From 2D Images to 3D Model: Weakly Supervised Multi-View Face Reconstruction with Deep Fusion

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Abstract

While weakly supervised multi-view face reconstruction (MVR) is garnering increased attention, one critical issue still remains open: how to effectively fuse multiple image information to reconstruct high-precision 3D models. In this regard, we propose a novel model called Deep Fusion MVR (DF-MVR) to reconstruct high-precision 3D facial shapes from multi-view images. Specifically, we introduce MulEn-Unet, a multi-view encoding to single decoding framework with skip connections and attention. This design allows for the

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extraction, integration, and compensation of deep features with attention from multi-view images. Furthermore, we adopt the involution kernel to enrich deep fusion features with channel features. In addition, we develop the face parse network to learn, identify, and emphasize the critical common face area within multi-view images. Experiments on Pixel-Face and Bosphorus datasets indicate the superiority of our model. Without 3D annotation, DF-MVR achieves 5.2% and 3.0% RMSE improvement over the existing weakly supervised MVRs respectively on Pixel-Face and Bosphorus dataset. Code will be available publicly at https://github.com/weiguangzhao/DF_MVR.

**Keywords:** Face reconstruction, Feature fusion, Multi-view, 3DMM.

1. Introduction

Reconstructing 3D shapes of human faces from 2D images is a challenging yet essential task for numerous applications (Hashemifar et al., 2024; Tolosana et al., 2020; Toshpulatov et al., 2023; Kong et al., 2023) such as virtual reality, augmented reality, and facial animations. The 3D Morphable Model (3DMM) (Blanz and Vetter, 1999) is the pioneer in converting the 3D face model to a parameter representation. Recently, adopting convolutional neural networks (CNN) to extract 2D image information to predict 3DMM coefficients has become the mainstream method of face reconstruction. Supervised CNN-based methods (Dou and Kakadiaris, 2018; Feng et al., 2018; Guo et al., 2018) demand a substantial quantity of 3D face meshes or point clouds (Zhao et al., 2023; Jiang et al., 2023) corresponding to 2D images as ground-truth, which are time and/or manpower consuming.

To alleviate the need for 3D face meshes or point clouds data, recent ef-
forts have shifted to weakly supervised and self-supervised methods (Tewari et al., 2017; Tran et al., 2018; Tewari et al., 2018; Basak et al., 2022; Wood et al., 2022; Li et al., 2023). Most of these methods use landmarks and differentiable rendering for training. However, these methods only exploit one single image for reconstruction, which usually fail to estimate facial depth appropriately. For instance, they cannot fully explain the geometric difference of facial features, such as the height of the mouth and eye sockets. Such limitation can however be resolved by the geometric constraints contained in a few face images of different views, or multi-view images. Surprisingly, only a handful of studies have been made on weakly supervised multi-view 3D face reconstruction tasks (Deng et al., 2019; Shang et al., 2020; Xiao et al., 2022). These methods are unfortunately limited because they simply concatenate multi-view image features and do not consider deep fusion of multi-view images features, nor do they pay attention to critical areas (e.g. eye, brow, nose, and mouth) which may impact the reconstruction quality the most.

To cope with these drawbacks, we propose a novel end-to-end weakly supervised multi-view 3D face reconstruction network which learns to fuse deep representations and identify critical areas. First, as multi-view images all represent the same face, we develop an encoding-decoding network (MulEn-Unet) with attention to extract features and deeply fuse them into one feature map. As shown in Fig. 1, multiple encoders are used to extract features from multi-view images, and one single decoder is engaged to fuse these features in deep. In order to compensate for the possible loss caused by sampling, skip connections with attention are introduced. Second, we bridge
Figure 1: MulEn-Unet with Face Mask. For conciseness, we do not draw the skip connection of the $E_C$, which is similar to the $E_A$.

the involution (Li et al., 2021) to extract more flexibly channel features than traditional convolution, which is typically utilized in face reconstruction networks. Finally, we develop a multi-view face parse network to learn, identify, and emphasize the critical common face areas. The face parse network is able to learn the face mask which not only acts as input features to help MulEn-Unet encode/decode common area of multi-view images for better deep fusion, but also plays the role of a weight map to calculate the pixel-wise photometric loss between rendered images and original images. Finally, combining pixelwise photometric loss, mask loss, and landmark loss, we design a novel weakly supervised training framework that is able to fuse deep
features comprehensively and pay attention to critical face features specially.

