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Face Modeling Based on Deep Learning and Traditional Methods: A Survey

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Abstract. 3D face modeling, as an important research field in computer graphics and vision, has undergone remarkable development in recent years. The technology is widely used in various scenarios, like film and television production, virtual reality, augmented reality, facial recognition, security monitoring, and medical diagnosis. This paper aims to systematically explore the main technologies of 3D face modeling, especially the application and development of deep learning methods in it, review traditional face modeling methods, introduce in detail the latest technical advances based on deep learning, and analyze the advantages and disadvantages of these methods in practical applications.

Keywords: 3D facial modeling, deep learning methods, facial recognition, Virtual Reality.

1. Introduction

Three-dimensional face modeling represents a significant research area within the broader fields of computer graphics and computer vision. In recent years, this area has attracted considerable attention and research activity. The advancement of computing power and the accelerated evolution of deep learning technology have facilitated substantial advancements in 3D face modeling technology across a multitude of domains, including film and television production, Virtual Reality (VR), Augmented Reality (AR), biometrics, security monitoring, medical diagnosis, and human-computer interaction.

Conventional 3D face modeling techniques rely primarily on geometric methodologies, such as laser scanning, structured light, and multi-view stereo vision. These techniques can provide high-precision geometric data, but they are often costly, intricate, and necessitate sophisticated equipment. In light of the advancements in statistical modeling techniques, researchers have put forth the concept of 3D shape models (3DMM), which are derived through the analysis of a vast repository of face data and the extraction of its statistical attributes. This approach markedly streamlines the modeling process by encapsulating the parametric representation of facial shape and texture. However, these methods remain constrained by limitations in the context of lighting changes, expression changes, and occlusion.

In recent years, the advent of deep learning technology has opened up new avenues for 3D face modeling. Deep learning models, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs), have proven to possess exceptional capabilities in the domains of image processing and generation. The application of deep learning technology enables the reconstruction of realistic and high-precision 3D face models from 2D images. In particular, the 3D-GAN method, which is based on generative adversarial networks, can generate highly realistic 3D face models through the adversarial training of generators and discriminators.

This paper is structured as follows: Section 2 presents the application of deep learning methods to face modeling. Section 3 illustrates statistical-based methods, such as the 3DMM approach. Section 4 describes image-based modeling techniques. Section 5 presents geometric modeling methods. Section 6 introduces scanning and sensor-based modeling methods, including those based on Kinect devices and depth cameras. Section 7 analyzes both the advantages and disadvantages of the previously described methods with tables and statistics. In conclusion, Section 8 presents a summary of the key findings.

2. Deep Learning Methods

The application of deep learning technology relies on the utilization of copious amounts of data and sophisticated computing capabilities to enable the automated identification and extraction of intricate characteristics within the data set. This has the potential to transform the domain of three-dimensional face modelling. The principal stages of the process encompass the collection and processing of facial data, the design and selection of an appropriate model architecture, the training of the model, and the evaluation and verification of the model. This approach offers the benefits of high automation and realistic results. However, it also presents challenges, including the necessity for a substantial quantity of high-quality data, the requirement for substantial computational resources, and the need for stability when dealing with complex scenarios. Nevertheless, this technology is developing rapidly and is gradually becoming the mainstream method in this field. As algorithms are continually refined and hardware capabilities advance, it is inevitable that this technology will prove invaluable in a growing number of applications.

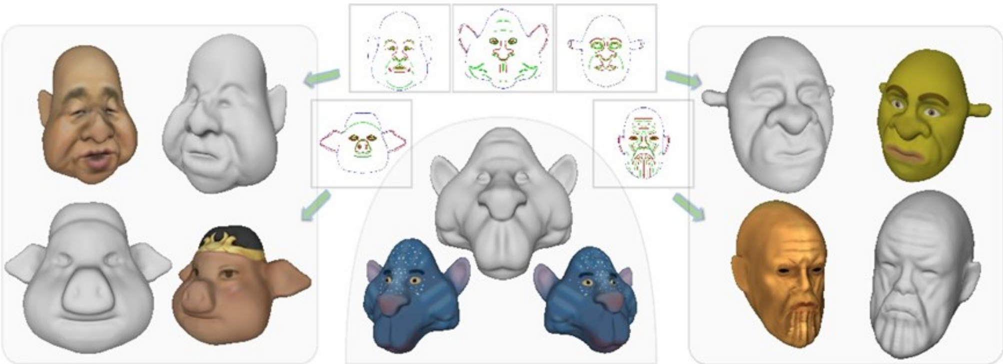

Figure 1. Users can create a 3D facial model by sketching a rough facial outline. [1]

