Do We Need Depth in State-Of-The-Art Face Authentication?

Amir Livne\textsuperscript{1}, Alex Bronstein\textsuperscript{1,2}, Ron Kimmel\textsuperscript{1,2}, Ziv Aviv\textsuperscript{2}, and Shahaf Grofit\textsuperscript{2}

\textsuperscript{1} Technion, Israel Institute of Technology, Haifa, Israel
\{alivne@campus,bron@cs,ron@cs\}.technion.ac.il
\textsuperscript{2} Intel EGI, Israel
\{ziv.aviv,shahaf.grofit\}@intel.com

Abstract. Some face recognition methods are designed to utilize geometric features extracted from depth sensors to handle the challenges of single-image based recognition technologies. However, calculating the geometrical data is an expensive and challenging process. Here, we introduce a novel method that learns distinctive geometric features from stereo camera systems without the need to explicitly compute the facial surface or depth map. The raw face stereo images along with coordinate maps allow a CNN to learn geometric features. This way, we keep the simplicity and cost efficiency of recognition from a single image, while enjoying the benefits of geometric data without explicitly reconstructing it. We demonstrate that the suggested method outperforms both existing single-image and explicit depth based methods on large-scale benchmarks. We also provide an ablation study to show that the suggested method uses the coordinate maps to encode more informative features.

Keywords: Stereo vision, face recognition, deep learning, geometry, photometry.

1 Introduction

Automatic face recognition is a trusted biometric modality that often replaces passwords in modern smartphones and smart locks, payment applications, identity verification systems at border controls, etc. Common face recognition systems frequently use a single image to identify the subjects. When more than a single image is provided, shape-from-X techniques can be applied to extract the geometry of the observed object. This information is useful to overcome some of the acute challenges when considering a single-image based method, for example, handling extreme head poses, illumination variations, expressions \cite{1}, makeup, and spoofing attacks \cite{2}. Depth-based face recognition methods use the geometric structure of the face in order to gracefully handle these challenges, see \cite{3,4,5} for early attempts in these directions. Furthermore, even without the texture image itself, the geometry alone is informative enough to recognize people \cite{6,7}. However, depth information is more complicated to acquire compared to traditional 2D (RGB) images, as it often requires costly sensors and calibration of the capturing system.
The question we address in this paper is: “can we design state-of-the-art face recognition systems that exploit geometric information without explicitly reconstructing the depth?”. We suggest a novel approach that uses the geometric structure of the face to encode distinctive features for face recognition systems, without the need to explicitly reconstruct its surface. We accomplish this by feeding stereo images of a given face to a convolutional neural network (CNN) model together with the face locations in the left and right images. As long as the imaging system is fixed, there is no need to calibrate the cameras as nowhere in the processing pipeline do we compute the depth image or even rectify the images. With this input, the network has the information required to learn both geometric and photometric characteristics for a given face.

Furthermore, we suggest a multi-task learning setting in which an auxiliary CNN is trained to receive the deep features from the face recognition CNN as the input, and construct a different viewpoint of the scene as the output. To accomplish this task, the deep features must represent some information regarding the geometric structure of the scene. Both the core face-recognition CNN and the auxiliary CNN are train jointly, hence encouraging the face recognition model to encode geometric features in its latent space in an implicit manner. Since the auxiliary CNN is only used at training, it introduces no additional system costs at inference time.

We emphasize that the face recognition CNN, whether trained with or without the auxiliary CNN, does not require any explicit geometric data as an input. Also, the method is general and can be adapted to any CNN architecture. We show that the proposed methods significantly outperform single-image based methods on large-scale real stereo data, when using state-of-the-art architectures as a baseline. Furthermore, we experiment on synthetic data generated by a 3D-morphable-model (3DMM) and show that the suggested method is more robust to head pose variability than traditional single-image based methods. Even more importantly, we show that our method attains performance level on par with a similarly-structured CNN explicitly receiving a ground-truth depth maps as an input.

Our main contribution is a novel method to utilize geometric features from raw stereo data, without the need to explicitly reconstruct the depth or surface of the captured object. Our experiments shows that in the domain of face recognition, using the suggested method makes explicit depth reconstruction superfluous at no performance cost. Consequently, it retains the strengths of 3D face recognition while enjoying the simplicity and cost-efficiency of existing 2D face recognition.