The contributions of our work are as follows:

• We develop face mask mechanism to facilitate feature fusion and facial reconstruction. It identifies common areas of multi-view images in the fusion progress. On the other hand, it acts as weight map to encourage the 3D face reconstruction network to pay more attention to critical areas (e.g. eye, brow, nose, and mouth).

• We propose a novel weakly supervised multi-view face reconstruction framework incorporating MulEn-Unet and involution. MulEn-Unet, enhanced with attention, is designed to extract multi-view features and fuse them into a unified feature map. Furthermore, the involution is adopted to enrich deep fusion features with the channel feature. To our best knowledge, we make the first attempt to bridge the involution to 3D face reconstruction.

• On the empirical side, our novel framework achieves 5.2% and 3.0% RMSE improvement over the existing weakly supervised MVRs respectively on Pixel-Face and Bosphorus dataset without 3D annotation.

2. Related Work

2.1. 3D Morphable Model

3D Morphable Model (3DMM) is a statistical model of 3D facial shape and texture which performs principal component analysis (PCA) on the face mesh training set (Blanz and Vetter, 1999; Koppen et al., 2018). Subsequently, the Basel Face Model (BFM) (Paysan et al., 2009) is released as a
generative 3D shape and texture model and demonstrates its application to several face recognition tasks. LSFM (Booth et al., 2018) has further expanded 3DMM to build models for specific ages, genders or ethnic groups. The current multi-view reconstruction methods mostly use BFM. For a fair comparison, we also exploit BFM to represent 3D faces in our model.

2.2. Mask in 3D face reconstruction

Currently, most 3D face reconstruction methods utilize the skin mask (Jones and Rehg, 2002) to obtain the pixel positions of the face, thereby eliminating background interference. Deep3DFace (Deng et al., 2019) proposes a robust, skinaware photometric loss to reduce the effects of occlusion. FOCUS-MP (Li et al., 2023) develops skin mask to attain the highly robust face reconstruction network. While there are some pioneer works probing face mask in the face reconstruction, THFNet (Lin et al., 2020) utilizes face mask to peel off eyes and brows to focus on the texture of the face skin. GFPMG (Zhao and Qi, 2021) adopts the face parsing network to remove the occlusion and restore the face image to achieve the full 3D face. Most of these methods utilize the face parsing network for the occlusion localization in the task of single-view 3D face reconstruction. Different from these approaches, our method develops the face parsing network to promote multi-view feature fusion and increases the reconstruction weight of critical areas.

2.3. Single-view 3D face reconstruction Methods

Most single-view face reconstruction methods take CNN as the deep learning network to predict 3DMM coefficients (Zhu et al., 2016; Tuan Tran
et al., 2017; Kao et al., 2023). For example, 3DFFA (Zhu et al., 2016) deploys CNN to predict 3DMM coefficients and achieves encouraging results. Rrd3d (Tuan Tran et al., 2017) designs a robust method, based on CNN and ResNet101 (He et al., 2016), to regress 3DMM shape and texture coefficients directly from an input photo without annotation of landmarks. UH-E2FAR (Dou et al., 2017) concatenates the last two pooling layers of CNN to create a Fusion CNN branch for predicting the expression base individually. It also generates synthetic rendered face images with predicted 3D scans. PerspNet (Kao et al., 2023) proposes to reconstruct 3D face shape in canonical space and learn the correspondence between 2D pixels and 3D points. However, these methods all require 3D mesh files as ground-truth, which greatly hinders their practical applications due to the shortfall of available annotated training data containing 3D shapes.