Zhongjin Luo et al. developed a learning-based method, designated "Implicit and Depth Guided Mesh Modeling" (IDGMM), for the conversion of a two-dimensional sketch map to a three-dimensional model. This approach incorporates a sketching system to generate high-fidelity three-dimensional facial representations [1]. Yajie Gu et al. proposed a method for 3D face modeling that used a continuous parts-based deformation field to map the diverse semantic components of a subject's face onto a template [2]. Guohao Li et al. introduced a weakly supervised disentanglement framework that facilitates the training of controllable 3D face models without imposing unduly stringent labeling requirements [3]. Zhenyu Zhang et al. presented a novel neural proto-face field (NPF) for the unsupervised generation of robust 3D face models [4]. Kai Yang et al. proposed a novel high-capacity parametric face model, the Adaptive Skinning Model (ASM), for the reconstruction of faces from multi-view, uncalibrated images. The model demonstrates a higher capacity and more natural results, eliminating the need for manual design or training data sets, and thus achieving state-of-the-art performance, as evidenced by [5]. Stathis Galanakis et al. put forth a 3D variable model (3DMM) based on the Neural Radiance Field (NeRF) for the precise modeling of the identity, pose, and expression of a face and the generation of realistic images under any lighting conditions. In comparison to traditional linear representation methods, this approach demonstrates enhanced expressiveness and a more realistic appearance. Moreover, the authors utilize a deep convolutional network to generate samples, resulting in enhanced computational efficiency [6]. Andrew Z. Hou et al. proposed a novel implicit generative model for facial morphing, which was integrated into the neural radiance field (NeRF) framework through the introduction of hypernetworks. This integration enhanced the representation capabilities of the NeRF in the context of numerous training subjects. Furthermore, they proposed a unique, data-driven approach to sampling for more efficient training of the NeRF model [7]. Yuta Kawanaka et al. presented a deep learning-based method for creating 3D human face models and proposed a sketch-based approach to face modeling, whereby 3D human face models are created via line drawing [8]. Ziyang Weng et al. presented a comprehensive perceptual model for the identification of facial expressions from a singular image sequence, encompassing a set of fundamental, interpretable characteristics [9]. Fengquan Zhang et al. offered a customized model method for Peking Opera faces with a depth camera. This approach classifies the Action Units (AUs) based on facial features and computes the weights of the different shape bases using the Blend Shape algorithm [10]. Cheng Di et al. devised and implemented a new convolutional neural network (CNN), designated as LW-CNN, with a separable convolution structure. This novel approach allows for the identification of three-dimensional (3D) feature points on human faces with greater precision, while simultaneously reducing the number of required parameters [11]. Feng-Ju Chang and colleagues presented a novel method for modeling 3D face structure, position, and expression from a sole, non-restrictive photograph. The method employs three deep convolutional neural networks, each of which is used to estimate a specific component [12]. Chi Nhan Duong et al. presented a novel deep appearance model that is more effective at handling the intricate variations observed in face images. In comparison to the conventional PCA-based appearance model, this model displays superior generalization capabilities and a higher degree of representational ability. The deployment of deep learning techniques permits the model to discern superior-order attributes without the necessity for a substantial amount of training data [13]. F. Liu et al. introduced a novel encoder-decoder framework that can learn face models directly from a multitude of disparate 3D scan databases and establish dense correspondences between these scans. A weakly supervised learning method was used to train the network and extract information from synthetic data [14]. Son Thai Ly et al. presented the advantages of 3D face modeling for naturalistic facial expression recognition (FER). The researchers constructed 3D facial data from existing 2D datasets using recently developed techniques for 3D reconstruction of facial geometry through deep learning methods [15]. Xiaoguang Han et al. presented DeepSketch2Face, a deep learning-based system for the generation of 3D facial and cartoon models based on user sketches. The system integrated deep learning techniques with conventional graphics methodologies to facilitate an efficient and natural user interaction modeling experience [16]. Chi Nhan Duong et al. put forth a novel model based on a time-limited Boltzmann machine for the simulation of human facial progression in naturalistic settings. A deep structured model was employed to represent faces and model age progression [17]. Donghyun Kim et al. presented a discussion of the technology of 3D face modeling and recognition from RGB-D streams in the presence of large pose changes, and proposed a method to improve recognition accuracy using deep learning methods [18]. Donghyun Kim et al. proposed an approach for analyzing facial expressions captured in an RGB frame and neutralizing the corresponding 3D point cloud, with the goal of constructing a precise neutral 3D face model from an RGB-D video, even when extreme expression changes are present [19]. Sucontphunt presented a novel approach to 3D facial modeling that employs automatic feature extraction techniques from 3D face models to facilitate the transfer of identity characteristics to 3D artistic face models. This methodology allows for a high degree of customization and control over the final result [20]. Vytautas Kaminskas et al. investigated the modeling of human emotions (e.g., excitement, depression, and boredom/concentration) through dynamic virtual 3D facial stimulation, and evaluated the accuracy and stability of different models in predicting emotional signals [21]. Noranart Vesdapunt et al. presented a novel approach to learning three-dimensional face models that integrated a joint-based face assembly model with a neural skin network. This approach has the advantage of a smaller model size and enhanced modeling capabilities, as well as the ability to add features such as mouth interior, eyes, and accessories [22].

