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The Role of Artificial Intelligence in 3D Development – Facial Reconstruction of Skull Bones as a Forensic Investigation Solution: A Comprehensive Review

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ABSTRACT

Forensic facial reconstruction plays a pivotal role in identifying unknown individuals based on skeletal remains, especially when traditional methods like dental records or DNA analysis are not viable. Recent advancements in artificial intelligence (AI), particularly in 3D facial reconstruction, have greatly enhanced the accuracy and efficiency of this process. AI-driven techniques, such as Convolutional Neural Networks (CNNs) and Three-Dimensional Deep Learning (TDD), have revolutionized facial reconstruction by analyzing and predicting tissue depth, facial morphology, and skeletal structure. This paper explores the integration of AI in forensic facial reconstruction, with a focus on methodologies like Stable Diffusion XL and FLAME models, which have improved anatomical precision in generating 3D facial structures. Furthermore, the research investigates how biological profiles (age, gender, and race) influence facial reconstruction and compares existing methods in terms of visual appearance and geometric accuracy. Despite the progress made, challenges remain, such as the variability in soft tissue prediction and limited forensic datasets. This study concludes that AI-based 3D facial reconstruction is an effective tool for forensic identification and highlights the need for future research to refine models and ex.

Introduction

Forensic facial reconstruction is a crucial method in identifying unknown individuals based on their skeletal remains. (Tyrell, Andrew J., Evison, Martin P., Chamberlain, Andrew T., Green, Michael A., 1997). Traditional forensic identification methods, such as dental records and DNA analysis, may not always be applicable, particularly when dealing with incomplete or severely degraded remains. This is where AI-driven 3D facial reconstruction plays a significant role in forensic investigations. (Mao et al., 2022; Tjahyaningtijas et al., 2018).

The advancement of AI and machine learning has enabled significant progress in reconstructing facial structures from skulls (Mao et al., 2022). Techniques such as Convolutional Neural Networks (CNNs) and Three-Dimensional Deep Learning (TDD) have been widely applied to improve accuracy and efficiency in reconstructing facial features. Additionally, the use of Stable Diffusion XL and FLAME models in generating

3D facial structures has revolutionized forensic facial reconstruction by offering a more detailed and anatomically precise approach (Diao et al., 2024; La Cava et al., 2023; Mao et al., 2022)

In the past two decades, researchers have studied computer-aided skull reconstruction algorithms to generate 3D faces. They access problems from a variety of perspectives and multidisciplinary backgrounds, from data to physical simulations, thus providing a solid research foundation. (Rinchon S et al., 2018; Sertalp et al., 2024). By incorporating AI-driven methods, forensic experts can generate highly accurate facial reconstructions, increasing the chances of successful identification. The integration of AI in 3D modeling has not only enhanced forensic investigations but also expanded applications in anthropology, archaeology, and historical research. (Thurzo et al., 2021; Tyrell et al., 1997). . Facial reconstruction using AI can be done using a variety of methods. Two commonly used methods are Convolutional Neural Networks (CNNs) and Three-Dimensional Deep Learning (TDD). The main contributions in this study are: (1) Incorporating biological profiles in skull reconstruction to the face. (2) Analyze how the tissue depth distribution on the face. (3) Compare existing methods, both qualitatively (visual appearance) and quantitatively (geometric measurements) (La Cava et al., 2023; Mao et al., 2022). This paper aims to explore the methodologies used in AI-driven facial reconstruction and evaluate their effectiveness in forensic identification.

Literature Review

Artificial Intelligence in 3D Facial Reconstruction

The application of AI in forensic facial reconstruction has significantly improved the accuracy and efficiency of the process. Convolutional Neural Networks (CNNs) have been widely used to analyze and reconstruct facial structures by learning patterns from large datasets. (You et al., 2023). CNN architectures such as VGGNet, ResNet, and Inception Net have been employed to identify facial features and predict tissue depth based on skeletal morphology (Mao et al., 2022).