2 Related Work

2.1 Computational face recognition

Face recognition in an open set scenario refers to a pre-defined algorithm that provides a distance between two given images of faces, where the distance reflects the similarity between identities. An optimal algorithm should yield zero
Do We Need Depth in State-Of-The-Art Face Authentication?

If the two images correspond to the same identity, and infinite distance otherwise. To that end, one often translates the given images into a more convenient representation space where they are referred to as feature vectors. Within the context of deep convolutional neural networks, these feature vectors are points in a latent space (also referred to as the embeddings of the input), and their similarity can be evaluated in standard ways such as the Euclidean distance, correlation, or angle. This solution is suitable for the real-life challenge of face recognition, as it can be applied to unseen subjects, namely images of people that were not part of the training set.

Multiple loss functions by which the embedding is learned have been suggested over the years, such as softmax, constructive and triplet loss. Recent papers that report state-of-the-art results in that arena suggest angular margin losses \([9,10,11]\) as a better measure of choice. In angular-loss based methods, during training time a linear classifier is trained to classify the different subjects based on their embedding vector. The training is typically done by minimizing the classification loss (e.g., cross-entropy)

\[
L_{\text{ang}} = \ell_{\text{class}}(h_{\text{class}}(h_{\text{emb}}(f)), y);
\]

where \(h_{\text{emb}}(f)\) denotes the embedding of the face image \(f\), \(y\) denotes the corresponding identity label, and \(h_{\text{class}}\) is a linear classifier predicting the label from the embedding vector. The loss is minimized with respect to the parameters of \(h_{\text{class}}\) and \(h_{\text{emb}}\).

At inference time, the classifier is discarded and a similarity score is given by the angle (or the cosine of the angle) between the two embedding vectors

\[
S(f_1, f_2) = \frac{h_{\text{emb}}(f_1)}{\|h_{\text{emb}}(f_1)\|} \cdot \frac{h_{\text{emb}}(f_2)}{\|h_{\text{emb}}(f_2)\|};
\]

Most current methods apply a CNN to face images cropped from a larger image of a scene (and then resized to match the model’s input dimensions). The cropping procedure often exploits a facial landmarks detector, like the one reported in [12]. When considering single image methods, the location of the face in the image is often ignored. When dealing with stereo images, the location of the face in the left and right images can be used to extract the depth profile of the face by using triangulation based methods. This additional geometric information can be useful for achieving better recognition rates.

2.2 Shape-from-stereo

Stereo depth reconstruction methods try to evaluate locations of objects in the 3D space given two images taken from slightly different viewpoints. Current practical stereo systems use two cameras, with a distance of several centimeters between their locations, also known as the camera baseline. By finding the projection of a specific point in the 3D space onto the two images (and the disparity between the projected coordinate in both images), it is possible to estimate the location of the point in 3D by back-projecting its location, a process known
as triangulation. Though the method is theoretically simple, it is sensitive to calibration of the stereo cameras and involves computationally intensive procedures to evaluate the exact correspondence between the two images, and the quality of the latter crucially depends on the image content. Hence, recovering a good quality depth map (or surface) of an object becomes a challenging task in “in-the-wild” scenarios. State-of-the-art systems often use active sensors with controlled illumination to overcome these difficulties, but these sensors are much more expensive than the passive triangulation-based cameras.

Recent efforts try to exploit the power of CNNs for object-specific depth reconstruction. Several papers had suggested methods to reconstruct the geometric surface of an object based on a single 2D-image. In particular, see the papers by Richardson et al. [13,14,15] who specifically target the reconstruction of geometric structure of a human face. Although achieving impressive results relevant to many applications in the fields of computer vision and graphics, these methods were trained to reconstruct the face geometry out of a single image rather than recognizing faces. Moreover, in a single image case, a printed image or a tablet screen could be easily used to fool the system.

Other methods try to use CNN with multi-view images to reconstruct the geometry of a scene. For example, Yao et al. [16,17] suggested a CNN that uses arbitrary N-view inputs to infer the depth map. Other methods [18] uses both the images and the camera parameters to enhance the results. Still, the above methods do not include specific priors relevant for face recognition. In addition, even after successful training of these CNNs, the depth map needs to be further processed in order to be integrated into face-recognition systems (i.e., fed into another CNN to be encoded at latent space). This results in multiple models, expanding the memory footprint and running time of the entire system.

