Reconstructing A Large Scale 3D Face Dataset for Deep 3D Face Identification

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Abstract—Deep learning methods have brought many breakthroughs to computer vision, especially in 2D face recognition. However, the bottleneck of deep learning based 3D face recognition is that it is difficult to collect millions of 3D faces, whether for industry or academia. In view of this situation, there are many methods to generate more 3D faces from existing 3D faces through 3D face data augmentation, which are used to train deep 3D face recognition models. However, to the best of our knowledge, there is no method to generate 3D faces from 2D face images for training deep 3D face recognition models. This letter focuses on the role of reconstructed 3D facial surfaces in 3D face identification and proposes a framework of 2D-aided deep 3D face identification. In particular, we propose to reconstruct millions of 3D face scans from a large scale 2D face database (i.e., VGGFace2), using a deep learning based 3D face reconstruction method (i.e., ExpNet). Then, we adopt a two-phase training approach: In the first phase, we use millions of face images to pre-train the deep convolutional neural network (DCNN), and in the second phase, we use normal component images (NCI) of reconstructed 3D face scans to train the DCNN. Extensive experimental results illustrate that the proposed approach can greatly improve the rank-1 score of 3D face identification on the FRGC v2.0, the Bosphorus, and the BU-3DFE 3D face databases, compared to the model trained by 2D face images. Finally, our proposed approach achieves state-of-the-art rank-1 scores on the FRGC v2.0 (97.6%), Bosphorus (98.4%), and BU-3DFE (98.8%) databases. The experimental results show that the reconstructed 3D facial surfaces are useful and our 2D-aided deep 3D face identification framework is meaningful, facing the scarcity of 3D faces.

Index Terms—3D face reconstruction, 3D face identification, deep convolutional neural networks (DCNN), deep learning.

I. INTRODUCTION

RECENTLY, deep learning, especially Deep Convolutional Neural Networks (DCNNs) have witnessed great successes in the computer vision community, significantly improving the state of the art in many tasks, such as image classification, segmentation, and object detection, etc [1], [2].

Due to the universality of DCNNs, 2D face recognition has achieved great breakthroughs by using massive 2D face images of different subjects to train deep face models. As shown in Table I, Google used 200 millions images of 8 millions unique identities to train the Facenet [3], and Parkhi et al. [4] have built the VGGFace database containing 2.6 millions face images for training. As for 3D face recognition, most recent work [5]–[7] focused on extracting robust feature points and descriptors containing geometric information of 3D faces in a hand-crafted manner. These methods achieve good recognition accuracy, but they suffer from slow feature extracting speed due to complex algorithms, compared with deep learning methods. However, existing 3D face datasets are too small to train a data-hungry DCNN based 3D face recognition model, and collecting millions of 3D face scans is still unrealized in both industrial community and academia. Table I also shows the largest publicly available 3D face dataset (i.e., FRGC v2.0) only contains 4,007 high-resolution 3D face scans of 466 subjects. The Lock3DFace dataset contains 5,711 video clips of 509 identities, but these 3D face scans were captured by a Kinect, thus with low spatial resolution and depth accuracy.

Therefore, the limitation of enough training data is currently the main bottleneck of developing DCNN methods for 3D face recognition. In recent years, Li et al. [19], Kim et al. [20] and Gilani et al. [21] have shown deep learning based 3D face recognition results. [19] does not generate 3D faces, but uses a pre-trained DCNN to extract deep normal patterns of 3D faces and proposes a location-sensitive sparse coding based classifier to improve recognition accuracy, so the recognition speed is relatively low. [20] synthesizes a number of depth maps of 3D faces with different facial expressions and poses based on 3D Morphable Model (3DMM). The depth maps generated are not rich enough due to the quite limited number of subjects in the training set. [21] generates faces from the space spanned by a pair of dense corresponding real 3D faces from different subjects. However, it is difficult to interpret the identity attributes of new 3D faces generated in this way. Fig 2 shows some examples of depth maps and 3D faces generated by [20] and [21]. The proposed existing deep 3D face recognition methods usually increase the training data by 3D face augmentation. Considering that it is easy to obtain massive 2D face images, a promising and efficient solution is to generate
TABLE I
COMPARISONS OF 2D AND 3D FACE DATASETS.