Another key AI technique used in facial reconstruction is Three-Dimensional Deep Learning (TDD), which focuses on reconstructing facial depth through neural networks trained on anatomical and forensic datasets. TDD allows for more accurate predictions of tissue depth and facial morphology, leading to more realistic reconstructions (Diao et al., 2024; Nguyen et al., 2022). The use of tissue depth modeling between facial components and the shape of facial bones will influence performing facial reconstruction. Modeling like this will first look at the combination of tissue depth to make a good estimate in performing facial reconstruction, especially on the shape of the face. This estimation of tissue depth modeling can be assisted by using Tissue Depth Distribution (TDD) (Dong, 2024; Liang et al., 2024).

There are several approaches and algorithms used to determine age, race, and gender using AI, one of which is Convolutional Neural Networks (CNNs). CNNs are a type of neural network that is often used to analyze images because they are considered very effective (Galzi & Mullins, 2016). This type of AI can automatically detect important features or aspects present in an image without requiring extensive image processing and without requiring long image processing times. The widespread use of CNNs in computer vision is indicated by the many architectures that have been developed for several problems. Here are some of the CNN architectures that are often used: (1) VGGNet, (2) ResNet, and (3) Inception Net (Berar et al., 2006; Galzi & Mullins, 2016; Lium et al., 2021). Conceptually, VGGNet is used to classify images and has very complex feature detection capabilities. ResNet is used to build networks that have a high level of complexity without the problem of vanishing gradients. Finally, Inception Net is used to combine multiple filter kernel sizes on the same layer.

CNN consists of two main stages, namely feature learning and classification. In the feature learning stage, it consists of a convolution layer, ReLU (activation function), and a pooling layer, while in the classification stage, it consists of a flattened, fully connected layer, and prediction. In each section of CNN, there are two main processes, namely feedforward and backpropagation. (Achmad et al., 2019).

Feature learning is a process that functions to obtain effective and useful information to distinguish different faces of people from the image of a face that has been harmonized. Classification is carried out to find out whose face is contained in the image. The classification process is carried out by comparing the value of the image in the database (classifier) with the input image data being tested. Similar trait values will be classified into the same class (Dewi & Ismawan, 2021).

The limitation of CNN modeling in 3D modeling is that there is a 3D space determined by the base of the face model or template, as a result of which it cannot maintain a low error value in increasingly complex poses (Achmad et al., 2019; Dewi & Ismawan, 2021).

3d Facial Reconstructions in Forensic Science

3D facial reconstruction has become an essential tool in forensic investigations, allowing for the recreation of an individual's appearance based on skeletal remains. This technique has evolved over the years, shifting from manual clay modeling to computer-assisted reconstructions powered by artificial intelligence. (Thurzo et al., 2021).

According to Rinchon (2018) Early 3D facial reconstruction methods relied on anthropological standards and manual sculpting techniques. However, these traditional methods were highly dependent on the expertise of forensic artists and often lacked accuracy due to individual biases in interpretation. With technological advancements, digital reconstruction methods incorporating AI have emerged as a more objective and reproducible approach. In general, the process of making 3D Facial Reconstruction has three components, including: (1) Tissue Depth Distribution (TDD), (2) Initial Face Generation, and (3) Anatomy-Guided Face Adaptation. Detailed illustrations are presented in Figure 1 (Liang et al., 2024).

Based on Figure 1, it can be seen that the initial stage in making 3D Facial Reconstruction is TDD Modeling by analyzing the network depth distribution on the training set so that valid combinations can be obtained for the skull. After that, two other stages were continued, namely the Initial Face Generation Stage and the Anatomy-Guide Face Adaptation (Liang et al., 2024; Nguyen et al., 2022). In the Initial Face Generation Stage, it is necessary to utilize the main biological profiles, such as gender, age, and breed using Stable Diffusion XL to obtain a 2D facial reconstruction portrait, which will then be converted into 3D using the FLAME model. The last stage is to modify the 3D face by the limitations of facial landmarks according to anatomical guidelines (Fishman et al., 2021; La Cava et al., 2022).

