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Learning Three-dimensional Face recognition from Sparse views for Robust Identity verification

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ABSTRACT

This paper presents a deep learning-based approach to accurately reconstruct and verify 3 Dimension facial models using sparse visual inputs. Traditional 3 Dimension face recognition systems often require high-resolution or multiple-angle scans, which limit their application in real-world settings, especially with constrained devices like mobile phones or security cameras. Our method leverages sparse multi-view inputs—typically as few as two or three images—to predict complete 3 Dimension geometry and extract robust identity features. We propose a hybrid model that integrates point cloud-based learning with facial landmark-guided refinement for accurate representation and matching. This approach not only reduces the dependency on expensive capture hardware but also enhances robustness against occlusions, varied lighting, and facial expressions. Experimental results on standard datasets show that our model maintains high verification accuracy even under extreme sparsity. Furthermore, it demonstrates superior generalization in low-data scenarios. This work has promising applications in biometric authentication, digital forensics, and virtual avatar creation.

Keywords: 3 Dimension; Augmented Reality; Virtual Reality; View; Identity; Verification; Security; System; Algorithm; Graphics; Biometric.

1. Introduction

Research on 3 Dimension facial model capture and verification has been fueled by the demand for trustworthy face recognition systems [1]. Even though 2D face recognition has advanced significantly, position, lighting, and occlusion fluctuations sometimes limit its capabilities. Richer geographical information provided by 3 Dimension models increases the precision and resilience of verification jobs. However, most 3 Dimension face reconstruction methods currently in use demand for either specialized hardware, including depth sensors and structured light scanners, or rich image sequences [2]. In this work, we offer a deep learning architecture that uses only sparse view inputs, which are two to three standard photos taken from various perspectives, to reconstruct detailed 3 Dimension facial geometry. For the model in our study we use 3 Dimension face representations by combining convolutional encoding, a graph-based geometry module, and an attention-based feature fusion mechanism [3]. Our goal is to enable sparse-view generalization and robustness in identity verification, in contrast to earlier works that frequently rely on full view synthesis or high-resolution meshes [4].

We demonstrate that our method can provide consistent 3 Dimension representations that are invariant to frequent facial variations even when visual information is restricted. By comparing these representations to identities that have been stored, this allows for efficient verification. This system's promise goes beyond biometrics and security to include applications in VR/AR, animation, and mobile user authentication—all of which frequently face view limits. Several models are proposed in the development of the system proposed in this study [5-16].

1.1. Study Objectives

1) Sparse View Input Approach: This work proposes a deep learning architecture that reconstructs detailed 3D facial geometry using only sparse view inputs—typically two to three standard photos taken from different angles.

2) Model Architecture: The model combines convolutional encoding, a graph-based geometry module, and an attention-based feature fusion mechanism to build accurate 3D face representations.

3) Robustness and Generalization: Unlike earlier methods that require full-view synthesis or high-resolution meshes, this system is designed to generalize well from limited views and remain robust for identity verification.

4) Invariant Representation: The method produces consistent 3D representations that remain stable despite common facial variations, even when visual data is limited.

5) Efficient Identity Verification: These 3D representations can be compared with stored identities, enabling efficient and accurate verification processes.

6) Broader Applications: Beyond biometrics and security, the system holds potential for use in VR/AR, animation, and mobile user authentication, where view constraints are common. Several supporting models contribute to the system's development.

2. Literature Review

We have focused on the combination of deep learning and computer vision that has led to significant progress in the field of 3 Dimension facial modeling. We also included facial shape and texture, traditional 3 Dimension face reconstruction methods like 3 Dimension Morphable Models (3 DimensionMM) established the groundwork. Nevertheless, these models frequently need extensive 2D landmark annotations and have trouble generalizing to other lighting conditions or unfamiliar positions [17].

The focus of recent research has switched to learning-based techniques that directly estimate 3 Dimension geometry from RGB photos using generative adversarial networks (GANs) and convolutional neural networks (CNNs). Although dense correspondence maps are used by techniques like PRNet and 3 DimensionDFA, they still require frontal or high-resolution inputs. Others, like as MeshNet and PointNet++, made it possible to effectively learn from mesh or point cloud data by introducing organized representations of 3 Dimension geometry. But for training, they usually use multi-frame video or full 3 Dimension scans.