To cope with this issue, recent research focus has been put on weakly supervised and self-supervised methods. Mofa (Tewari et al., 2017) and UT3DMMR (Genova et al., 2018) propose a model that can be trained without 3D labels by adopting differentiable rendering for calculating the pixel difference between the rendered image and the original image. SFSNet (Sengupta et al., 2018) designs an end-to-end learning framework for accurately decomposing an unconstrained human face image into shape, reflectance and illuminance. THFNet (Lin et al., 2020) uses a similar method to predict 3D shapes while further adding GAN to generate more detailed texture information.
2.4. Multi-view 3D face reconstruction Methods

Multi-view methods (Dou and Kakadiaris, 2018; Bai et al., 2020; Ramon et al., 2019; Wu et al., 2019) can provide more geometric constraints and structural information than single-view methods. DRFAR (Dou and Kakadiaris, 2018) proposes to use Recurrent Neural Network (RNN) to fuse identity-related features extracted from deep convolutional neural network (DCNN) to produce more discriminative reconstructions, but their approach does not exploit multi-view geometric constraints. MVFNet (Wu et al., 2019) adds multi-view geometric constraints and introduces the optical flow loss to improve the reconstruction accuracy. In the feature extraction of multiple images, they only concatenates the deep features. All these methods require ground-truth of 3DMM, which is hardly available practically.

Surprisingly, there are few multi-view 3D face reconstruction methods based on weakly supervised machine learning in the literature. Deep3DFace (Deng et al., 2019) designs two CNN models for predicting 3DMM coefficients and scoring each image. The image with high confidence is used to regress shape coefficients, and the rest images will be used to regress coefficients such as expression and texture. MGCNet (Shang et al., 2020) adopts the concept of geometry consistency to design pixel and depth consistency loss. They establish dense pixel correspondences across multi-view input images and introduce the co-visible maps to account for the self-occlusion. Furthermore, HRN (Lei et al., 2023), to be precise, is a semi-supervised approach that utilizes the complete 3D ground-truth to generate deformation and displacement map for training. However, these methods pays less attention to the local features of the face and the feature fusion of multiple images. In
contrast, our method not only designs the MulEn-Unet and involution framework to fuse multi-view features, but also employs the mask mechanism to promote multi-view feature fusion and focus on the reconstruction of critical areas.

3. Main Methodology

3.1. Overview

We first provide an overview of our proposed framework, which is shown in Fig. 2. We decide to exploit three multi-view images of a subject for generating a corresponding 3D face and introduce the face parse network (a) to process these three images separately to generate unified standard face masks. An encoding-decoding network (b) is designed to fuse the features of multi-view images in deep by sharing a decoder with an attention mechanism to obtain information from the encoder. Moreover, RedNet (Li et al., 2021) with involution is used as parametric regression (c) to regress 3DMM and
pose coefficients. The reconstructed 3D face is reoriented utilizing the pose coefficients and then rendered back to 2D. The photo loss between the re-rendered 2D image and the input image at the target view is calculated while the masks are exploited as the weight map to enhance the back propagation of the facial features. In this section, we will provide details on each component as below.

3.2. Face Parse Net

We introduce the face parse network based on BiSeNet (Yu et al., 2018) to perform preliminary analysis of the input image and identify the elements of the image. The generated face mask has only one layer of channel. For example, if the size of the input image is $224 \times 224 \times 3$, the size of the face mask will be $224 \times 224 \times 1$. In order to better highlight the face, excessive elements of face masks such as hair and neck, will be removed, and the following parts will be kept: background, face skin, left brow, right brow, left eye, right eye, nose, mouth, upper lip, and lower lip. The reserved parts are marked with different numbers in order to distinguish facial features. As shown in Fig. 3, one-hot encoding is leveraged to assign the label for these parts. On one hand, the face masks are concatenated with the original images to help the network understand the common area of the multi-view image. On the other hand, the face masks serve as weight map to calculate the photo loss and mask loss for training.

3.3. Deep Fusion

The existing multi-view face reconstruction networks all deploy CNN or VGG as the feature extractor. These networks concatenate the multi-graph
features in the fully connected layer, which cannot perform feature interaction well. In addition, the previous networks mostly adopt shared weights or one backbone to process multi-view images, making it difficult for the network to pay attention to the unique information of each view. Differently, we design a novel feature fusion network, MulEn-Unet, to extract features of multi-view images inspired by attention Unet (Oktay et al., 2018).