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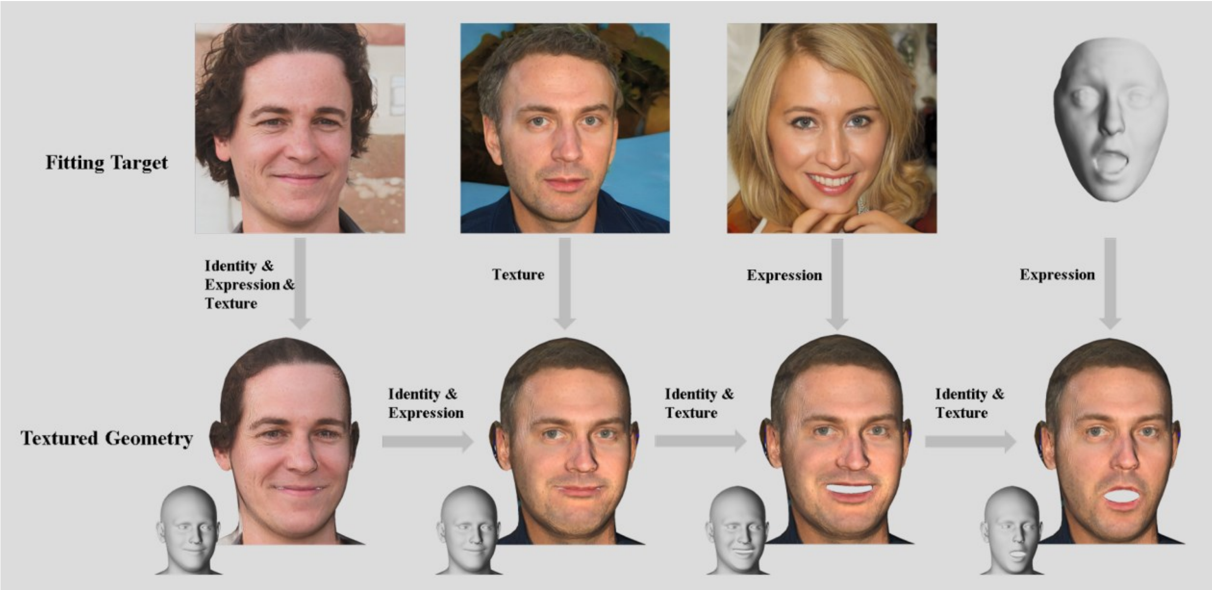

Figure 2. Reconstruction and editing of face models. [3]

Figure 3. Qualitative comparison of predicted facial geometry. [4]

3. Statistical-based Modeling

In contrast, statistical-based methods construct parametric models that can represent the shape and texture of faces by learning statistical features from large datasets. One of the most renowned examples is the 3D Morphable Model (3DMM), which has proven effective in capturing facial variations and enabling shape and texture manipulations. These models offer flexibility and ease of use, albeit with potential limitations in capturing extreme facial expressions or individual-specific features.

Figure 4. Comparison between results of different modeling methods. [6]

Bindita Chaudhuri et al. developed an in-depth framework that enables the construction of a customized face model for each user, along with the extraction of per-frame facial movement parameters from a substantial corpus of naturally occurring video footage depicting user expressions [23]. Changwei Luo et al. presented a face modeling system based on the head pose estimator. This system produces a face model by applying an iterative closest point (ICP) algorithm to a depth image for the purpose of matching a deformable face model to the image [24]. Shan Liu et al. optimized the algorithm for filtering and aligning point clouds in 3D modeling, thereby reducing measurement error and accelerating the analysis of point cloud data. The current filtering algorithm was analyzed, and its shortcomings were identified; consequently, a novel method of point cloud filtering was developed and implemented [25]. Weilong Peng et al. discussed a 3D facial modeling method based on structural optimization and B-Spline surface reconstruction technology, using a given set of facial images and corresponding 2D structural points for modeling [26]. Fuqing Duan et al. proposed a craniofacial reconstruction method based on regression modeling by constructing statistical shape models for the skull and the face, respectively, and extracting the relationship between them in the shape parameter space by partial least squares regression (PLSR) [27]. Yu, Z. et al. studied and designed a humanoid robot face based on an active driving point model that can generate human-like facial expressions to enhance the interaction experience between robots and humans [28]. Chun-Yang Tseng et al. used non-contact scanning technology to construct 3D face models, and applied principal component analysis (PCA) to reduce data complexity and retain sufficient data variance. Subsequently, a parametric model was constructed based on linear regression and Kriging, which correlated the coordinates of the grid points on the face model with a set of feature parameters in order to efficiently generate a 3D facial geometry that approximated that of the individual user [29]. Muhammad Aurangzeb Khan et al. put forth a multi-model AAM framework (MM-AAM) for the modeling of face images. By constructing corresponding component models and model matrices for each cluster, the modeling accuracy of traditional AAM was enhanced, particularly when confronted with previously unseen input face images [30]. Yan Luximon et al. proposed a methodology for the generation of a homology 3D head and face model utilizing 3D point cloud data obtained from the SizeChina survey. Anatomical and virtual landmarks were employed in the construction of the model, and a surface modeling algorithm based on point cloud data was utilized [31]. Xin Geng et al. discussed the modeling of facial images with missing values using a multi-linear subspace analysis method, and proposed a new method for representing and classifying facial images using tensor theory and pattern multiplication [32]. Song et al. presented a three-camera-based method for 3D face modeling. By combining active appearance model (AAM) and principal component analysis (PCA) techniques, facial shape and texture information was extracted from multi-view images to achieve accurate 3D face reconstruction [33]. Ying Zheng et al. proposed a data-driven approach to 3D face modeling, conducted via near-infrared (NIR) images and learning. By employing near-infrared (NIR) images and depth images of a select number of known faces, it is possible to observe the mapping relationship between the two image modalities. Subsequently, the mapping correlation can be utilized to recover the depth data of an uncertain face from the NIR image [34]. Alexandru-Eugen Ichim et al. discussed the physics-based facial modeling and animation technology, analyzed the complex connection between bones and muscles, and skin, and implements physics-based simulation to support a variety of advanced facial animation effects [35]. Wei Jiang et al. discussed 3D facial modeling technology based on hand-drawn sketches, studied how to cluster point clouds based on hand-drawn sketches to extract facial feature points to construct the basic shape of the face. A 3D facial model of a virtual character was automatically constructed from a simple sketch drawn by the user [36].