The above methods are all tuned to reconstruct the depth profile of an imaged face rather than recognizing its identity. Although the reconstructed surface can play an important role in distinguishing between different individuals, it is still a fundamentally different task. In this paper, we suggest to use the raw images only, without the need to explicitly estimate the face surface. Hence, the CNN encodes only features that are relevant for the recognition task, utilizing the face geometry in an implicit manner. In addition, this results in a single model, trained end-to-end with the raw images, without any need for acquisition or supervision of explicit depth maps during training and inference time.

### 2.3 3D Face Recognition

Many methods had shown the potential of a given depth map or face surface for face recognition systems. Early papers [3,6,7] suggested a model that describes facial expressions as isometric deformations of the facial surface. Then, different methods can be used to embed the facial intrinsic geometric structure into a low-dimensional expression-invariant space, used to measure the distance between different face samples. Furthermore, Bronstein et al. [19] suggested a method to embed the isometric deformations without explicitly reconstructing the surface itself.
Other approaches harness 3D morphable models as the embedding model, even in the case of multi-view images, see [20] as an example. In that case, a CNN, or other regression model, estimates the 3DMM’s parameters for the input images, and these parameters are used as the embedding vector on which the similarity measure is calculated. One of the advantages of using a 3DMM is the disentangling of shape and texture, both of which can be used independently for the recognition task.

Current methods [21] also use CNN to process the depth maps directly, and use the deep-features for classification as done in the single-image based methods. Here, we use synthetic data with ground truth depth data to show that the proposed method achieves comparable results to that approach, without the need to use the depth maps.

3 Proposed Method

3.1 Core Method

In the suggested method we would like to implicitly consider disparity, and hence the geometric surface of the face, as part of the identification phase. However, by cropping the face images from the full stereo scene the absolute disparity information is lost as visualized in Figure 1. In other words, we need to provide the network with the location of the face in each image to maintain the disparity information. To that end, we add new channels to each of the cropped face images, containing a mapping of the $x$ and $y$ coordinates of each pixel in the original image before the face was cropped and rescaled (see Figure 2 for a

![Fig. 1. Visualization of the stereo data before and after cropping the face images. In the first row are the original stereo images, in the second row are the cropped images. The third column visualises the differences between the left and right images. The disparity information is lost if the relative cropping location is not registered as part of the process.](image-url)
visualization). In other words, instead of feeding the CNN with a single input channel (in the case of a gray-scale image), we provide the network with a six-channels input: a stereo pair (left and right), and the \( x \) and \( y \) coordinate maps for each image. This information is sufficient to extract the geometry of the imaged face.

Fig. 2. Extracting cropped face image and a matching coordinate map. The values of the pixels in the coordinates map correspond to the original column and row indices of the matching pixel in the face image.

Since the geometric structure of the face can be used to learn discriminative features, we propose to train the face-recognition network by providing it the identity of the pictured subject without any explicit information about its geometry. We assume that the new channels, left image, right image, and the coordinate maps, will promote the encoding of geometric features in the embedding space in an unsupervised manner, that is, without any use of ground-truth depth data. As we show in the sequel, the proposed method significantly improves the recognition performances of two state-of-the-art architectures, in comparison to methods that use a single image as an input trained on the same data. In addition, we suggest a method to encourage the network to encode meaningful geometric features in order to improve the recognition rates even further. Concretely, we use an auxiliary net and loss function to infer geometry-dependent transformations from face-recognition deep features, as described below.

3.2 Auxiliary Geometric Net

To utilize the geometric structure of the face we propose to tune the network towards learning it, at least implicitly. An auxiliary CNN model uses deep features extracted from the last convolution block of the core face-recognition network to estimate a frontal passport view of the input, as can be seen in Figure 3. The motivation for the auxiliary net is the observation that the “frontalization” (normalization into the frontal pose) of a given face requires understanding of
its geometry. The suggested method does not require explicit estimation or supervision of the geometry. Nevertheless, since the auxiliary CNN monitors the deep features of the main face-recognition CNN, it leads those features to include information required for pose normalization. In other words, it steers the network to express the geometric structure in its embedding space.

In order to obtain a good estimate of the passport view, and hence a more refined geometrical features encoded in the latent space, we use two separate losses. The losses require the supervision of ground truth passport view image for each subject in the training set. We note that an optimal passport image will be a frontal image in natural light and a smooth constant background. However, the passport estimation auxiliary task is simple to use also in real data scenarios. Given a set of images from a single subject, one can estimate the head pose from the detected landmarks, and choose the most frontal image as the ground truth passport view image. This will cause some variance of small angles in head pose between different passport view images, as well as background and illumination variations. Nonetheless, we show that this approach is sufficient for increasing the core face recognition performance.

