolation method. Given that face reenactment systems offer no control over the target’s head pose and eye gaze, there might be cases where the person’s expressions do not match with the overall head movement and therefore seem unnatural. Even so, face reenactment can be very useful for specific applications, such as video dubbing \cite{8}, which aims to alter the mouth motion of the target actor to match the audio track spoken by the dubber.

A more holistic approach on reenactment involves generating all pixels within frames, including the upper body, hair and background of the target identity. In contrast to video manipulation techniques, such as face reenactment, full head reenactment methods \cite{4, 9} aim to transfer the entire head motion from a source identity to a target one, along with the eye blinking and gaze, providing complete control over the target subject. Most head reenactment approaches fall into two categories: a) Warping-based methods \cite{2, 10, 11}, which are mainly learning-based and do not involve computing priors such as facial landmarks or 3D face models, b) object-specific methods \cite{3, 4, 9, 12}, which assume knowledge (e.g. 3D reconstruction, 68 landmarks) of the source and target faces. On the one hand, warping-based methods usually suffer from distortions in the face and background \cite{2}. On the other hand, object-specific methods relying on facial keypoints are affected from the so-called identity preservation problem. As keypoints encapsulate identity attributes of the source (e.g. head geometry), the more the identity of the source diverges from that of the target, the more distorted the head shape of the generated subject might appear. On the contrary, 3D morphable models (3DMMs) \cite{13, 14} have proven to be a reliable means of decoupling expression and identity from each other. Deep Video Portraits (DVP) \cite{4} is a full head reenactment system that capitalises on 3DMMs and utilises a neural network to translate 3D face reconstructions to realistic frames. Nonetheless, DVP, as a purely image-based model, does not take into account temporal dependencies...
between frames.

Our recently proposed Head2Head [15] model overcomes the aforementioned limitations, as it combines the benefits of conditioning synthesis on 3D facial shapes with the advantages of a sequential, video-based, neural renderer. In this paper, we extend the work of Head2Head in the following directions:

- We prevail over the limitations of the 3D reconstruction stage of Head2Head by designing a novel Dense-FaceReg network for the robust and fast estimation of semantic facial images based on 3D facial geometry. Our semantic facial images, referred to as Normalised Mean Face Coordinates (NMFC) images, capture pose, expression and identity information of the subject from the 3D facial mesh and are used to condition video synthesis.
- We propose a simple yet fast method for detecting the eye gaze, based on 68 facial landmarks. When combined with 3D Facial Recovery and Video Rendering Network, our system can operate in nearly real-time speeds.
- We conduct an extensive set of experiments, including user, automated and ablation studies. Our results reveal the significance of video-based modeling.
- We make our code and dataset publicly available.  

2 RELATED WORK

2.1 3D Face Reconstruction

Recovering the 3D geometry of human faces from monocular images is a challenging problem that has attracted much attention due to its major role in many applications, ranging from facial reenactment, performance capture and tracking [16], facial expression recognition [17], [18], etc. Owing to their pose and illumination invariance, 3D facial data constitute an indispensable geometrical description of faces for various facial image processing systems. The Computer Vision field is rich in approaches targeting this problem under different assumptions and constraints. Some of these attempts [19], [20], named Shape from Shading, approximate the image formation process and make simplified assumptions about the lighting and illumination models leading to the formation of the image, while others, known as Structure from Motion (SfM), benefit from the geometric constraints in multiple images of the same object to solve the problem [21], [22]. One common approach for addressing this task are the 3D Morphable Models (3DMMs) of the human face. 3DMMs are linear statistical models that have been used substantially since the pioneering work of Blanz and Vetter [23], with many extensions [13], [14], [24]. With the rise of deep neural networks, nonlinear face models have been proposed to recover the 3D geometry and appearance of human faces from images or videos using deep Convolutional Neural Networks (CNNs) [25], [26], [27], [28]. For a very recent and comprehensive review of the state-of-the-art methods on monocular 3D face reconstruction and the open challenges of 3DMMs, we refer the readers to [29], [30].

In this work, we employ 3DMMs and a 3D shape regression network for: 1) estimating the 3D geometry of faces appearing in videos, and 2) utilising the estimated 3D geometrical information for driving our Deep Video Rendering Neural Network.

2.2 Facial Synthesis and Re-targeting

Various deep architectures have been proposed for the image and video synthesis tasks with the aid of Recurrent Neural Networks (RNNs), Variation Auto-encoders (VAE) [31], Gaussian mixture VAE [32], Hierarchical VAE [33], Generative Adversarial Networks (GANs) [34] and VAE-GAN [35].