We denote the three-view input images as $I_A$, $I_B$, and $I_C$, representing the three perspectives of left, front and right. Since the information and focus of each view are different, we set up three encoders to extract the features from three views respectively. Corresponding to the input images, these three encoders are represented by $E_A$, $E_B$, and $E_C$. The weights of the three encoders are not shared. Encoders are mainly composed of double convolution and maximum pooling. At the end of encoders, the deep features of $I_A$, $I_B$, $I_C$ will be concatenated as $F_D$. Considering that $I_A$, $I_B$, and $I_C$ actually describe the same object, we only set up a shared decoder for better fusing features as well as emphasizing the common features. The decoder is mainly composed of ConvTranspose, convolution, concatenate and skip connection. We adopt the attention mechanism (Bahdanau et al., 2015; Ye et al., 2019; Chougule et al., 2023) to extract the feature $F_A$, $F_B$, and $F_C$.
from $E_A$, $E_B$, and $E_C$ to enrich the information in the $F_D$ decoding process. Finally, the fusion feature size we retain is $224 \times 224 \times 64$, in the case where the image size is $224 \times 224 \times 3$.

3.4. Parametric Regression

We adopt RedNet50 to process the fusion features and regress parameters. RedNet replaces traditional convolution with involution on the ResNet architecture. The inter-channel redundancy within the convolution filter stands out in many deep neural networks, casting the flexibility of convolution kernels w.r.t. different channels into doubt. Compared with traditional convolution, involution is spatial-specific and able to obtain features on the channel. Therefore, we choose RedNet to perform parameter regression, and ablation experiments also verify its effectiveness.

3DMM Parameters regressed in this work include identification, expression, and texture parameters. The 3D face shape $S$ and the texture $T$ can be represented as:

\[
S = S(\alpha, \beta = \bar{S} + B_{id}\alpha + B_{exp}\beta, \\
T = T(\gamma = \bar{T} + B_t\gamma, \tag{1}
\]

where $\bar{S}$ and $\bar{T}$ are the average face shape and texture. $B_{id}$, $B_{exp}$, $B_t$ are the PCA bases of identity, expression, and texture respectively. $\alpha$, $\beta$, and $\gamma$ are the parameter vectors that the network needs to regress ($\alpha, \beta \in R^{80}$ and $\gamma \in R^{64}$). By adjusting these three vectors, the shape, expression and texture of the 3D face can be changed. In order to compare with MGCNet (Shang et al., 2020) and Deep3DFace (Deng et al., 2019) fairly, we use the same face model. BFM (Paysan et al., 2009) is adopted for $\bar{S}, B_{id}, T$, and $B_t$.
\( B_{exp} \) (Guo et al., 2018) is built based on Facewarehouse (Cao et al., 2013). Pose Parameters are used to adjust the angle and position of the 3D face in the camera coordinate system. We exploit the differentiable perspective rendering (Ravi et al., 2020) to render the 3D face back to 2D. When the camera coordinates are fixed, we could change the size and angle of the rendered 2D face by adjusting the position of the 3D face in the camera coordinate system. Meanwhile, the position of the 3D face in the camera coordinate system can be determined by predicting the rotation angle and translation in each axis. In order to enhance the geometric constraints of the multi-view reconstruction, we respectively predict the pose of the 3D faces in the multi-view (Dai et al., 2023), instead of only predicting the pose of one perspective to render 2D images.

4. Weakly Supervised Training

In order to alleviate the strong need for the labeled data, we design a weakly supervised method for training. First, we render the predicted 3D face model back to 2D and compare the rendered image with the original image pixel by pixel. Then, the rendered 2D images are fed into the face parse network to generate rendered face masks. According to the consistency principle, the rendered face masks should be consistent with the original face masks. Therefore, the L2 distance is treated as a mask loss. Finally, the landmark loss and regularization loss are introduced to shape 3D face and suppress the generation of distorted faces.
4.1. Photo Loss

Photo loss is often used in weakly supervised face reconstruction tasks (Thies et al., 2016; Tewari et al., 2018; Deng et al., 2019; Shang et al., 2020). Distinct with the traditional methods, we impose a weight for each pixel according to the facial features. The weight map is learned by the face mask $M$ of the original image $I$. In order to enhance the robustness of the weight map, we dilate $M$ with 20 pixel as $M_d$, as shown in Fig. 4. The dilated image is divided into three levels to be the weight map. In weight map, facial features are marked as 254, the rest of the facial area is marked as 128, and the background is marked as 32. The multi-view photo loss can be expressed as:

$$L_p = \frac{1}{V} \sum_{v=1}^{V} \frac{\sum_{i \in P^v} M_{di} \cdot \| I_i^v - I_i^v' \|_2}{\sum_{i \in P^v} M_{di}^v},$$  