| 2D Face Dataset | Identities | Images | 3D Face Dataset | Identities | Images |
|-----------------|------------|--------|-----------------|------------|--------|
| LFW             | 5,749      | 13,233 | FRGC v2.0 (2005)| 4.66       | 4,007  |
| WDRef[9]        | 2,995      | 99,773 | BU-3DFE (2006)  | 100        | 2,500  |
| CelebFaces[11]  | 10,177     | 202,599| Bosphorus (2008)| 1.05       | 4,666  |
| VGGFace[4]      | 2,622      | 2.6M   | 3D-TEC (2011)   | 214        | 428    |
| FaceBook[14]    | 4,030      | 4.4M   | Florence Superface (2012)| 50| 50^* |
| WebFace[16]     | 10,575     | 494,414| KinectFaceDB (EURECOM) (2013)| 52| 936^* |
| Google[18]      | 8M         | 200M   | Lock3DFace (2015)| 5,09      | 5711^* |

3D face scans from 2D face images by 3D face reconstruction methods. Regressing the parameters of 3DMM parameters with a DCNN is a kind of deep learning and 3DMM based 3D face reconstruction methods. This kind of method usually constructs a training set including face images and their corresponding 3DMM parameters, and then uses a DCNN to learn the regression mapping between face images and shape and texture parameters of 3DMM. The idea of regressing 3DMM parameters with a DCNN is applied to solve the problem of large-pose face alignment and reconstruction[22]–[25] at first. The core of these papers is using cascaded CNN to regress the shape, texture and pose parameters of 3DMM. In order to make reconstructed 3D faces identifiable, [26] uses a multitask DCNN to regress the identity and expression parameters of 3DMM separately, and obtains the final reconstruction result by a fusion DCNN. [27] proposes to train a 101-layer CNN regression to learning the mapping between face images and their corresponding 3DMM shape and texture parameters. However, to our knowledge, there is no literature has explored whether the 3D faces reconstructed from 2D face images can contribute to deep 3D face recognition at present.

In this letter, we propose a 3D face reconstruction based 2D-aided framework for deep 3D face identification. We show that the proposed approach yield state-of-the-art performance for deep 3D face identification.

II. METHOD

The proposed 2D-aided deep 3D face identification framework includes four main stages: (1) Given a large scale 2D face dataset with identity labels, training a DCNN as used for deep 2D face recognition. (2) Reconstructing a large scale 3D face dataset by using the given 2D face images, and generating their normal component images (NCI). (3) Training the pre-trained DCNN by using NCI, NCI_y and NCI_z of the reconstructed 3D faces, respectively. (4) 3D face identification is conducted by comparing and fusing the scores of the deep normal patterns of 3D face scans from gallery and probe.

To the best of our knowledge, 2D-aided deep 3D face recognition methods have never been researched. We will describe our approach specifically in the following subsections.

A. Large Scale 3D Face Reconstruction by ExpNet

In our 2D-aided deep 3D face identification framework, we need to reconstruct a large number of 3D facial surfaces from 2D face images. There are many available 3D face reconstruction methods. In this letter, we choose the ExpNet[28] to reconstruct corresponding 3D facial surfaces from 2D face images. The traditional 3DMM models control the intensity of deformations by optimizing the coefficients, but the ExpNet[28] uses a DCNN directly regressing 3DMM parameters. Given a face image, the ExpNet will output it’s corresponding shape and expression coefficients, and the corresponding 3D face is generated by combining the coefficients and the shape, expression components. The ExpNet is landmark-free and much faster than other methods at the same level of accuracy.

The ExpNet[28] models a 3D face shape by using the BFM 3DMM shape components [29] and the expression components offered by 3DDFA[22]:

\[
S' = \hat{s} + S\hat{\alpha} + E\hat{\eta}
\]

where \(\hat{s}\) is the average 3D face shape, \(S \in \mathbb{R}^{3n \times 99}\) represents shape components, and \(E \in \mathbb{R}^{3n \times 29}\) represents expression components. \(\hat{\alpha} \in \mathbb{R}^{99}\) and \(\hat{\eta} \in \mathbb{R}^{29}\) are shape and expression coefficients respectively.

As some examples shown in Fig. 2, the 3D facial surfaces generated by the ExpNet[28] have consistent shapes and expressions with the face images. However, since the ExpNet is designed to simulate the whole face at once, it is difficult to represent small details on reconstructed 3D faces, which will affect the identification accuracy of our framework. Since any 3D face reconstruction method can be selected as long as the quality of reconstructed 3D faces is guaranteed.

B. Facial Normal Maps

After reconstructing a large scale 3D face dataset, we need to consider how to apply deep learning methods to 3D face surfaces. The idea of using normal component images (NCI) is inspired by Li et al. [31, 32], which claimed that encoding normals of facial surface can generate more discriminative descriptors for 3D face recognition than directly encoding the 3D coordinates of facial surfaces. And [19] extracts features of
NCI for face identification. Transforming 3D facial surfaces to NCI makes it natural to perform 2D convolutions on 3D faces and efficiently use the deep learning machines.