Traditional methods of reenactment, transfer the facial expressions either with 2D warping techniques [10], [11], or by utilizing 3D face models [3], [6], [7]. These methods do not provide complete control over the generated video, as they manipulate only the interior of the face. Recently, there has been a substantial effort in the direction of both expression and pose transfer [2], [4], [9], [36], [37]. One of the first approaches, X2Face [4], designs an embedding and a set of auto-encoders. X2face follows a warping-based approach that causes deformations in the generated heads and inconsistent upper-body motions. Wang et al. [12] propose vid2vid, a GAN-based spatio-temporal approach for the video-to-video synthesis, relying on a Temporal Discriminator for improving the temporal quality of the synthesised videos. In a follow-up work, Wang et al. [38] extend their approach with an attention mechanism, making it trainable in a few-shot manner and leading to better generalisation performance. Both [12] and [38] can perform reenactment with face sketches drawn from landmarks, leading to a target identity preservation problem. Moreover, the synthesised mouth regions do not look very realistic.

Zakharov et al. [9] propose a few-shot, image-based adversarial learning approach, as their network learns to generate unseen target identities even from a single image. Nonetheless, their neural network relies on landmarks, causing an identity distortion of the target. Siarohin et al. [39] animate objects via a deep motion transfer framework. Given a single image and a driving sequence, their method estimates a dense motion field appearing in the sequence and transfers it to the target image while preserving its appearance. When used for facial reenactment, the faces synthesised by this approach suffer from head distortions and non-naturalistic mouth and teeth areas. To tackle this issue, the authors extended their work [40] to account for complex motions with a first-order motion model and an occlusion-aware Generator. Although this extension considerably improved the results on various tasks, synthesised faces still exhibited visual artifacts appearing as expression-dependent continuous scale changes. This can be attributed to the estimated 2D dense motion field that does not fully describe the actual intricate 3D facial motion.

As far as we are aware, DVP [4] is the only learning-based head reenactment system, prior to our work, that uses 3D facial information to condition video synthesis. Their image-based model requires a long video footage of the target person, while training a new model for each target takes many hours. Moreover, generated mouths look unnatural, since the 3D reconstruction method they adopt does not encode the inner-mouth region or the teeth.

1. https://github.com/michaildoukas/head2head
Unlike other studies, our approach employs efficiently the 3D geometry and conditions frame generation on a compact and meaningful representation in the image space derived from 3D facial reconstruction. When combined with our novel video-based neural rendering stage, the result is a faithful and photo-realistic full head video reenactment, indistinguishable from real videos. Additionally, we focus specifically on the mouth area and improve its visual quality by designing a dedicated discriminator.

3 Methodology

Our Head2Head++ framework proposes a solution for the largely ill-posed full head reenactment problem. Our method is capable of transferring the time-varying head attributes (pose, expression, eye gaze) and mainly consists of two subsequent modules: a) 3D Facial Recovery (Sec. 3.1), and b) a Video Rendering Network (Sec. 3.4). Our video rendering network capitalises on a carefully designed GAN-based framework. Please refer to Fig. 1 for an overview of our Head2Head++ pipeline.

Shape representation. Using 3DMMs, a 3D facial shape \( \mathbf{x}_t = [x_1, y_1, z_1, ..., x_N, y_N, z_N]^T \in \mathbb{R}^{3N} \) can be written mathematically as:

\[
\mathbf{x}_t = \mathbf{x}(\mathbf{s}_t^{id}, \mathbf{s}_t^{exp}) = \bar{\mathbf{x}} + \mathbf{U}_{id}\mathbf{s}_t^{id} + \mathbf{U}_{exp}\mathbf{s}_t^{exp}
\]

where \( \bar{\mathbf{x}} \in \mathbb{R}^{3N} \) is the mean shape of the morphable model, given by \( \bar{\mathbf{x}} = \bar{\mathbf{x}}_{id} + \bar{\mathbf{x}}_{exp} \) with \( \bar{\mathbf{x}}_{id} \) and \( \bar{\mathbf{x}}_{exp} \) standing for the mean identity and expression of the model, respectively. \( \mathbf{U}_{id} \in \mathbb{R}^{3N \times n_i} \) is the identity orthonormal basis with \( n_i \) principal components \( (n_i \ll 3N) \), \( \mathbf{U}_{exp} \in \mathbb{R}^{3N \times n_e} \) is the expression orthonormal basis with the \( n_e \) principal components \( (n_e \ll 3N) \) and \( \mathbf{s}_t^{id}, \mathbf{s}_t^{exp} \in \mathbb{R}^{n_i}, \mathbb{R}^{n_e} \) are the identity and expression parameters of the morphable model. We designate the joint identity and expression parameters at time-step \( t \) by \( \mathbf{s}_t = [\mathbf{s}_t^{id}, \mathbf{s}_t^{exp}]^T \). In the adopted model [1], the 3D facial shape \( \mathbf{x} \) is a function of both identity and expression coefficients \( (\mathbf{x}(\mathbf{s}_t^{id}, \mathbf{s}_t^{exp})) \), where expression variations are effectively represented as offsets from a given identity shape.