(2)

where $V$ is the number of the reconstructed views. $V$ is 3 in the proposed model. $P^v$ is the area where the rendered image $I_i^v$ and the original image $I_i^v$ intersect in the current view. $i$ denotes pixel index, and $\| \cdot \|_2$ denotes the L2 norm.
4.2. Mask Loss

Photo loss focuses on the pixel difference between two pictures. It is difficult to constrain the size of the facial feature area in the two pictures. For example, the nose color is very similar to that of the cheeks, thereby leading to difficulties for the photo loss to notice the boundary line between them. For this reason, we introduce mask loss to narrow the facial features of the input image and the rendered image. The division and labeling of the facial features are shown in Fig. 3. According to BiSeNet (Yu et al., 2018) we adopt cross entropy to calculate the mask loss $L_m$:

$$L_m = -\frac{1}{N_p V} \sum_{v=1}^{V} \sum_{p=1}^{N_p} (y_p \log (\hat{y}_p) + (1 - y_p) \log (1 - \hat{y}_p)),$$

(3)

where $N_p$ is number of pixels in face mask. $\hat{y}_p$ donates the category prediction of pixels in face mask and $y_p$ is the label.

4.3. Landmark Loss

We also adopt 2D landmarks and 3D landmarks for weakly supervised training. We use 3D face alignment method (Bulat and Tzimiropoulos, 2017) to generate 68 landmarks $\{l_n\}$ as the ground-truth. Then the corresponding points in the predicted 3D face point cloud are projected to 2D as predicted 2D landmarks $\{l'_n\}$. Then the multi-view 2D landmark loss can be calculated:

$$L_{l_{2d}} = \frac{1}{NV} \sum_{v=1}^{V} \sum_{n=1}^{N} \omega_n \left\| l'_n - l''_n \right\|_2,$$

(4)

where $\omega_n$ is the weight for each landmark. We set the weight to 20 only for the nose and inner mouth landmarks, and to 1 otherwise.
2D landmarks are still insufficient for the reconstruction of 3D face shapes. In order to obtain better reconstruction effect, we select 101 3D landmarks \( \{q'_n\} \) to impose a weak constraint on the shape of the 3D face. According to the 3DMM index, 101 predicted landmarks \( \{q_n\} \) can be found. Then, we select 7 points \( \{a'_n\} \) and \( \{a_n\} \) in \( \{q'_n\} \) and \( \{q_n\} \) respectively as alignment points to calculate the alignment parameters of \( \{q'_n\} \) and \( \{q_n\} \). The alignment parameters include: scale \( s \), rotation \( R \) and translation \( t \). These parameters can be obtained by the following optimization equation (Sanyal et al., 2019):

\[
\text{Optim}(s, R, t = \min_{s, R, t} \sum_i \|a'_i - s (R \cdot a_i + t)\|_2). \tag{5}
\]

After the optimal \( s, R \) and \( t \) are obtained, the predicted 101 landmarks \( \{q_n\} \) can be converted to the space of \( \{q'_n\} \) as \( \{q_{nt}\} = s (R \cdot q_n + t) \).

Then the multi-view 3D landmark loss can be calculated:

\[
L_{l3d} = \frac{1}{N} \sum_{n=1}^{N} \|q_{nt} - q'_n\|_2. \tag{6}
\]

In summary, the landmark loss can be expressed as:

\[
L_l = \omega_{2d} L_{l2d} + \omega_{3d} L_{l3d}, \tag{7}
\]

where \( \omega_{2d} \) and \( \omega_{3d} \) represent respectively the weight of 2D landmark loss and 3D landmark loss. In this work, we set them to 0.02 and 1 as tuned empirically.

4.4. Regularization Loss

To suppress the generation of distorted faces, we add the regularization loss which is commonly-used in face reconstruction task (Thies et al., 2016;
where $\alpha$, $\beta$, and $\gamma$ are 3DMM parameter vectors that the network predicted. $\omega_\alpha$, $\omega_\beta$ and $\omega_\gamma$ are the weights for 3DMM parameter vectors. Following Deep3DFace (Deng et al., 2019), we set them to 1, 0.8 and 0.017 with fine tuning.