Figure 5. Real-time customized simulation of Peking Opera masks. [10]

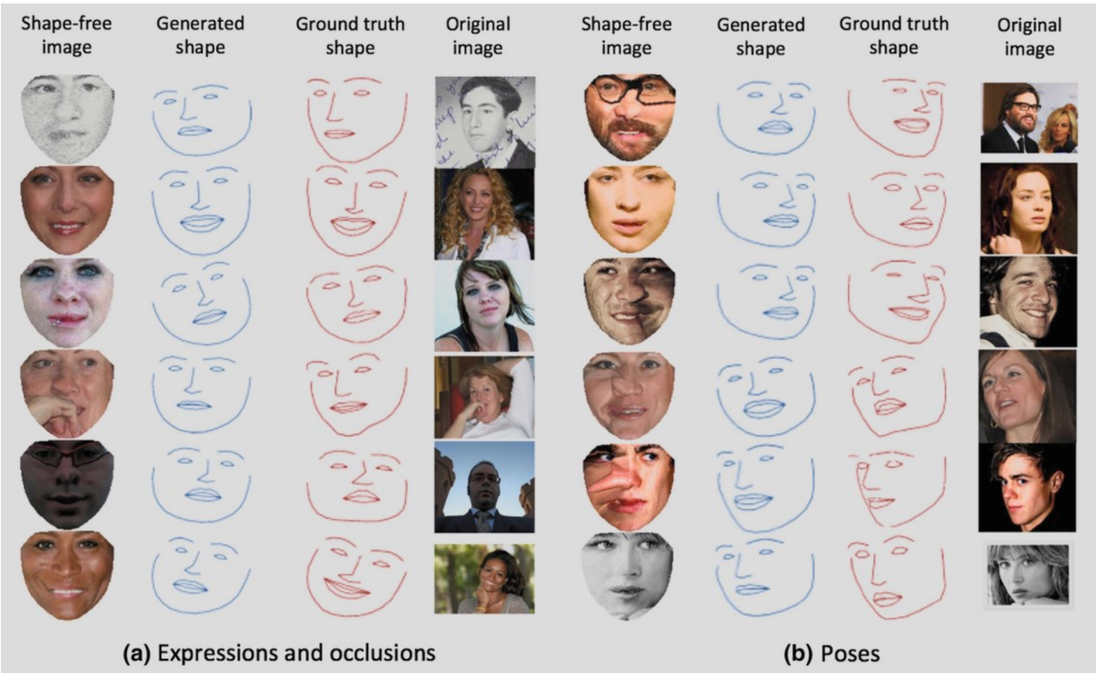

Figure 6. Generation of facial features utilizing texture data. [13]

4. Image-based Modeling

Image-based modeling approaches employ single or multiple two-dimensional (2D) images as input to reconstruct three-dimensional (3D) face models. Techniques such as shape-from-shading, shape-from-profile, and texture mapping are utilized to achieve this. These methods offer the advantage of being less reliant on specialized hardware and can be applied to readily available image data. However, the

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accuracy and realism of the reconstructed 3D models can vary depending on the quality and quantity of the input images.

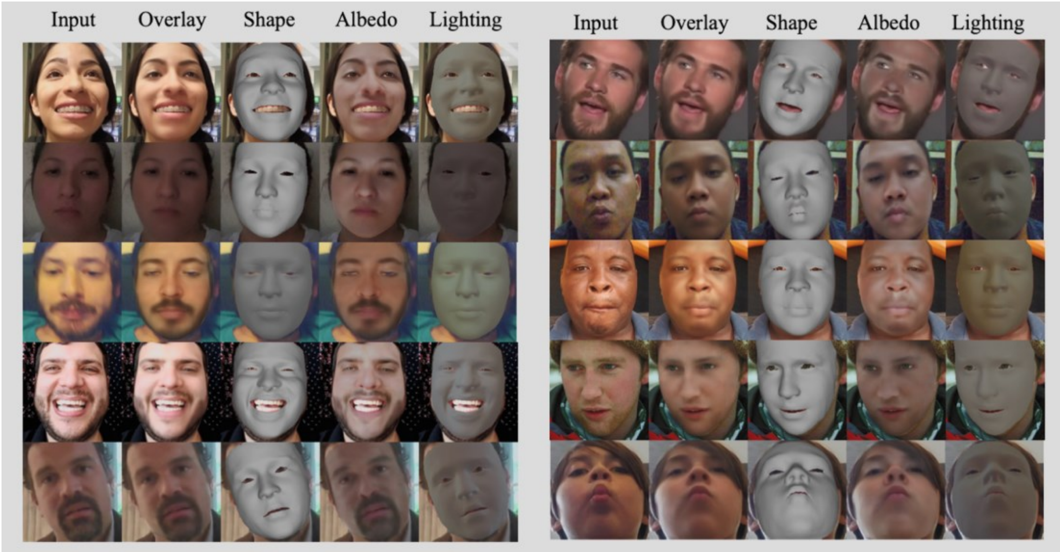

Figure 7. Different results of the JNR method. [22]