Video-based 3D reconstruction. The video fitting approach followed in Head2Head [15] to estimate the 3D facial geometry is based on a set of sparse landmarks extracted from the entire input sequence. This method has three main drawbacks: 1) the fidelity of the 3D reconstruction relies heavily on the accuracy of extracted landmarks which are also sparse (68 in total), 2) it might require a large number of frames with enough reconstruction cues (various rotations) to produce good accuracy, 3) it makes a quite strong assumption in the initialisation stage about the rigidity of the face to estimate the camera parameters. To overcome these limitations, we propose to perform the 3D facial reconstruction in this work by training a deep CNN, we call DenseFaceReg, the purpose thereof to produce a dense 3D facial mesh from a single RGB frame. We use a thousand annotated videos from the Face3D Vid dataset of Koujan et al. [16] to train this network in a supervised manner. The adopted loss function during training is:
\[ \mathcal{L}(\Phi) = \sum_{i=1}^{N} ||v_i^{GT} - v_i||^2. \]  

Equation (2) penalises the deviation of each vertex from the corresponding ground-truth vertex \( (v_i = [x, y, z]) \). We use the camera parameters provided with the Face3Dvid dataset to project the 3D ground-truth mesh, so that our DenseFaceReg produces 3D vertices (dense landmarks) directly in the image space. We use the dense 3D vertices (~5K) estimated by our trained DenseFaceReg on each video frame to: 1) estimate the camera parameters, 2) generate the 3DMM identity and expression coefficients by projecting the dense shape onto the 3DMM bases. For all our experiments in this work, we use the same 3DMMs utilised in [15].

The analysis-by-synthesis approach, which is used by many state-of-the-art approaches [3], [4], estimates a lot of parameters (e.g. illumination, reflectance, shape, etc) and solves a highly ill-posed problem for fitting 3DMMs to images. On the contrary, our facial reconstruction stage is a fast CNN-based approach (6ms test runtime) trained on a large number of in-the-wild videos. The facial representation extracted with our method is informative enough to synthesise photo-realistic and temporally smooth videos, eliminating the need for more elaborate and slower 3D facial reconstruction techniques.

### 3.2 Facial Semantic Representation - NMFC Rendering

Our video rendering network receives as input a facial semantic representation of the target subject, with the head pose and facial expression guided by the source frames. This representation disentangles identity from expression, allowing us to train our video rendering network on a specific target person. During test, we are able to transfer the expression and pose of any source, with different head characteristics, to the target. Given the recovered identity and expression parameters (facial shape) \( s_t = [s_t^I, s_t^E] \) and camera parameters \( p_t \), at frame \( t \), we rasterize the 3D shape, producing a visibility mask (\( M \in \mathbb{R}^{W \times H} \)) in the image space. Each pixel of \( M \) stores the index of the corresponding visible triangle on the 3D face seen from this pixel. Thereafter, we store the normalised x-y-z coordinates of the centre of this triangle in the NMFC \( \in \mathbb{R}^{W \times H \times 3} \) image, which is the facial semantic representation that is utilised as conditional input to the video rendering network. Equation (3) details this process.

\[ \text{NMFC}_t = \mathcal{E}(\mathcal{R}(x_t(s_t^I, s_t^E), p_t), \bar{x}), \]  

where \( \mathcal{R} \) is the rasterizer, \( \mathcal{E} \) is the encoding function and \( \bar{x} \) is the normalised version of the 3DMM mean face (see [1]), so that the x-y-z coordinates of this face belong in [0, 1]. This representation is more compact and easy-to-interpret by our video rendering network, since it associates well with the corresponding RGB frame to be generated, pixel by pixel, and, subsequently, leads to a realistic and novel video synthesis. Note that during test time, the expression coefficients \( s_t^E \) and camera parameters \( p_t \) are estimated from the source video at frame \( t \), while the identity coefficients \( s_t^I \) are the average identity parameters estimated using all frames of the target video (see Fig. [1]).

### 3.3 Eye Pupils Detection

We choose a real-time operating method for the extraction of the eye movements from the source frames, which does not require fitting an eye model [41], but is based on 68 facial landmarks [42]. Given the subset of landmark points \( L^{ge}_{e} \in \mathbb{R}^{6 \times 2} \) that correspond to the left or right eye, we estimate one more landmark \( I^{pupil} \in \mathbb{R}^{2} \), which corresponds to the eye pupil. The location of the eye pupil is estimated as the centre of mass within the eye region, which is defined as the set of pixels \( \Omega \) that are bounded by the polygon formed with the eye landmarks \( L^{ge}_{e} \). Then, similarly with [43], the eye centre of mass is given as

\[ I^{pupil} = \frac{\sum_{p \in \Omega} I(p)p}{\sum_{p \in \Omega} I(p)}, \]  

where \( I(p) \) is the inverse intensity of pixel \( p \) in the source frame. In this way, \( I^{pupil} \) corresponds to the center of “darker” pixels within the eye region.