4.5. Overall Loss

The overall loss required by our end-to-end net for weakly supervised training can be represented as:

$$L_{all} = \omega_p L_p + \omega_m L_m + \omega_l L_l + \omega_{reg} L_{reg},$$

where $\omega_p$, $\omega_m$, $\omega_l$, $\omega_{reg}$ are the weights for photo loss, mask loss, landmark loss and regularization loss. Following Deep3DFace, we set $\omega_{reg} = 3.0 \times 10^{-4}$. Since $\omega_{2d}$ and $\omega_{3d}$ have been determined, we adjust other parameters as $\omega_l = 1$, $\omega_p = 4$ and $\omega_m = 3$ respectively.

Note that 3D landmarks is not a must for our method. For general weakly supervised methods, we do not incorporate $L_{l,3d}$ for comparison (Deng et al., 2019; Shang et al., 2020). Since semi-supervised methods HRN (Lei et al., 2023) adopts the entire 3D scans to attain training label, we add $L_{l,3d}$ for comparative analysis.

5. Experiment

5.1. Implementation Details

**Dataset.** Following BiseNet (Yu et al., 2018), we adopt CelebAMask-HQ (Lee et al., 2020) to pretrain Face Parse Net. Furthermore, Pixel-Face (Lyu et al.,
Multi-PIE (Gross et al., 2008) are introduced to provide 3D landmarks label and multi-view faces. Pixel-Face contains 855 subjects ranging in age from 18 to 80 years old. Each subject has 7 or 23 samples of different expressions. Pixel-Face has 3D mesh file of each sample as ground-truth but not 3DMM parameters or angle of multi-view images. In the experiment, the training/test split was set to 0.8. For Multi-PIE, we leverage the version provided by TP-GAN (Huang et al., 2017), which will reduce a lot of data preprocessing work. This dataset contains about 140k multi-view images and does not provide 3D mesh and landmarks. We utilize the method of STNet (Chen et al., 2016) to detect and align faces. Then each input image is cropped and resized to 224×224.

**Network.** Our network structure is shown in Fig. 2 and described in the methodology section. Based on the pre-trained BiseNet (Yu et al., 2018) with frozen weights, the face parse network is located in the beginning and end of the network. We implement DF-MVR by pytorch (Paszke et al., 2019). It is trained on 2 NVIDIA RTX 3090 GPUs card with a batch size of 16 for 512 epochs. We adopt Adam as the gradient descent method. The initial learning rate is set to 0.0001 which decays with the cosine anneal schedule. The average inference time of DF-MVR is 244ms.

**Evaluation Metric.** Following the previous works, RMSE (mm) (Wu et al., 2019; Deng et al., 2019; Shang et al., 2020) is used to compute point-to-plane L2 distance between predict 3D scans and ground-truth 3D scans. Concretely, the front face area is cropped for metrics calculation instead of using a complete BFM model (Sanyal et al., 2019; Deng et al., 2019; Shang et al., 2020). Before calculating point-to-plane L2 distance, the predicted 3D
scans need to be registered with ground-truth 3D scans. Also, we take the ICP registration method (Li et al., 2017), the same as Deep3DFace (Deng et al., 2019).

5.2. Comparison to SOTAs

We compare our method with the existing weakly supervised MVRs on both Pixel-Face and Bosphorus datasets. More specifically, only the four methods with codes can be found in the literature related to multi-view weakly supervised 3D face reconstruction. MGCNet (Shang et al., 2020) takes multiple images for training, and then uses one single image for testing. We select the best results among the three images for display. Deep3DFace (Deng et al., 2019) does not release their source codes of its scoring network. Therefore, we use their codes to train/test on Pixel-Face to select the best results among the three images. Moreover, MVFR (Xiao et al., 2022) necessitates scale_RT data, rendering it currently effective only for the Facescape dataset (Yang et al., 2020; Zhu et al., 2023). HRN (Lei et al., 2023) does not release its training code, but it provides a pretrained model based on numerous data. To this end, we use its pretrained model and source code for multi-view face reconstruction. Given the scarcity of open sources for this task, we release our full codes (training & test) and pretrained model in GitHub².