In this letter, all facial surfaces are preprocessed and normalized into range images with the \( x \), \( y \), and \( z \) coordinates. Specifically, given a facial range image \( P \) represented by an \( m \times n \times 3 \) matrix:

\[
P = [p_{ij}(x, y, z)]_{m \times n} = [p_{ijk}]_{m \times n \times (x,y,z)},
\]

where \( p_{ij}(x, y, z) = (p_{ijx}, p_{ijy}, p_{ijz})^T \), \((1 \leq i \leq m, 1 \leq j \leq n, i, j \in \mathbb{Z})\) represents the 3D coordinates of the point \( p_{ij} \). Let its unit normal vector matrix \((m \times n \times 3)\) be

\[
N(P) = [n(p_{ij}(x, y, z))]_{m \times n} = [n_{ijk}]_{m \times n \times (x,y,z)},
\]

where \( n(p_{ij}(x, y, z)) = (n_{ijx}, n_{ijy}, n_{ijz})^T \), \((1 \leq i \leq m, 1 \leq j \leq n, i, j \in \mathbb{Z})\) denotes the unit normal vector of \( p_{ij} \). As described in \([33]\), the normal vector \( N(P) \) of range image \( P \) can be estimated by fitting local plane. That is to say, for each point \( p_{ij} \in P \), its normal vector \( n(p_{ij}) \) can be estimated as the normal vector of the following local fitted plane:

\[
S_{ij} = n_{ijx}q_{ijx} + n_{ijy}q_{ijy} + n_{ijz}q_{ijz} = d,
\]

where \((q_{ijx}, q_{ijy}, q_{ijz})^T\) represents any point within the local neighborhood of point \( p_{ij} \) and \( d = n_{ijx}p_{ijx} + n_{ijy}p_{ijy} + n_{ijz}p_{ijz} \). In this paper, a neighborhood of \( 5 \times 5 \) window is used. To simplify, each normal component in equation (2) can be represented by an \( m \times n \) matrix:

\[
N(P) = \begin{bmatrix}
N(X) = [n_{ijx}]_{m \times n}, \\
N(Y) = [n_{ijy}]_{m \times n}, \\
N(Z) = [n_{ijz}]_{m \times n}.
\end{bmatrix}
\]

where \( \| (n_{ijx}^x, n_{ijy}^y, n_{ijz}^z) \|_2 = 1 \).

Fig. 4 shows a normalized range image of a facial surface which comes from the FRGC v2.0 database and its estimated three NCI. It’s not difficult to find that the normal images contain more informative geometric information than their corresponding range image which looks quite smooth. The shape details around the eyes and mouth regions are well highlighted in the normal images.

C. Deep 3D Face Identification

In order to make full use of the 2D face images and consider that the reconstructed 3D faces are not perfect enough, we adopt a two-phase training process. In the first phase, we use millions of 2D face images to pre-train a DCNN. In the second phase, we use NCI\(_x\), NCI\(_y\) and NCI\(_z\) of reconstructed 3D faces to train the pre-trained DCNN. Finally, given a 3D facial surface, NCI\(_x\), NCI\(_y\) and NCI\(_z\) of which are input to corresponding deep model and the scores of the three networks are fused as the prediction results in the test stage.

In theory, any DCNN for deep 2D face recognition can be used here. We choose the Sphere20 \([34]\) as the DCNN in our framework, which is one of the state-of-the-art deep 2D face recognition models. It comprises 20 convolutional layers and followed by a fully connected (FC) layers(512 dimensions) and a softmax layer. We transfer all the weights from the pre-trained DCNN but initialize the FC layer and the softmax layer in the second phase of training process. In the test stage, we transform every 3D facial surface into NCI\(_x\), NCI\(_y\) and NCI\(_z\), which are fed into the corresponding Sphere20 to extract a 512 dimension feature (the FC layer). After extracting features of probe and gallery, we calculate a Euclidean distance between normalized features of a probe and a gallery. The corresponding identity of a feature from the probe is determined by the closest feature from the gallery. We choose the late fusion of results from the three deep models as the final prediction result.

III. EXPERIMENTS

In this section, we evaluate the effectiveness of the reconstructed 3D faces in 3D face identification firstly. Then, we compare the proposed method against the state-of-the-art methods on public 3D face datasets.

A. Datasets and Evaluation

VGGFace2 database \([30]\): This database contains 3.31 millions face images of 9,131 subjects, with an average of 362.6 images per person. The face images in this database are downloaded from Google. Face images cover different ages, postures, illuminations, races and occupations. In addition to identity information, the dataset includes face frames, five key points, and estimated age and posture.