### 3.4 Deep Video Rendering Neural Network

Our carefully-designed video rendering network receives as conditional input two sequences of images, namely: the NMFC video \( \text{NMFC}_1:T \) and the corresponding eye video \( E_{1:T} \), collectively as \( X_{1:T} = \{X_t = (\text{NMFC}_t, E_t)\}_{t=1,...,T} \), with \( X_t \in \mathbb{R}^{H \times W \times 6} \). With this input, the video rendering network yields a highly realistic and temporally coherent output video \( \hat{Y}_{1:T} \) picturing the target actor mimicking exactly the same expressions, head pose and eyes reflected in \( X_{1:T} \). While training, we follow a self reenactment setting where the source and target videos are the same footage. In this way, the reenacted video in the output should be a replication of the RGB training target video \( Y_{1:T} \), which serves as ground truth. Our video rendering network is trained within a GAN-based structure with: 1) a Generator \( G \), which is the video rendering network itself, 2) an Image Discriminator \( D_I \), 3) a multi-scale Dynamics Discriminator \( D_D \) enforcing the temporal coherence and realism of the produced facial performance, and 4) a dedicated Mouth Discriminator \( D_M \), which further improves the visual quality of the mouth area.

**Generator** \( G \). To successfully synthesise smooth and convincing temporal facial performances, we condition the synthesis of the t-th frame \( \hat{Y}_t \) not only on the conditional input \( X_t \), but also on the previous inputs \( X_{t-1} \) and \( X_{t-2} \), as well as the previously generated frames \( \hat{Y}_{t-1} \) and \( \hat{Y}_{t-2} \), thus:

\[ \hat{Y}_t = G(X_{t-2:t}, \hat{Y}_{t-2:t-1}). \]  

The Generator is applied sequentially, producing the output frames one after the other, until the entire output sequence has been created. Similar to Head2head [15], the Generator consists of two identical encoders, operating in parallel, as well as a decoder. The first encoder receives the concatenated NMFC and eye images \( X_{t-2:t} \), while the second is given the two previously generated frames \( \hat{Y}_{t-2:t-1} \).
The two extracted feature maps are first added and then passed through the decoder, which brings the output $\hat{Y}_t$ in a normalised $[-1, +1]$ range, using a tanh activation function.

**Image Discriminator** $D_I$ and **Mouth Discriminator** $D_M$. Both of these networks aim at telling real and synthesised frames apart, and are used only during training. At time-step $t$, the Image Discriminator $D_I$ processes the real pair $(X_t, Y_t)$ and the fake one $(\hat{X}_t, \hat{Y}_t)$. Concurrently, the corresponding mouth regions $(X^m_t, Y^m_t)$ and $(\hat{X}^m_t, \hat{Y}^m_t)$ are cropped and sent to the Mouth Discriminator $D_M$.

**Dynamics Discriminator** $D_D$. With the aim of learning complex facial dynamics in mind, we further equip our GAN framework with a Dynamics Discriminator $D_D$. During training, $D_D$ receives a set of three consecutive real frames $Y_{t:t+2}$ or fake frames $\hat{Y}_{t:t+2}$. They are passed to $D_D$ after being associated with the optical flow $W_{t:T-1}$, computed from the real frames (training video $Y_{1:T}$ of target subject). Following this, the Generator is encouraged to create fake frames showing the same flow (dynamics) as the corresponding real ones. The Dynamics Discriminator learns to differentiate between the real $(W_{t:t+1}, Y_{t:t+2})$ and fake $(\hat{W}_{t:t+1}, \hat{Y}_{t:t+2})$ pairs. In practice, we employ a multiple-scale Dynamics Discriminator, which operates in three different temporal scales. The first scale receives frame sequences in the original frame rate. Then, the two extra scales are formed by sub-sampling the frames by a factor of two for each scale.

**Objective function**: In order to train our Generator to synthesise samples as real as possible, we formulate an adversarial loss. More specifically, we use LSGAN [44] with labels $a = c = 1$ for fake samples and $b = 0$ for real ones, resulting in the following adversarial objective for the Generator:

$$L_{adv}^G = \frac{1}{2} \mathbb{E}_t[(D_D(W_{t:t+1}, Y_{t:t+2}) - 1)^2] + \frac{1}{2} \mathbb{E}_t[(D_I(X_t, Y_t) - 1)^2 + (D_M(X^m_t, Y^m_t) - 1)^2]. \quad (6)$$