The first loss term we use is an $\ell_1$ discrepancy between the estimated passport view image to the most frontal image of the given subject from the train set used as the ground-truth. An additional terms is the $\ell_2$ discrepancy between the embedding vector of the estimated passport view image produced by a pre-trained single-image (mono) model and the embedding vector of the ground-truth passport view image. The auxiliary loss assumes the form

$$L_{aux} = \|h_{aux}(h_S(f)) - p\|_1 + \alpha \cdot \|h_M(h_{aux}(h_S(f))) - h_M(p)\|_2^2$$

where $p$ denotes the groundtruth passport view corresponding to face $f$, $h_S$ and $h_M$ denote the stereo and the mono face embedding models, respectively (we remind that while $h_M$ accepts a single image $p$ as the input, its stereo counterpart $h_S$ operates on the 6-channel stereo images augmented by the coordinate maps $f$ as previously described), and $h_{aux}$ denotes the auxiliary network receiving the face embedding vector and producing an estimated passport view.

The total loss of the net is composed of the angular classification loss and the auxiliary one, $L = L_{ang} + \beta \cdot L_{aux}$ with $h_S$ being used as the embedding model in the first term. The constants $\alpha$ and $\beta$ control the relative contribution of each loss term in the final objective function. The selection of $\beta = 0$ yields the core method.

This approach is general in the sense that it is independent of the face-recognition network architecture. Furthermore, the auxiliary net is relevant only during the training process and can be discarded at the inference phase. Thus, it does not affect the system’s memory and running-time performance. Here, we suggest to use a ResNet [22] shaped architecture for the auxiliary CNN, which uses upscale operations at the end of each convolution block.
Fig. 3. Using auxiliary CNN to account for the geometry. The auxiliary net uses deep features of the core stereo face-recognition CNN to estimate a passport view image, thus, enforcing the core CNN to, at least implicitly, capture the geometry.

4 Experiments and Evaluation

4.1 Data

To the best of our knowledge, there is no public large-scale dataset of stereo face images. Therefore, we created our own dataset of real (and synthetic) stereo images. First, we captured gray-scale images by a standard stereo camera with a baseline of 30mm, and resolution of 1920 × 1080 per image. The training set includes a total of 344,075 left and right images of 7,214 different subjects. The test set includes 88,024 left and right images of 1,809 different subjects. The images were taken under a variety of lighting conditions and various poses. The subjects were located at a distance of less than 1m from the camera. It is important to mention that the images are not rectified or processed, but rather we use the raw images taken by the stereo camera. For the ground truth passport images, we chose the most frontal image for each individual subject, as explained in Section 3.2.

In order to improve our analysis we also generated synthetic data, based on the 3DMM model [8]. We synthesized geometric (and photometric) profiles of 13,473 different individuals. For each subject, we rendered 20 – 30 stereo image pairs, with a baseline of 30mm between the left and right images, random pose, random lighting condition, and location in the scene. The pose was randomly selected with pitch and yaw angels limited to ±25°. The distance from the camera was randomly selected within a range of 0.25m – 1m. We used random images as a background and added random geometric structures behind the synthetic faces to generate non-flat background information. Also, for each image the ground truth depth profile is provided, and for each subject we provide one centered frontal image, that would serve as reference for our auxiliary passport view with pitch = 0° and yaw = 0°. The synthetic training set contains images of 10,103 distinct subjects and the synthetic test set includes the remaining 3,370 subjects.
4.2 Network Architecture

As our CNN backbone, we used two state-of-the-art architectures that were introduced and tested in face-recognition challenges, the CosFace [10], and the ArcFace [11] models. Both architectures use the same ResNet backbone, with different classifiers and angular loss function. For both stereo and single image models (denoted as “stereo” and “mono” models) we used 20 ResNet layers with the same number of filters at each layer, as described in [9], and an embedding vector of dimension 512. Both stereo and mono models have the same architecture, with the exception that the stereo input involves six channels instead of the mono model's single channel. That affects only the number of parameters in the first convolution layer and is negligible in comparison to the overall size of the network.