Zhenyu Zhang et al. presented a new framework, Physically-guided Disentangled Implicit Rendering (PhyDIR), for highly accurate 3D face modeling that guarantees the features of 3D-aware perception and realistic image generation [37]. Weilong Peng et al. developed a method for precise geometrical consistency modeling on the B-spline parameter field, which enables the generation of accurate facial surfaces from a range of images [38]. Dan Zhang et al. put forth a novel approach to 3D face modeling, whereby a new 3D face model is constructed from a low-dimensional feature space comprising a vast array of blend shapes. This is done under the principles of discrete shape space theory [39]. Abdallah Dib et al. proposed a novel method for modeling 3D faces from monocular images. This approach addresses the challenge of de-entangling facial and scene parameters through parametric ray tracing and explicit separation of facial geometry, reflectivity, and self-shadowing [40]. Hai Jin et al. introduced a novel three-dimensional face modeling and construction solution that is effective in acquiring three-dimensional face models from several images taken with a smartphone camera, with the capability of producing precise and robust results. [41]. Hu Han outlined a methodology for constructing a 3D face texture model from uncalibrated frontal and lateral face images, encompassing landmark localization and shape alignment between the two image sets [42]. Li Li et al. proposed a method for generating realistic wrinkles on a 3D face model based on face images, which includes image preprocessing, automatic extraction of wrinkle curves, and wrinkle generation on the 3D surface [43]. Jingu Heo et al. proposed a method for fast 3D face modeling using frontal and lateral face images, aiming to accurately synthesize face images in different 2D poses. The frontal and lateral face images were combined into a single 3D face model through scale and rotation normalization [44]. Yong Sun Kim et al. proposed a novel algorithm that used a single pair of color and time-of-flight (TOF) depth images to achieve realistic 3D facial modeling by using facial features in the color image and geometric information in the depth image, combined with a general deformable model [45]. S. Chung et al. explored 2D/3D virtual facial modeling techniques based on statue facial images and real human facial images, aiming to synthesize virtual sculptures that retain both the appearance of statues and the facial structure of real people [46]. Hongjun Zhao et al. presented a 5G virtual reality binocular stereo vision technology. Following the collection of numerous sets of facial image data and correction thereof using an image correction process, the graph-cut aligning method was selected to align the collected data sets and generate a multi-angle parallax map of the face [47]. Hong Song et al. proposed an efficient technique to build a textured 3D face model by processing videos containing a face rotating from the front to the side. After the user specified the eye corners and chin position with two clicks, the system automatically generated a realistic 3D face model [48]. Nguyen and Hoang Thanh discussed the technology for personal 3D face mapping and identification in video networks. They analyzed the relevant algorithms and system design and improved the accuracy and reliability of face recognition systems [49].

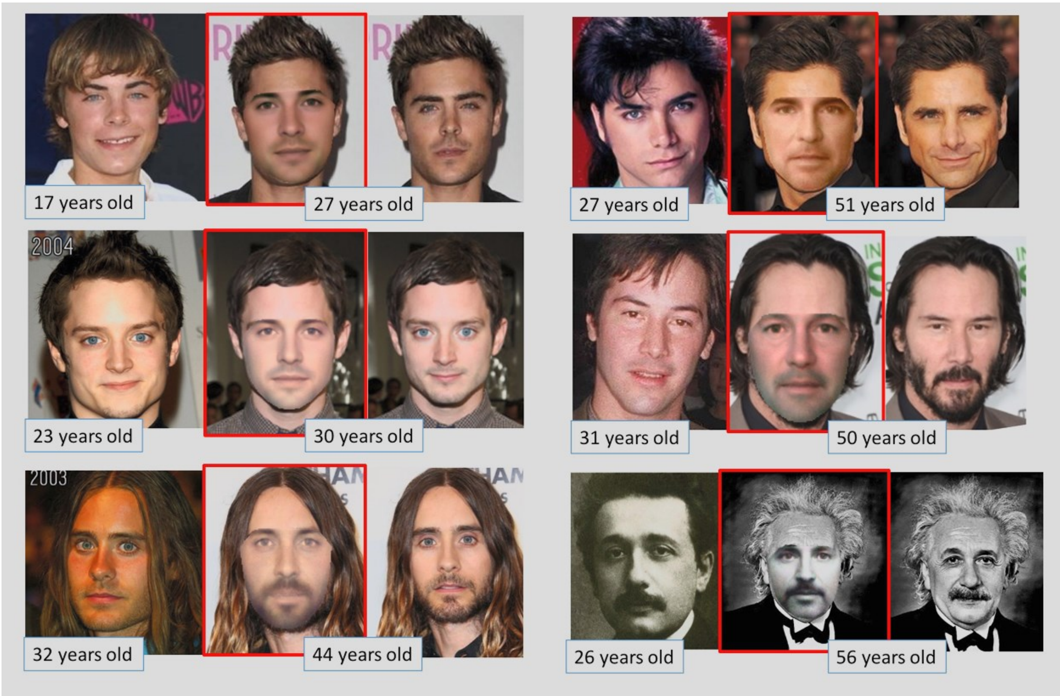

Figure 8. Examples of age progression using the Deep Restricted Boltzmann approach. [23]