We add two more losses in the learning objective function of the Generator: 1) a VGG loss $L_{vgg}^G$ and 2) a feature matching loss $L_{feat}^G$, which is based on the activations of the Image and Dynamics Discriminators. Given a ground-truth frame $Y_t$ and the synthesised frame $\hat{Y}_t$, we use the VGG network [46] to extract visual features in different layers for both frames and compute the VGG loss as in [45] and [12]. Likewise, the feature matching loss is computed by extracting features with the two Discriminators $D_I$ and $D_D$ and computing the $\ell_1$ distance of these features for a fake frame $\hat{Y}_t$ and the corresponding ground truth $Y_t$. The total objective for $G$ is given by:

$$L^G = L_{adv}^G + \lambda_{vgg} L_{vgg}^G + \lambda_{feat} L_{feat}^G \quad (7)$$

To achieve a balance between the loss terms above, we set $\lambda_{vgg} = \lambda_{feat} = 10$. The Image, Mouth and Dynamics Discriminators are optimised under their corresponding adversarial objective functions (see Supplementary Material).

**Facial dynamics**. One key factor to consider while designing the Dynamics Discriminator, is how it could learn the complex realistic facial muscular interactions observed in monocular videos of facial performances. As discussed and validated experimentally in [16], off-the-shelf state-of-the-art optical flow methods solve this problem without any prior knowledge, since they target any moving objects in the scene. When applied to faces captured in the wild, the estimated flow does not reflect faithfully the non-rigid and composite facial deformations. To tackle this, we employ a state-of-the-art network, termed as FlowNet2, for the optical flow estimation [47]. The authors of [47] trained this network on publicly available images after rendering them with synthesised chairs modified by various affine transformations. Starting from the pretrained models of [47], we fine-tune their network on the 4DFAB dataset [48]. This dataset has dynamic high-resolution 4D videos of subjects eliciting spontaneous and posed facial behaviours.

### 4 Experiments

#### 4.1 Dataset and Implementation Details

We train and test Head2Head++ on a newly collected video dataset, which we make publicly available, consisting of eight different individuals. Each individual is depicted in one video, which is at least 10 minutes long and presents the target in diverse head poses and facial expressions. First, we apply face detection on each video, as a pre-processing step. We utilise [49] to obtain a bounding box per frame, and then we compute the average bounding box throughout frames. We extract the facial ROI of $256 \times 256$ pixels for each frame, according to this fixed bounding box. This way, the background remains as stable and unchanged as possible, from the beginning of the video until the end. Finally, the frames of each subject are split into a training and a test set. Please refer to the Supplementary Material for more details on the dataset.

We base our Generator’s architecture on our previous work [15]. All discriminators have the same architecture, adopted by pip2pixHD [45]. We train a separate person-specific Video Rendering Network for each one of the eight target identities. Given a target video footage of 10 minutes, extracting the eyes and NMFC conditional input sequences and training, the GAN framework requires around 20 hours. Networks are optimised with Adam [50], for 40 epochs with an initial learning rate $\eta = 2 \cdot 10^{-4}$, $\beta_1 = 0.5$, $\beta_2 = 0.999$, on a single NVIDIA GeForce RTX2080 Ti. During test time, our Head2Head++ pipeline performs head reenactment from web-camera captures in nearly real-time speeds (18 fps).

#### 4.2 Supported Reenactment Methods

As already mentioned, we have chosen to use 3DMMs for the retrieval of 3D facial shapes from the source and target videos in order to address the target identity preservation problem, allowing us to disentangle expression from identity seamlessly. Therefore, Head2Head++ can be used both for full head reenactment and simple facial reenactment, depending on which set of camera parameters (source or target) are used during the creation of the conditional NMFC sequence.

**Head Reenactment**. This is the main functionality of our method and arguably the most challenging, since it involves transferring the complete head motion from any driving
Fig. 2. Head reenactment aims at transferring the expressions, pose and eye movements from the driving sequence to the target identity.

Fig. 3. Self reenactment is used for evaluating the performance of models. Here, the source identity coincides with the target one. We display Average Pixel Distance (APD) and Masked Average Pixel Distance (MAPD) between the generated and ground truth frames, in the form of RGB heatmaps. Please refer to Sec. 4.2 for more details on those metrics.

Although prior works have mainly used it as a manipulation method \[3, 7\], we perform face reenactment by generating all pixels within frames, not only a masked area of the face.

**Self Reenactment.** During self reenactment, the source identity coincides with the target one. This is extremely useful for training and evaluating our model, since we are given access to the ground truth frames. Note that the driving sequences used during test have not been seen during training, since they belong to the test data split. Fig. 3 shows a self reenactment experiment. Ideally, the generated frames should be identical with the source ones. For the evaluation of the reconstructive ability of models in the experiments that follow, we use metrics such as the average pixel distance (APD) or masked average pixel distance (MAPD) between the synthesised and ground truth frames. In Sec. 4.3 we provide more details on APD and MAPD.