BU-3DFE database \([10]\): This database contains 2500 3D facial scans of 100 subjects. For each subject, six prototypic expressions (happiness, disgust, fear, angry, surprise, and sadness) of four intensity levels in addition to a neutral one. This dataset is regarded as one the most challenging benchmarks for expression-robustness 3D face recognition algorithms due to the diversity of different expressions.
FRGC v2.0 database [8]: This database has been widely used for 3D face recognition in the past decades. It consists of 4007 textured 3D face scans of 466 subjects with different facial expressions (1642 samples) captured under controlled lighting conditions. The resolution of each face scan is $640 \times 480$.

Bosphorus database [12]: This database contains 4666 textured 3D face scans of 105 subjects with six types of basic facial expressions in addition to neutral. The first neutral scan per subject is used in the gallery (105 samples) and the remaining scans with different expressions and near frontal head poses (without occlusions) are used as probes (2797 samples).

For every dataset except FRGC v2.0, we choose the first neutral scan of each subject to be placed in the gallery and the rest of scans are used as probes. As for FRGC v2.0, we choose the first scan of each identity as a part of the gallery because not every identity in the dataset has a neutral scan.

### TABLE II

| Testset   | Training data | DNP$_x$ | DNP$_y$ | DNP$_z$ | DNP$_{xyz}$ |
|-----------|---------------|---------|---------|---------|-------------|
| BU-3DFE   | 2D            | 66.1%   | 71.0%   | 75.5%   | 80.3%       |
|           | 2D+3D         | 92.2%   | 94.2%   | 96.5%   | 98.0%       |
| Bosphorus | 2D            | 70.0%   | 80.8%   | 78.4%   | 84.6%       |
|           | 2D+3D         | 94.2%   | 96.5%   | 96.5%   | 98.0%       |
| FRGC v2.0 | 2D            | 73.8%   | 78.6%   | 77.4%   | 81.3%       |
|           | 2D+3D         | 86.7%   | 84.1%   | 87.1%   | 90.2%       |

C. Comparison with the state-of-the-art Methods

In order to achieve better 3D face identification accuracy, we adopt a better loss function LMCL [35], used in deep 2D face recognition. Table III reports the performance comparisons of the proposed method and the state-of-the-art ones. Table III compares the performance of the proposed method and the state-of-the-art ones. Our method achieves rank-one scores of 98.8%, 97.6% and 98.4% on the BU-3DFE, the FRGC v2.0 and the Bosphorus databases, respectively. It should be noted that the model of [21] is trained with 3D faces and then fine-tuned on the gallery scans. For fairness, we only compare the results with those that are not fine-tuned on the gallery scans. Considering that these test datasets contain quite a few subjects, especially the BU-3DFE database and the Bosphorus database. To better illustrate the effectiveness of our proposed framework, we merge these three databases and our method achieve a high rank-one score of 98.2% on the merge database.

### TABLE III

| Testset | BU-3DFE | FRGC v2.0 | Bosphorus | All |
|---------|---------|-----------|-----------|-----|
| Li et al. [20] | 92.2% | 96.3% | 96.6% | - |
| Lei et al. [19] | 94.0% | 96.3% | - | - |
| Li et al. [19] | 96.1% | 98.0% | 97.6% | - |
| Kim et al. [23] | 95.0% | - | 99.2% | - |
| Gilanet et al. [24] | 98.6% | 97.1% | 96.2% | - |
| Ours | 98.8% | 97.6% | 98.4% | 98.2% |

We also try to use NCI of 6000 subjects and 9000 subjects to train the pre-trained Sphere20, and the corresponding 3D face identification accuracy are not much improved. We analyse the reason is that 3D faces reconstructed by the ExpNet are not good enough to discriminate. When the number of subjects is larger, the ID information noises will increase, so the improvement of 3D face identification accuracy is not obvious.

IV. CONCLUSION AND DISCUSSION

In this letter, considering the difficulty of collecting 3D faces, we have proposed a 2D aided deep 3D face identification framework based on 3D face reconstruction and facial normal component images. Extensive experimental results demonstrated that our proposed framework can achieve comparable performances to the state-of-the-art results in term of 3D face identification.

Our method is only a preliminary exploration of 2D aided deep 3D face recognition, since there is no relevant research at present. The quality of reconstructed 3D faces will seriously affect the 3D face recognition result in our framework, but in this letter we only use the ExpNet. In future work we will analyze the effectiveness of different 3D face reconstruction methods and explore the recognition-driven 3D face reconstruction method, making the reconstructed face more favorable to the 3D face recognition.

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