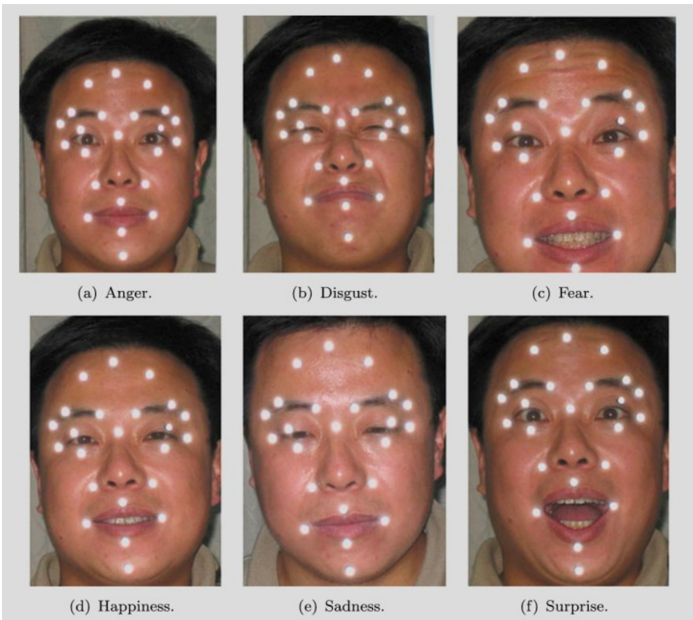

Figure 9. Six emotions and their characteristic points. [28]

5. Geometry-based Modeling

Geometry-based modeling is a fundamental approach in 3D face modeling, employing sophisticated techniques such as laser scanning, structured light, and multi-view stereo vision. These techniques facilitate the acquisition of highly precise facial geometry data, which is essential for attaining realistic 3D face reconstructions. However, they frequently necessitate the use of specialized hardware and may be constrained by factors such as environmental conditions and subject cooperation, which can limit their applicability in certain scenarios.

Figure 10. Evaluation of various approaches on their stability to rotation and relighting. [37]

Chengchao Qu et al. utilized the geometric properties of rotation constraints and implemented the Newton method on the rotation manifold to address the constraints within the optimization problem. This approach was employed to recover the 3D structure and motion of human faces in 2D image sequences through a probabilistic model-based study [50]. Vandana D. Kaushik et al. presented a discussion of the geometric modeling methods of 3D facial features and their applications, introduced the methods of segmenting specific regions (such as eyebrows, nose, and lips) from 3D facial data, and discussed the applications of these features in subsequent processing [51]. Chih-Hsing Chu et al. proposed a computer-based method for the custom design of eyeglass frames, which aligns with the concept of human-centered design by integrating parametric face modeling. This approach improves the utility of 3D human data by providing a framework for personalized eyewear design [52]. Hwang Jinkyu et al. discussed the use of the Multi-Deformable Method for 3D face modeling. By comparing the traditional multi-resolution spline stitching method with the gradient domain image stitching method, the performance of different overlap widths was evaluated [53]. Shaun Canavan et al. discussed a component-based 3D face sketch modeling and evaluation method, and proposed an effective facial component segmentation method that can be applied to the construction of 3D face models, which used a physical-anatomical model to analyze and synthesize facial image sequences to support the generation of 3D face sketches [54].

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Figure 11. Varied outcomes of face expression modification in facial photographs. [39]

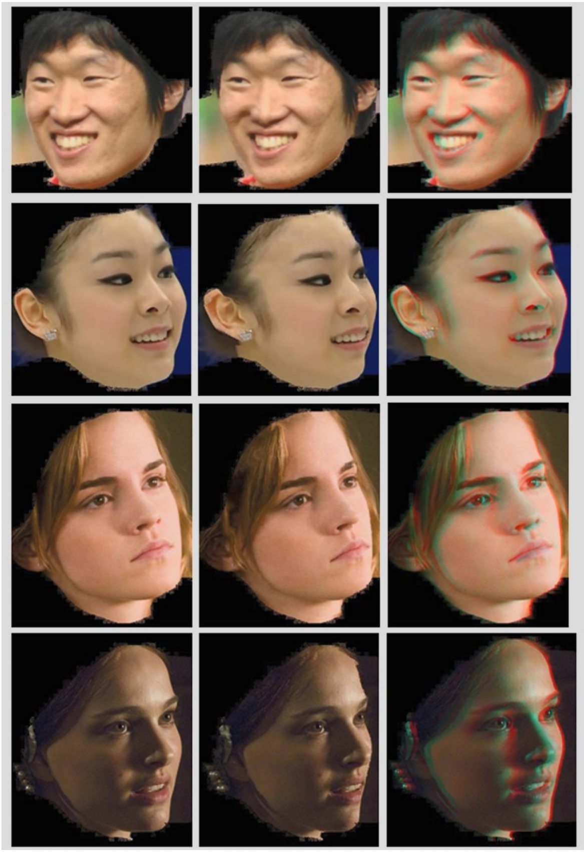

Figure 12. Generated stereoscopic view for 3D display. [46]