### 4.3 Quantitative Evaluation Metrics

We evaluate the performance of our system both qualitatively and quantitatively. Most experiments were performed under self reenactment. That is, given a set of test frames \( Y^{(i)} \) for each target identity \( i \) in the dataset, we generated the corresponding synthetic frames \( \tilde{Y}^{(i)} \) and used \( Y^{(i)} \) as ground truth. We assessed our method’s reconstructive ability, target identity preservation, pose and expression transferability as well as the photorealism of generated frames, using the metrics below:

- **Average Pixel Distance (APD):** is computed as the average L2-distance of RGB values across all spatial locations and frames, between the ground truth and generated data.
- **Masked Average Pixel Distance (MAPD):** similar to APD, it tests the reconstructive performance. A mask computed from NMFC frames is used to constrain the metric on the facial area, where conditional information is available.
- **Distance between Average Identities (DAI):** after performing 3D face reconstruction on \( Y^{(i)} \) and \( \tilde{Y}^{(i)} \) sequences, we compute the average identity coefficients for each sequence, and then the L1-distance between those average identities.
- **Average Expression Distance (AED):** after reconstructing the fake and ground truth sequences, we measure the average L1-distance between the expression coefficients across frames.
- **Average Rotation Distance (ARD):** this metric is used to measure pose transferability. Using the estimated camera parameters from the generated and ground videos, we compute the Euler angles that correspond to head poses. Then, the average Euler angles discrepancy across sequences is determined in terms of degrees.
- **Frchet Inception Distance (FID):** this is a widely used metric for evaluating the visual quality of individual frames, originally proposed in [51]. We use [52] as a feature extractor and we report the mean FID throughout the experiments.
- **Maximum Mean Discrepancy (MMD\(^2\)):** is a very useful metric for measuring the discrepancy between real and fake frames [53].
Fig. 4. Significance of Mouth Discriminator. Please zoom in for details.

Fig. 5. Significance of conditioning on the eyes. The blinking of the source is successfully transferred to the target when using eye landmarks to condition synthesis. On the contrary, conditioning solely on NMFC frames is not sufficient for transferring eye gaze and blinking.

4.4 Ablation Study

We conducted an ablation study, in order to assess the significance of several “key” components of our Head2Head++ system. First, we evaluate numerically the contribution of the two reconstructive loss terms, namely the feature matching and VGG loss. As can be seen in the first two rows of Table 1, all metrics demonstrate the contribution of these loss terms on the quality of the generated samples. The next row of the table validates the importance of a sequential Generator, as opposed to its non-sequential variation (“w/o seq. G”). The results indicate that considering previously generated frames in the Generator has a very positive effect on the visual quality of samples. Finally, the majority of metrics show that removing the Dynamics Discriminator (“w/o $D_D$”) might slightly improve the quality of frames, when seen as individual images. We believe this is due to the fact that the proposed metrics analyse solely the spatial content of frames and do not evaluate temporal information. Removing $D_D$ network would actually reduce the temporal stability and coherence of videos. Such behaviour is more apparent in areas where no conditional information is available (e.g. hair, background, upper body). In order to understand better the significance of the Dynamics Discriminator in the visual plausibility of the output video, please refer to our Supplementary Video.

Arguably, the eyes and the mouth, are the facial areas that might be the first to expose the “fakeness” of a synthetic video. In Fig. 4 we illustrate the importance of the dedicated Mouth Discriminator, initially proposed in [15]. As can be seen in the second row of Fig. 4, when the Mouth Discriminator is not included in GAN training, teeth details make the generated video appear less realistic, as opposed to the results in the first row, where the Generator was supervised by $D_M$ network. Additionally, Fig. 5 demonstrates the significance of conditioning the Generator on the eyes input sequence. Given that NMFCs do not adequately reflect eye gaze and blinking, conditioning solely on the NMFC input sequence does not provide substantial information to the Generator, for transferring the eye movements of the source to the target.

4.5 Effect of Training Video Length

Fig. 6 displays the influence of training footage duration on the generative performance of the the Video Rendering Network. For that experiment, we trained five separate models per target identity. Each model was trained on frame sequences of different length: one, two, four, eight, up to sixteen thousand frames. We found that FID and MMD scores, which indicate visual quality, are the metrics affected the most by the number of training frames. Furthermore, it is visible that there is still room for improvement in the performance of our Video Rendering Network, provided that even longer training videos are available. However, this would require additional footage with enough head pose variability, which in practice does not scale linearly with the number of training frames available.

In Fig. 7 we demonstrate the impact of training video length on the visual quality of synthetic frames. We observe visually that as the number of available training frames increases, artifacts become less severe and eventually disappear. This behaviour comes in agreement with the decrease of evaluation metrics, shown in Fig. 6.

4.6 Pre-training on Face Forensics++ Dataset

We further explore how the generative performance of the Video Rendering Network can be improved in the case of limited video footage, for instance when training sequences
Fig. 6. The effect of the number of training frames on the quality of generated frames. All metrics were computed for the subset of four target identities (Macon, Sanchez, Trump, Von Der Leyen).