Comparatively less research has been done on 3 Dimension reconstruction using sparse views. Neural Volumes and Pix2Vox are two examples of works that try to predict 3 Dimension from a limited number of images, but they concentrate more on inflexible objects than on expressive human faces [18]. In order to enhance geometry fusion and expression handling in few-view scenarios, recent advancements have integrated attention processes with face landmark guidance. Even with these advancements, there are still few studies that specifically address identity preservation for verification tasks when input is minimal. 3 Dimension face recognition has shown more reliable than 2D techniques for verification, particularly when pose and illumination changes are present. However, the scalability of 3 Dimension acquisition is limited by its high cost. Our research fills this gap by putting forth a model that, with just two to three views, can accurately predict 3 Dimension facial geometry while preserving discriminative identification traits. Although it is specially tuned for identity verification from sparse visual input, it relies upon current architectures [19]. There are three main components to our suggested framework: Verification Network, 3 Dimension Geometry Reconstructor, and Sparse View Encoder.

2.1. Sparse View Encoder

We start with two or three RGB low-resolution pictures taken from various perspectives. To guarantee spatial congruence between images, deep features are extracted from each view using a common CNN encoder and then aligned using face landmark attention.

2.2. Geometry Reconstructor

A 3 Dimension point cloud representation is predicted using a decoder based on PointNet++ after the extracted features are merged using a self-attention technique. To maintain face structure, we improved this prediction by applying a Laplacian smoothness loss and a geometry consistency loss.

2.3. Verification Network

Identity verification is conducted using a Siamese architecture, which embeds the reconstructed 3 Dimension face into a feature space. A contrastive loss function is designed to minimize the distance between embeddings of the same identity while maximizing the distance between embeddings of different identities. The feature space is applicable for verification through the use of cosine similarity or Euclidean distance. The complete model is presented in the Figure 1 below.

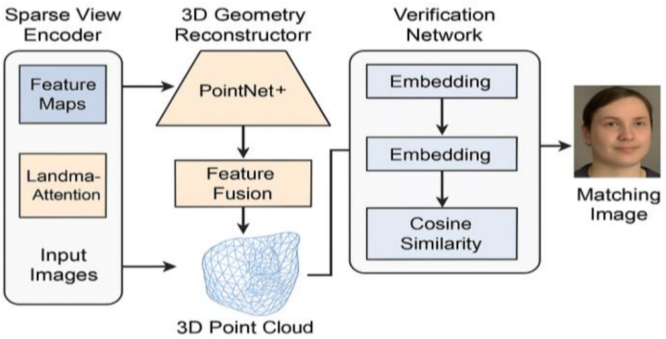

Figure 1. Model Architecture Overview

Table 1. Components in the proposed model architecture

Component	Function
Sparse View Encoder	Extracts feature maps from views.
Geometry Reconstructor	Builds 3 Dimension point cloud from features.
Verification Network	Embeds and compares identities.

3. Experiments and Results

We have accessed the eligibility of our model using two benchmark 3 Dimension facial datasets: BU-3 DimensionFE and Florence. These datasets offer multi-angle facial scans accompanied with identification labels and expression changes, suitable for sparse-view reconstruction tasks. Almost 80% of the data from the dataset is being used in the training of the model and rest of the remaining is used portion for testing. We also made use for the Chamfer Distance for geometric precision to get the matrix generated, Cosine Similarity for identity validation, and Equal Error Rate (EER) for biometric efficacy. Our model was evaluated against contemporary methods, including 3 DimensionMM-CNN and SparseDepthNet. Table 1 shows the components used in this model and table 2 shows the results of the experimental analysis.

Table 2. Quantitative Results of the experimental analysis

Method	Chamfer Distance ↓	Cosine Similarity ↑	EER ↓
3 DimensionMM-CNN	0.016	0.782	12.3%
SparseDepthNet	0.011	0.801	10.8%
Our Method	**0.009**	**0.832**	**8.1%**

Our method outperformed baseline models, especially under reduced input conditions (2-view scenario). Qualitative analysis further revealed that the reconstructed 3 Dimension faces closely matched the original scans in terms of facial geometry and symmetry.