4.3 Pre-processing and Data Augmentation

We used several common data augmentation techniques. For each image, without relation to it’s stereo pair, we detected face landmarks using automatic facial landmarks detection. Then, we cropped a square bound-box around the landmarks, and kept a margin of background around the face. Next, we resized the image into a frame size of $144 \times 144$. Finally, we normalized the gray-scale values of the pixels to be in the range of $[-0.5, 0.5]$. Illustration of normalized stereo images can be seen in Figure 4. As can be seen, as a result of the small baseline of the stereo camera, the images only slightly differ from one another.

Fig. 4. Examples of normalized stereo face images (left and right images). The stereo model gets both images in two different channels as input. The mono model processes each image as a separate single-channel input.

We also constructed a matching coordinate map for each cropped frame. Since the coordinates values are in image plane scale (i.e. $1920 \times 1080$), we normalize each column and row index by reducing half of the source image width or height respectively (“zero centering”) and dividing by the diagonal length of the source image; given an image of size $W \times H$, the normalized coordinates are given by

$$ (\hat{i}, \hat{j}) = \left( \frac{i - \frac{W}{2}}{\sqrt{W^2 + H^2}} \right), $$

During training, we cropped a $128 \times 128$ sized image in a random locations out of the $144 \times 144$ face image and its corresponding coordinate map. This augmentation purpose is to be robust to the error in the landmark detector, which
effects the resulting cropped face image. Consequently, The input dimensions are $128 \times 128 \times 6$ for the stereo model, and $128 \times 128 \times 1$ for the single image model. Also, we added random noise and blur augmentation to the texture channels. Finally, for testing, we cropped the center $128 \times 128$ bounding box of the normalized input, and did not add noise to the input data.

### 4.4 Training

Both stereo and mono models were trained with the same hyper-parameters, except for the batch size, as will be explained shortly, for the same amount of epochs, and using the same data. While the stereo model was trained based on a couple of left-right images, the mono model was trained with both the left and right images treated independently. Thus, the batch size used for training the mono model was twice as large as that of the stereo, compensating for the fact each sample of the stereo model involves two images. For training the auxiliary net, we used $\alpha = 50, \beta = 1$, as loss normalization factors.

We used Stochastic Gradient Descent optimizer to train all of the models for 100 epochs, with an initial learning rate of 0.01 and reduced the learning rate by a factor of 0.1 each 20 epochs. We used batch size of 64 for the mono model and 32 for the stereo model, and a weight decay factor of 0.0005.

### 4.5 Evaluation and Results

**Experimental Results on Real Data** A total of 1,635,336 subjects pairs have been evaluated, with 2,288,368 positive samples of the same subject at different positions, poses, and illumination conditions, and 472,612,104 negative samples, of two different subjects.

For each model separately, we set thresholds that enabled us to achieve certain false-positive rate (FPR) for the negative samples, that is, different subjects that were identified as the same subject. For each threshold and FPR, we measured the false-negative rate (FNR) of the positive pairs, that is, samples of the same subject that were identified as two different subjects. In order to compare the same samples in both models, in the mono model the embedding vectors of the left and right images pair were combined to form a single vector. We tested several methods: concatenating the vectors, averaging, and choosing only the left or only the right image vector. Averaging the embedding vectors achieved the best performance, and this is the method displayed in the results below.

The results are presented in Table 1. The methods are denoted as either *Mono* or *Stereo*. In addition, a full ROC-curve is displayed in Figure 5. In both tested architectures, the stereo model significantly outperforms the mono model.

**Ablation Study** We performed multiple experiments to study the effect of the suggested method and auxiliary task. We used the CosFace classifier to test different variants of the proposed methods. First, we trained a stereo model without supplying the coordinate maps as part of the input. That is, the input
Table 1. FNR at different FPR on the real images dataset, for Stereo and Mono methods implemented with different models.

| Model           | FPR = 10^{-5} | 2 \cdot 10^{-6} | 10^{-6} |
|-----------------|----------------|-----------------|---------|
| CosFace - Mono  | 0.0567         | 0.1048          | 0.1329  |
| **CosFace - Stereo** | **0.0161**     | **0.0297**      | **0.0378** |
| ArcFace - Mono  | 0.0640         | 0.1211          | 0.1496  |
| **ArcFace - Stereo** | **0.0135**     | **0.0243**      | **0.0304** |

Fig. 5. ROC curve for the real images dataset. The dashed lines correspond to the mono models, while the solid lines correspond to the stereo counterparts.

was only a stereo image pair, with dimensions 128 \times 128 \times 2, denoted as No Coords. We also trained a model that uses the coordinate maps, without using the auxiliary net, denoted as With Coords. Then, we trained a model with the auxiliary net but with just the $\ell_1$ loss ($\alpha = 0, \beta = 1$), and finally, the complete method ($\alpha = 50, \beta = 1$), both denoted as With Aux. The results are shown in Table 2.