Comparison on Pixel-Face. The quantitative results of the comparison are shown in Table 1. Since Deep3DFace (Deng et al., 2019) and MGCNet (Shang et al., 2020) did not use 3D landmarks, to be fair, we also pro-

²https://github.com/weiguangzhao/DF_MVR
Table 1: Comparison to SOTAs. † stands for the necessity to leverage 3D ground-truth (GT) data for semi-supervised training. HRN† utilizes the entire 3D ground-truth scan to attain both deformation and displacement maps. Ours† only takes a sparse set of 3D landmarks.

| Method               | Dataset     | RMSE (mm) ↓ |
|----------------------|-------------|-------------|
| Deep3DFace (Deng et al., 2019) | Pixel-Face   | 1.6641      |
| MGCNet (Shang et al., 2020)    | Pixel-Face   | 1.8877      |
| Ours                  | Pixel-Face   | **1.5770**  |
| Deep3DFace (Deng et al., 2019) | Bosphorus    | 1.4777      |
| MGCNet (Shang et al., 2020)    | Bosphorus    | 1.4418      |
| Ours                  | Bosphorus    | **1.3994**  |
| HRN† (Lei et al., 2023)       | Pixel-Face   | 1.4061      |
| Ours†                 | Pixel-Face   | **1.4040**  |

Provide the results of our model without using 3D landmarks for comparison. As observed, Our model (without 3D landmarks) shows 5.2% improvement compared to the existing methods. While HRN (Lei et al., 2023) adopts the complete 3D ground-truth scan to attain deformation map and displacement map, we only take very light annotation, 101 3D landmarks to constraint the face reconstruction. Ours† shows very competitive results with fewer 3D annotation, compared to HRN†.

The visual comparison is shown in Fig. 5 given 3-view faces. It is evident that our predicted model is more accurate, especially in terms of facial depth estimation in the facial features.

Comparison on Bosphorus. Since Pixel-Face dataset is collected based on Asian faces, the samples it contains are limited by regions. On the other
hand, Pixel-Face dataset is only made under one lighting environment and three fixed camera angles. Taking into account the diversity, we adopt the richer Multi-PIE dataset for training and Bosphorus dataset for testing. Both datasets contain faces across continents and are collected in various lighting environments and shooting angles. Because Multi-PIE does not provide 3D landmarks, we remove $L_{l,3d}$ to train DF-MVR for this part. The traditional delaunay algorithm is utilized to generate mesh files from point clouds for Bosphorus dataset. We set the left and right inputs to 45 degrees for comparison. More angle robustness experiments can be later seen in Table 4. The quantitative results of the comparison are shown in Table 1. Our model (without 3D landmarks) exhibits 3.0% improvement compared to the existing methods. The qualitative comparison is also provided in Fig. 6.
5.3. Single-view Reconstruction.

The single-view reconstruction method only requires one image to generate the 3D face. From the practical viewpoint, it is more flexible though it may be inferior to multi-view methods in terms of accuracy. Our method can also be adapted in the single view scenario. More specifically, during the training process, we only change the input, without changing other parts. As shown in Fig. 7, the original input has been changed to four different forms, according to the probability: $P'_a, P_1, P_f, P_r$. The input of multi-view images still needs to be dominant to preserve accuracy, so we set its probability to 2/3, and the other inputs equally distribute with the probability of 1/3.

The parameterized results of the comparison are shown in Table 2. As observed, our proposed model also attains the superior performance. In the case of single image testing, our model is more effective than Deep3DFace and MGCNet.
Table 2: Comparison of RMSE (mm)

| Method                        | Dataset      | RMSE (mm) |
|-------------------------------|--------------|-----------|
| Deep3DFace (Deng et al., 2019) | Pixel-Face  | 1.6641    |
| MGCNet (Shang et al., 2020)   | Pixel-Face  | 1.8877    |
| Ours (single-view)            | Pixel-Face  | **1.5437**|