6. Scanning and Sensor-based Modeling

3D scanning technology is used to construct a 3D model of an object by using a physical device to capture 3D coordinate information about the object's surface. In face modeling, this usually involves using high-precision 3D scanners such as structured light scanners, laser scanners, or stereo vision systems. The 3D model is reconstructed by taking images of the face from different angles with multiple cameras and using computer vision algorithms to calculate the parallax between the images. This method is more common in consumer-grade applications, such as the 3D selfie function on smartphones. In addition, sensors play a key role in 3D face modeling, and they are not only used for data acquisition but may also be used for real-time tracking and dynamic modeling. Depth cameras: such as Microsoft's Kinect, can directly measure the depth information of points in the scene to quickly generate 3D point cloud data. RGB-D cameras: combining the functions of traditional RGB cameras and depth sensors, they can simultaneously acquire color images and depth information, providing a richer data source for 3D face modeling.

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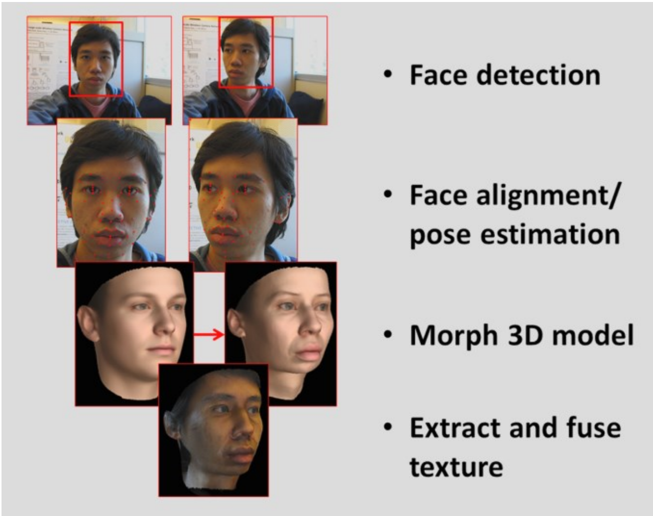

Figure 13. Overview of the Video Network system. [49]

Changwei Luo et al. proposed a method for effective three-dimensional (3D) face modeling and monitoring. This approach enables the generation of precise 3D face models from an RGB-D image or a sequence of images, and it also allows for the stable tracking of the face, despite the individual's wide range of head rotations and a variety of facial expressions [55]. Jia Li et al. introduced a personalized 3D facial modeling method based on deep detection and image processing technology. The intermediate results were optimized by applying traditional features with muscle constraints and mesh deformation, resulting in a 3D facial model that more accurately reflects individual characteristics [56]. Yanhui Huang et al. put forth an adaptation algorithm based on region information for the efficient reconstruction of a face model from a 3D face scan. This approach enables the representation of the individual facial shape under different expressions and the establishment of a dense correspondence for the entire facial expression sequence [57]. Pavan Kumar Anasosalu et al. proposed a method for real-time generation of compact and accurate 3D face models using an RGB-D camera, and solved the shortcomings of traditional methods in terms of computational complexity and model compactness [58]. Qi Sun, Yanlong Tang et al. introduced a new three-dimensional super-resolution method based on the compressive sensing (CS) technique for the reconstruction of detailed facial models from the low-resolution data obtained by the Kinect device. The objective was to obtain compressed data for storage and then generate high-resolution images [59]. Gregory P. Meyer et al. addressed the potential of ordinary depth cameras for real-time 3D face modeling. By employing the ICP algorithm and vertex mapping technology, an accurate 3D reconstruction of the face was achieved [60]. Matthias Hernandez et al. investigated a method for 3D facial modeling using a low-cost depth camera and compared it with a commercial laser scanning system. The study validated the efficacy of the technique in capturing the depth of the hair region and evaluated the accuracy of the resulting model [61]. Jongmoo Choi et al. put forth a methodology for monitoring the three-dimensional head motion of a user in real time via a webcam and for generating an accurate textured face model by employing a generic three-dimensional face model and a real-time three-dimensional face tracking and modeling system. The system is comprised of three principal modules: preliminary 3D model matching, 3D head tracing, and repetition of the acquisition process [62]. Won Beom Lee et al. proposed a method for efficiently creating realistic 3D face models on smartphones, which automatically extracted facial features and used the ACM and deformable ICP methods to generate corresponding 3D models, and then mapped skin texture maps [63].