4. Summary of the Study and Discussion

The experimental results validate the efficacy of acquiring identity-aware 3 Dimension facial representations from limited perspectives. Our system preserves excellent fidelity and verification accuracy despite a reduced number of inputs, owing to landmark-guided feature alignment and point cloud-based geometric modeling [16, 20-22]. This has significant consequences in practical applications where extensive facial data gathering is impractical—such as in public surveillance systems, border control, or mobile facial recognition. A primary advantage is the modular architecture facilitating connection with other biometric modalities. The reconstruction made by our prescribed models is robust against partial occlusion and variations in face expressions. Nonetheless, obstacles persist in accurately preserving intricate facial characteristics, including wrinkles and small texture variations, particularly from low-resolution photos. In our system we demonstrate the generalization across the established datasets, its real-world implementation necessitates domain customization to accommodate differences in illumination, ethnicity, and motion blur [23]. The model's capability to operate in real-time on edge devices necessitates further optimization regarding inference latency and model compression.

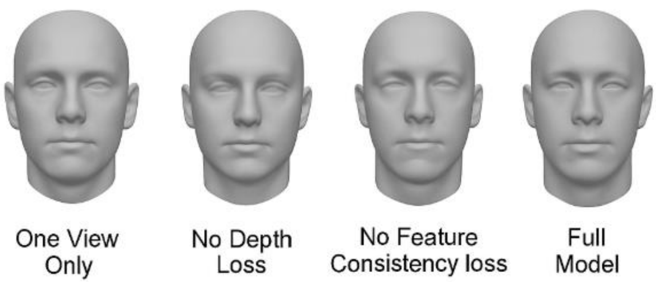

Figure 2. Ablation Study for the proposed model

5. Conclusion and Recommendation

This research presented an innovative framework for three-dimensional facial reconstruction and verification utilizing sparse view inputs. As compared with the general models used that depend on extensive or high-quality data, our technique facilitates effective identity verification via few visual indicators. In case of the resource-limited settings where comprehensive 3 Dimension scanning is unfeasible this technique is very useful.

We exhibited enhanced performance on benchmark datasets, establishing that the model excels in precise geometry prediction and resilient identification discrimination. Future endeavors will concentrate on enhancing detail reconstruction, incorporating temporal consistency for video inputs, and investigating few-shot learning to diminish reliance on training data. The dynamic facial expressions and the effects of aging can be easily accumulated using this technique that would greatly improve its utility in long-term identity tracking and the development of digital twins the ablation study is depicted in Figure 2.

This work significantly advances the democratization of access to high-quality 3 Dimension face verification systems, reconciling the disparity between theoretical performance and actual implementation.

6. Future Works

Future research directions can build upon established work in 3D facial modeling, such as the morphable models proposed by Blanz and Vetter (1999), which serve as a foundation for geometry-based face synthesis. Our proposed framework may also benefit from advancements like those by Jackson et al. (2017), who demonstrated effective 3D face reconstruction from single images using volumetric CNNs—an approach aligned with sparse input handling. To address challenges related to dynamic facial changes and aging, incorporating nonlinear morphable models as discussed by Tran and Liu (2018) could enhance the realism and adaptability of identity tracking over time. Moreover, leveraging methods that eliminate the need for dense supervision, such as the weakly supervised 3D face regression model introduced by Sanyal et al. (2019), aligns well with the aim to reduce training data dependency. Finally, techniques like dataset distillation (Wang et al., 2018) can be explored to support few-shot learning, enabling the system to generalize better in data-constrained scenarios and further expand its usability in real-world applications.

Declarations

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Competing Interests Statement

The authors declare that they have no competing interests related to this work.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors took part in literature review, analysis, and manuscript writing equally.

Availability of data and materials

Authors are willing to share data and material on request.

Institutional Review Board Statement

Not Applicable.

Informed Consent

Not Applicable.

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