Fig. 7. Significance of training video length. We show the same image generated with a GAN trained on 1K, 2K, 4K, 8K and 16K frames, as well as the ground truth (last image).

Fig. 8. The effect of pre-training the Video Rendering Network on Face Forensics++ dataset. The importance of pre-training is very prominent when a limited number of training frames (1K, 2K) is available.

Table 2: Effect of pre-training GAN on Face Forensics++ dataset, when training video footage is limited, namely less than 4K frames. All metrics are averaged across all eight target identities in our dataset. For all metrics, lower values indicate better quality or performance.

<table>
<thead>
<tr>
<th>Number of train frames</th>
<th>APD</th>
<th>MAPD</th>
<th>AED</th>
<th>ARD</th>
<th>×10^2 FID</th>
<th>×10^5 MMD^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1K</td>
<td>22.62</td>
<td>20.32</td>
<td>0.844</td>
<td>0.955°</td>
<td>16.01</td>
<td>39.59</td>
</tr>
<tr>
<td>w/ pre-train</td>
<td>21.95</td>
<td>19.02</td>
<td>0.575</td>
<td>0.562°</td>
<td>15.93</td>
<td>39.76</td>
</tr>
<tr>
<td>2K</td>
<td>20.41</td>
<td>18.27</td>
<td>0.719</td>
<td>0.737°</td>
<td>11.04</td>
<td>24.83</td>
</tr>
<tr>
<td>w/ pre-train</td>
<td>20.17</td>
<td>17.84</td>
<td>0.526</td>
<td>0.516°</td>
<td>11.22</td>
<td>24.93</td>
</tr>
<tr>
<td>4K</td>
<td>18.87</td>
<td>17.46</td>
<td>0.610</td>
<td>0.577°</td>
<td>7.41</td>
<td>15.08</td>
</tr>
<tr>
<td>w/ pre-train</td>
<td>18.90</td>
<td>16.71</td>
<td>0.483</td>
<td>0.453°</td>
<td>7.80</td>
<td>15.63</td>
</tr>
</tbody>
</table>

To that end, we pre-trained Head2Head++ on the large-scale Face Forensics++ dataset [54], containing 1000 different identities. At this stage, the Generator learned to create a “average identity”, since there is no mechanism to dictate which identity to be synthesised over this multi-person dataset. As a next step, we fine-tuned eight person-specific models, one for each target identity in our dataset, using a subset of their available footage (1K, 2K or 4K frames). In Table 2, we report a quantitative evaluation with and without pre-training on [54] data. As suggested by the results, pre-training on Face Forensics++ data appears advantageous, especially for shorter sequences (1K or 2K frames). This could be explained if we consider pre-training as a head start for the GAN, where the Generator is already capable of creating a realistic “average identity” and then it remains to learn a specific one. The same trend can be seen in Fig. 8. Especially for a training footage of 1K or 2K frames, the quality of generated frames is clearly inferior in comparison with samples created with pre-training.

4.7 Comparison with the State of the Art

We compare our Head2Head++ system with the image-based method of DVP [4]. This is done by performing a full head reenactment experiment on the same source and target video footage. First, we trained our method on the target sequence, which was kindly provided by the authors of [4], and then we used the same source to drive synthesis. In Fig. 9 we display some examples, in which our method outperforms DVP in terms of head pose and expression transferability.

For a quantitative comparison of the two methods, we performed 3D face reconstruction on the two synthetic videos and computed the average expression distance (AED) and average rotation distance (ARD) across frames, between the source video and the two generated videos. Then, we applied 3D face reconstruction on the target video and computed the distance between the average identities extracted from this real and each one of the two fake sequences. Finally, we used the FID and MMD^2 scores as a photorealism metric, both computed between the fake videos and a set of frames from the target’s original footage. The results are presented in Table 3 and suggest that our method outperforms DVP on every single metric.
We further compare our method with the warping-based X2Face method [2] as well as the one-shot, image-based First Order Motion Model for Image Animation (FOMM) [40] system. As suggested visually in Fig. 10 and the quantitative results in Table 4, Head2Head++ outperforms both few-shot methods by a large margin.

### Table 3
Quantitative comparison with DVP under full head reenactment. For all metrics, lower is better.

<table>
<thead>
<tr>
<th>Method</th>
<th>AED</th>
<th>ARD</th>
<th>DAI</th>
<th>FID ($\times 10^2$)</th>
<th>MMD$^2$ ($\times 10^5$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DVP [4]</td>
<td>2.089</td>
<td>2.54°</td>
<td>23.01</td>
<td>15.94</td>
<td>61.32</td>
</tr>
<tr>
<td>Ours</td>
<td>1.509</td>
<td>0.83°</td>
<td>8.86</td>
<td>12.42</td>
<td>39.15</td>
</tr>
</tbody>
</table>

### Table 4
Quantitative comparison with X2Face and FOMM, using all eight target identities in our dataset, under self reenactment.