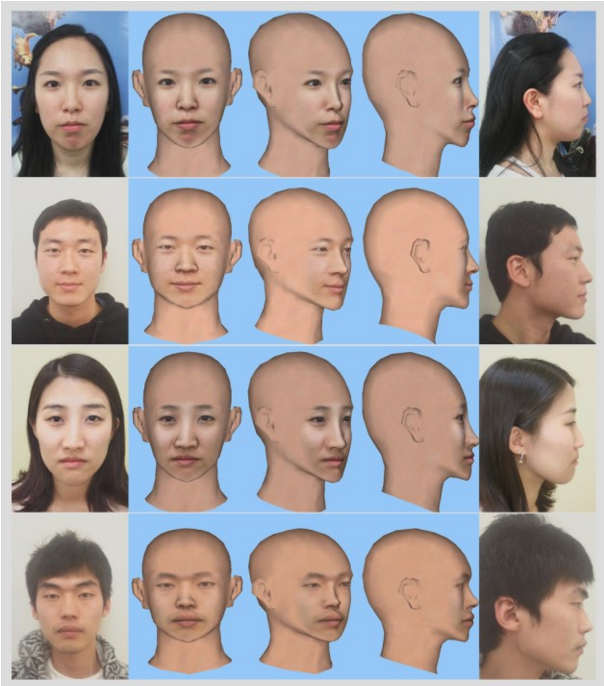

Figure 14. 3D face models for several test samples on a smartphone. [63]

7. Discussion

Three-dimensional face modeling methods based on deep learning offer notable advantages in terms of automation, flexibility, and generative ability. However, these methods have high data and computing resource requirements, as well as model complexity and unstable training. Traditional methods are characterized by robustness, accuracy, and technical maturity; however, they are costly, computationally complex, and have limitations in terms of flexibility and scalability. Nevertheless, both can generate high-quality faces. To facilitate comparison of the aforementioned methods, Table 1 provides a summary of representative methods in each category, along with a listing of the advantages and limitations of each method.

Table 1. Advantages and limitations of different types of 3D face modeling method.

Types of Methods			Advantages	Limitations
Methods with deep learning	CNN	Lightweight convolutional neural network (LW-CNN) [8]	Fewer parameters, high computational efficiency, strong feature extraction ability and high flexibility	Limited feature expression ability, high hardware requirements, difficult optimization, and possible “small sample” problems
	GAN	3D face reconstruction from 2D images [1]	Strong generative ability, adaptive learning, strong generalization ability, potential space exploration	Unstable training, hyperparameter sensitivity, difficult to evaluate, poor model interpretability

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Table 1. (continued)

	Weakly-supervised learning and unsupervised learning	Weakly-supervised Disentanglement Network [3]	Reduced dependency on expressive annotations, improved ability to untangle identity and expression, improved performance with the introduction of neutral library modules	Requirements for data quality, model complexity and computational cost, adaptability to specific tasks to be verified
		Novel Neural Proto-face Field (NPF) for unsupervised 3D face modeling [4]	Strong reconstruction ability, improved identity consistency and untangling ability, outperforms supervised methods, broad applicability	Vulnerable to identity changes, input restrictions, performance dependent on data, computational resource requirements
	Facial expression modeling	An improved version of the 3D Morphable Model (3DMM) [6]	Flexibility and controllability, improved accuracy, no neutral expression, robustness, dynamic expression modeling	Computing costs, data dependency, rendering fidelity and hardware requirements
	Multi-perspective and multi-modal learning	3D face modeling from multi-view images [33]	Significant advantages in improving model accuracy and robustness	High equipment requirements, complex data processing, synchronization issues, and environmental constraints
		3D face modeling and tracking from RGB-D images [55]	Significant advantages in robustness, accuracy, and expression modeling capabilities	High computational complexity, strong dependence on depth data, model generalization capabilities to be verified, and tedious parameter tuning
Traditional Methods	Statistical-based Modeling	Adaptive skinning model (ASM) [5]	Excels in providing high capacity, flexibility and semantic control	Faces challenges such as long inference time, dependence on initial settings and model complexity
		3DMM-RF(3DMM-Radiance Fields) [6]	Controllability and flexibility, high-quality rendering, efficient learning	Data dependency computational complexity model generalization ability

Table 1. (continued)

Image-based Modeling	3D face modeling using multi-perspective face images [44]	Efficient and fast, no complex hardware or calibration required, overcomes the problem of insufficient depth information, applicable to a wide range of situations	Dependent on image quality, insufficient adaptability to specific faces, limitations of texture mapping
Scanning and Sensor-based Modeling	Face modeling based on Kinect [25]	High precision, real-time performance, robustness and simplified modeling process	Hardware cost, measurement range and accuracy limitations, sensitivity to materials and colors, and data processing complexity
Geometry-based Modeling	B-Spline surface reconstruction [26]	High parameter efficiency, accurate local information registration, local deformation constraints, flexible mesh generation and refinement, suitable for a limited number of images	Less reliance on large amounts of image data, insufficient realism of depth information, sensitivity to noise

8. Conclusion

This paper presents a review of the existing literature on both deep learning and traditional methods for three-dimensional face modeling. Deep learning approaches offer exceptional adaptability, extensively automated feature extraction, and formidable generative powers. Although new techniques have been introduced, traditional approaches remain significant in many applications because of their strong resilience, precise accuracy, and well-established technology. The progress of deep learning technology, along with the accessibility of superior data sets and computational resources, has resulted in the development of more lifelike and resilient synthetic faces. These developments have the potential to expand the range of their applications in domains such as virtual reality, biometrics, and medical imaging. The future development of 3D face modeling is expected to involve the merging of deep learning methods and traditional methods. The goal is to combine the strengths of both approaches to improve the efficiency, accuracy, and applicability of modeling. By engaging in continuous research and invention, it is possible to tackle and surpass current technological constraints.

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