5.4. Ablation Study

In order to verify the effectiveness of MulEn-Unet and the mask mechanism we designed, we perform more ablation experiments as shown in Table 3. The mean and standard deviation of RMSE are again used as the evaluation metric. First, from v1, v2, v6, it can be found that the multi-view feature fusion network we designed is superior to traditional CNN and Unet in this task. Then, the results of v2 and v6 hint that the multi-layer feature inter-
action in the feature extraction stage is better than the direct concatenation of features at the end. To be fair, we set the number of layers of RedNet and ResNet to 50. Through the RMSE of v3 and v6, it is clear that RedNet performs better than ResNet in this task. For v4, we not only remove the mask loss but also the face mask $I_A$, $I_B$ and $I_C$, which are concatenated to the original image. By comparing v5 and v6, we can see that the face mask mechanism promotes the network to generate a higher-precision model. Moreover, we verify the face mask and mask loss separately. Mask loss has a much smaller effect on the accuracy of the model than face mask. While the qualitative result of mask loss is positive for the adjustment of the model during training, we retain this part for reference. Finally, we remove $L_{lan,3d}$, which means that our model can be trained with only three multi-view images without any 3D label (as denoted as v5). The result also shows that our model is accurate and stable.

| Ours  | Backbone | Facemask | $L_{lan,3d}$ | RMSE (mm) |
|-------|----------|----------|--------------|-----------|
| v1    | CNN      | RedNet   | Y            | Y         | 1.5415    |
| v2    | Unet     | RedNet   | Y            | Y         | 1.5207    |
| v3    | MulEn-Unet | ResNet   | Y            | Y         | 1.5206    |
| v4    | MulEn-Unet | RedNet   | N            | Y         | 1.4656    |
| v5    | MulEn-Unet | RedNet   | Y            | N         | 1.5770    |
| v6    | MulEn-Unet | RedNet   | Y            | Y         | 1.4040    |
5.5. Robustness Analysis

Multi-PIE and Bosphorus are collected by different cameras. DF-MVR uses Multi-PIE for training and achieves good test results on Bosphorus, which implies that our model has a certain robustness to camera device changes. Moreover, we further explore robustness of DF-MVR for shooting angles. We fix the $I_B$ and $I_C$ face angles while adjusting the $I_A$ face angle. Table 4 and Fig. 8(a) show that our model consistently achieve the best results in different shooting angles, implying that our model exhibits the best robustness. Random means we choose the degree from 10°, 20°, 30° and 45° randomly. The light environment is also random in this experiment.

| Method          | 10°  | 20°  | 30°  | 45°  | Random |
|-----------------|------|------|------|------|--------|
| Deep3DFace      | 1.5030| 1.4975| 1.4924| 1.4777| 1.4905 |
| MGCNet          | 1.4419| 1.4412| 1.4413| 1.4418| 1.4416 |
| Ours (v5)       | 1.4251| 1.4134| 1.4043| 1.3994| 1.4125 |

We also validate the angle robustness of our model visually. These results are plotted in Fig. 8(a). Detailed error maps are introduced to display the error for each facial area directly. Take the second sample of Fig. 8(b) for a typical example where we fix $I_B$ and $I_c$ while changing the face angle of $I_A$ from 10° to 45°. Obviously, the error maps generated from these angles do not change much. Furthermore, we provide the error maps of Deep3DFace (Deng et al., 2019) for comparison. At different angles, DF-MVR reconstructs the face with less error, especially in critical areas (e.g. eye, brow, nose and mouth).
6. Conclusion

In this paper, we design a novel end-to-end weakly supervised multi-view 3D face reconstruction network that exploits multi-view encoding to a single decoding framework with skip connections, able to extract, integrate, and compensate deep features with attention. In addition, we develop a multi-view face parse network to learn, identify, and emphasize the critical common face area. Combining pixelwise photometric loss, mask loss, and landmark loss, we complete the weakly supervised training. Extensive experiments verify the effectiveness of our model.

7. Ethics Statement

In this paper, we presented visualizations of the results for Pixel-Face and Bosphorus dataset. Specifically, we have only showcased Pixel-Face facial information for a single individual, and this information has been obtained with
the explicit consent of the individual and the Pixel Face dataset team, allowing for publication. Additionally, we presented Bosphorus facial information for three individuals, all of whom are included in the publicly disclosed roster of the Bosphorus dataset. Our approach leverages multi-view images to generate high-fidelity 3D facial models, meeting the demands of industries such as film, gaming, virtual characters, and more. Due to the strong privacy implications associated with facial data, we suggest establishing detailed rules to regulate the use of facial reconstruction.

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