Table 2. FNR at different FPR on the real images dataset using different components of the suggested method.

| Method            | FPR = 10^{-5} | 2 \cdot 10^{-6} | 10^{-6} |
|-------------------|----------------|-----------------|---------|
| Stereo - No Coords| 0.0254         | 0.0479          | 0.0628  |
| Stereo - With Coords | 0.0235     | 0.0407          | 0.0503  |
| Stereo - With Aux ($\alpha = 0, \beta = 1$) | 0.0216 | 0.03823 | 0.04719 |
| **Stereo - With Aux ($\alpha = 50, \beta = 1$)** | **0.0161** | **0.0297** | **0.0378** |

Even without the coordinate maps the stereo model outperforms the mono model. It means that the joint learning of slightly different viewpoints allow
Fig. 6. Results of the auxiliary CNN, estimating the passport view of a given face. The input to the auxiliary net is the deep features from the core face recognition CNN.

the net to learn more distinctive features in comparison to the processing of each image independently. Nonetheless, adding the coordinate maps channels significantly enhanced the results. These channels contain only the geometric location of the head in the scene, without any additional data regarding the face texture or other conditions in the scene such as pose or lighting conditions. Thus, we conclude that the net uses the coordinate maps to encode geometric features in the latent space, possibly by computing the geometric relations between some facial features.

The auxiliary net also demonstrates a significant improvement in performance. Using both the suggested auxiliary losses provided the best results. Once again, the auxiliary net uses only the deep features to estimate a new viewpoint of the scene, without any additional input. This supports our assumption that the suggested auxiliary task promotes learning of geometric features in the latent space, and thus leads to better recognition rates. A visualisation of the estimated passport views is presented in Figure 6.

Experimental Results on Synthetic Data In addition to the evaluation of the real dataset, we trained and evaluated our system using the synthetic dataset. We explored the robustness of the different methods that deal with head pose variation. We look at the positive samples, that is, two samples of the same subject, and record the similarity scores together with the head pitch and yaw angles of both samples. A visualization of the average score per pitch and yaw angles can be seen in Figure 7.

Next, we set a threshold for each of the models, that achieves FPR of $10^{-6}$. Then, we measured the relative FNR per yaw and pitch angles, that is, which fraction of the samples with a given yaw and pitch angles got similarity score smaller than the threshold. The results are shown in Figure 8. The stereo model is more robust to both high pitch and high yaw angles compared to the mono model. Also, while it seems that the mono model is much more sensitive to big pitch angles than big yaw angles, the stereo model presents a more similar degradation in large angles for both pitch and yaw, suggesting it is more robust to these variations.

Finally, we compared our method to a method that uses the explicit depth profile as input. To that end, we use the ground truth depth profiles of the
synthetic data. We trained a CNN of the same architecture with a two channels input - the face image and the matching ground-truth depth profile, both cropped from the original image at the same locations. The ROC curve of this experiment is displayed in Figure 9. The suggested method achieved better performance, especially for low FPR. Although we do not claim the method used to process the explicit depth profiles is the optimal one, the experiment does give us quantitative results to support the claim that the proposed method is at least comparable to using explicit depth profiles as an input.
5 Conclusions

We presented a novel method to encode geometric facial features in a face-recognition CNN model, without the need to explicitly capture or calculate geometrical data. We showed that our method outperforms traditional single-image based methods, and is comparable to methods that use explicit and accurate depth data. Thus, we bridge the gap between the advantages of 3D face recognition methods and the simplicity and cost-efficiency of existing 2D face recognition methods.

The proposed method is simple to implement, can be used with any general CNN architecture, and is robust to both classic face-recognition challenges such as extreme poses, and geometric data acquisition and calibration distortions. We demonstrated the potential of using the raw data from multiple view scenarios to improve computational face recognition rates and robustness, without the need to explicitly reconstruct the geometry. Future study can expand this method to additional applications that currently requires explicit depth information such as anti-spoofing systems, hand-gesture recognition and body pose estimation.