<table>
<thead>
<tr>
<th>Method</th>
<th>APD</th>
<th>FID ($\times 10^2$)</th>
<th>MMD$^2$ ($\times 10^5$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>X2Face [2]</td>
<td>30.54</td>
<td>63.3</td>
<td>253.2</td>
</tr>
<tr>
<td>FOMM [40]</td>
<td>22.43</td>
<td>24.6</td>
<td>90.3</td>
</tr>
<tr>
<td>Ours</td>
<td>14.82</td>
<td>4.2</td>
<td>6.5</td>
</tr>
</tbody>
</table>

Such a discrepancy can be explained by the fact that we train an individual person-specific model for each target identity, instead of relying on a few image samples of the subject.

In order to demonstrate the significance of the NMFC representation, we conducted a head reenactment experiment conditioning on landmarks. To that end, we trained vid2vid [12] on the task of landmark-to-RGB video translation. We demonstrate the results in Fig. 11. As can be seen, the facial shape of the source has been transferred along with the pose and expression to the generated target.

As a final experiment, we show that our new eye motion extraction method results in more reliable eye synthesis, compared to head2head [15], in terms of photo-realism and eye shape. In Fig. 12, we present such examples. We observe that the eye regions generated by head2head seem unnatural, while Head2Head++ has successfully rendered photo-realistic eyes.
4.8 Automated Study

The progress recently made by generative deep learning methods is so impressive to the extent that manipulated videos (deepfakes) by such approaches are indistinguishable from the real ones. Consequently, a new research topic has emerged to tackle the detection of what is commonly known as ‘deepfakes’. A recent attempt in that direction is the Face Forensics ++ [54]. The authors of [54] collected a dataset of 1000 YouTube videos and manipulated them with graphics-based [3], [55] and learning-based [7], [56] facial reenactment methods. With this dataset, a CNN was trained to outrank the performance of human observers in detecting manipulated videos. Such a network was trained on 1.8 million facially manipulated frames and reached a very high detection accuracy on the test split of their dataset (around 99%). We use their pre-trained best-performing network and fine-tune it on around 14K frames synthesised from eight different subjects by our Head2Head++ approach. While fine-tuning, we set the learning-rate to 0.0001 and batch-size to 32. Adam optimiser [50] was also used with the default parameters. We then test the fine-tuned network on 1.6K frames generated by our Head2Head++ method and not seen during training. The trained network reports an accuracy of 76% of fake frames detection. In comparison, the same network performs way better (around 99%) in detecting fake frames synthesised by any of the four head-reenactment methods tested in [54]. Thanks to our carefully designed Head2Head++ framework, the trained forgery detection network finds it harder to identify our fake frames, which can be attributed to the increased realism of our results.

4.9 User Study

We further evaluate the photo-realism of our generated videos, by conducting a user study. For that, we synthesised five videos of 75 frames (3 seconds) each, using different reenactment methods (head, face and self reenactment). Then, we coupled each fake video with two real ones, with the same duration and same target identity, forming triplets of videos. Next, we asked 50 participants on MTurk to detect the fake sample of each triplet. We presented the video triplet to the participants, allowing them to watch them only once.

Our recorded results indicate a human fake detection accuracy of 43.1%, which demonstrates the strong photo-realism of samples created by our Head2Head++ system. In Fig. [13a] we show the relative frequency of participants on the number of fake videos that were successfully detected. As can be seen, the majority managed to spot between 4 and 8 out of the 15 synthetic samples we displayed. The comparison of our statistics with a Binomial distribution (red curve) indicates that user study participants performed slightly better than random selection. Nonetheless, a significant percentage of them, around 18%, managed to detect 9 or more fake samples. Finally, Fig. [13b] displays the predictive accuracy of participants on each video triplet. It is evident that self reenactment samples were indistinguishable from real ones, with just 32.8% predictive accuracy. Videos generated under face and head reenactment were identified a little more successfully, with an accuracy of 47.2% and 49.2% respectively.

5 Conclusion and Future Work

We proposed Head2Head++, a pipeline consisting of a novel 3D facial reconstruction system and a Video Rendering Network, able to perform full head reenactment from a source to a target identity. Our new 3D face recovery and eye tracking methods allow our system to operate in nearly real-time speeds. The extensive set of experiments we performed demonstrated the generative abilities of our system, as well as the significance of its components. Furthermore, qualitative and quantitative comparisons suggest that Head2Head++ outperforms other state-of-the-art methods, in terms of photo-realism, expression and pose transferability, as well as target identity preservation. For future work, we aim to make the network trainable in a few-shot manner, reducing the training time and eliminating the need for learning a different model per person. Additionally, we plan to transfer the facial expressions from the source in a way that preserves the target’s speaking style.

References