References

1. Singh, S., Prasad, S.: Techniques and challenges of face recognition: A critical review. Procedia computer science 143 (2018) 536–543
2. Erdogmus, N., Marcel, S.: Spoofing 2d face recognition systems with 3d masks. In: 2013 International Conference of the BIOSIG Special Interest Group (BIOSIG), IEEE (2013) 1–8
3. Bronstein, A.M., Bronstein, M.M., Kimmel, R.: Expression-invariant 3d face recognition. In: international conference on Audio-and video-based biometric person authentication, Springer (2003) 62–70
4. Blanz, V., Vetter, T.: Face recognition based on fitting a 3d morphable model. IEEE Transactions on pattern analysis and machine intelligence 25(9) (2003) 1063–1074
5. Paysan, P., Knothe, R., Amberg, B., Romdhani, S., Vetter, T.: A 3d face model for pose and illumination invariant face recognition. In: 2009 Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance, Ieee (2009) 296–301
6. Bronstein, A.M., Bronstein, M.M., Kimmel, R.: Expression-invariant face recognition via spherical embedding. In: IEEE International Conference on Image Processing 2005. Volume 3., IEEE (2005) III–756
7. Bronstein, A.M., Bronstein, M.M., Kimmel, R.: Expression-invariant representations of faces. IEEE Transactions on Image Processing 16(1) (2006) 188–197
8. Blanz, V., Vetter, T.: A morphable model for the synthesis of 3d faces. In: Proceedings of the 26th annual conference on Computer graphics and interactive techniques. (1999) 187–194
9. Liu, W., Wen, Y., Yu, Z., Li, M., Raj, B., Song, L.: Sphereface: Deep hypersphere embedding for face recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. (2017) 212–220
10. Wang, H., Wang, Y., Zhou, Z., Ji, X., Gong, D., Zhou, J., Li, Z., Liu, W.: Cosface: Large margin cosine loss for deep face recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2018) 5265–5274
11. Deng, J., Guo, J., Xue, N., Zafeiriou, S.: Arcface: Additive angular margin loss for deep face recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2019) 4690–4699

12. Zhang, K., Zhang, Z., Li, Z., Qiao, Y.: Joint face detection and alignment using multitask cascaded convolutional networks. IEEE Signal Processing Letters 23(10) (2016) 1499–1503

13. Richardson, E., Sela, M., Or-El, R., Kimmel, R.: Learning detailed face reconstruction from a single image. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2017) 1259–1268

14. Richardson, E., Sela, M., Kimmel, R.: 3d face reconstruction by learning from synthetic data. In: 2016 Fourth International Conference on 3D Vision (3DV), IEEE (2016) 460–469

15. Sela, M., Richardson, E., Kimmel, R.: Unrestricted facial geometry reconstruction using image-to-image translation. In: Proceedings of the IEEE International Conference on Computer Vision. (2017) 1576–1585

16. Yao, Y., Luo, Z., Li, S., Fang, T., Quan, L.: Mvsnet: Depth inference for unstructured multi-view stereo. In: Proceedings of the European Conference on Computer Vision (ECCV). (2018) 767–783

17. Yao, Y., Luo, Z., Li, S., Shen, T., Fang, T., Quan, L.: Recurrent mvsnet for high-resolution multi-view stereo depth inference. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2019) 5525–5534

18. Ji, M., Gall, J., Zheng, H., Liu, Y., Fang, L.: Surfacenet: An end-to-end 3d neural network for multi-view stereopsis. In: Proceedings of the IEEE International Conference on Computer Vision. (2017) 2307–2315

19. Bronstein, A.M., Bronstein, M.M., Spira, A., Kimmel, R.: Face recognition from facial surface metric. In: European Conference on Computer Vision, Springer (2004) 225–237

20. Tran, A., Hassner, T., Masi, I., Medioni, G.: Regressing robust and discriminative 3d morphable models with a very deep neural network. In: Proceedings of the IEEE conference on computer vision and pattern recognition. (2017) 5163–5172

21. Kim, D., Hernandez, M., Choi, J., Medioni, G.: Deep 3d face identification. In: 2017 IEEE international joint conference on biometrics (IJCB), IEEE (2017) 133–142

22. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. (2016) 770–778