The TDD by Liang (2024) The method uses 78 landmarks on the face that help in determining the distribution of tissue depth to perform facial reconstruction. Principal Component analysis (PCA) to project the distribution points of the 78 Landmarks, was used to determine the depth of the network on the face. It was found that the variance was 51.9% which made a reduction in the degree of freedom for the combination of 78 landmarks in the determination of network depth. The next process is to adjust the distribution value by selecting the average value from the top, bottom, and middle sides of 33% of C, as a representative value to perform a combination of network depth and visualize it. (Thurzo et al., 2021).

At this stage, the displacement between the face marker and the skull marker is determined. This is done to determine the accuracy of facial reconstruction and reduce errors when performing reconstruction. Distribution patterns are also used to facilitate facial reconstruction to further adjust the depth of the tissue to explore various realistic faces on the skull. (Berar et al., 2006; Galzi & Mullins, 2016; Liang et al., 2024).

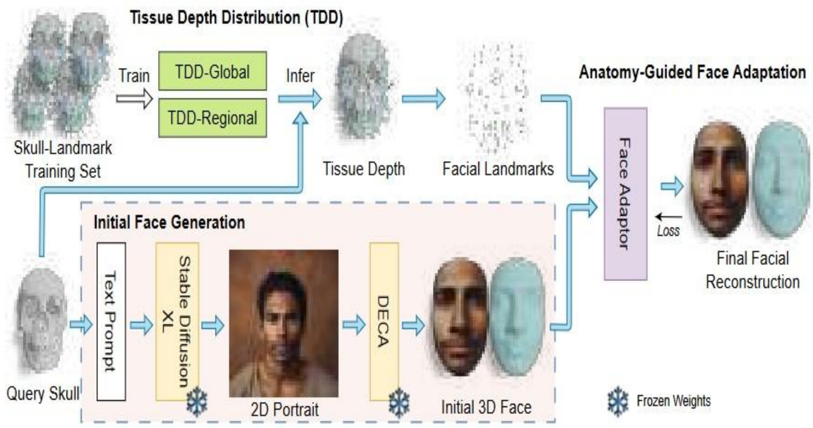

Figure 1
Illustration of 3D Facial Reconstruction making that includes three (Liang et al., 2024)

Principle Component Analysis (PCA) is used to project the combined distribution of network depth from an n-dimension to a lower dimensional space. Generally, the first major component will set up a network depth distribution of 51.9% of the variance which is used to significantly reduce the degree of freedom for the j78 network/landmark depth combination (Tjahyaningtijas et al., 2018). The projection of the depth of the joint tissue to the axis of the first component, denoted as C. After the tissue depth projection is carried out, the depth of the tissue will automatically change from short to long, and the shape of the skull that was initially thin because it is still in 2D form will change to round (3D). Representative Values and Changes in Face Shape are illustrated in Figure 2 (Fishman et al., 2021; Liang et al., 2024).

It should be noted that not infrequently in cases found in the field, tissue depth modifications do not result in unrealistic facial shapes. This is influenced by the distribution of joints in different individuals, so detailed facial editing is required and significantly improving editing capabilities (Liang et al., 2024; S et al., 2018).

Global TDD modeling in reconstruction faces experience limitations when determining facial landmarks in a certain group or region (Liang et al., 2024; Thurzo et al., 2021).

In initial face generation, this stage produces a face beginning that is appropriate to the characteristics population that has been determined, age, gender, face shape, and race. Used Stable Diffusion XL software to produce 2D images with high resolution (Galzi & Mullins, 2016).

After obtaining a 2D image that is considered appropriate, the image is synthesized into a 3D face image using DECA. At this stage, the image is encoded into latent space, the aspects that are considered are shapes, expressions, poses, and albedo codes (color classification), which are then represented using FLAME. (Andersson & Valfridsson, 2005; Fishman et al., 2021).

In anatomy-guided face adaptation, at this stage, the appropriate vertex index is manually marked on one face as a consistent facial landmark across the resulting faces. After that, an initial transformation estimate is carried out by estimating the H transformation by doing a rough registration between the initial face landmark (Qf_in) and the target landmark (Pf). This process involves optimizing Procrustes to estimate scaling, rotation, and translation parameters from H. (Dong, 2024; Liang et al., 2024).

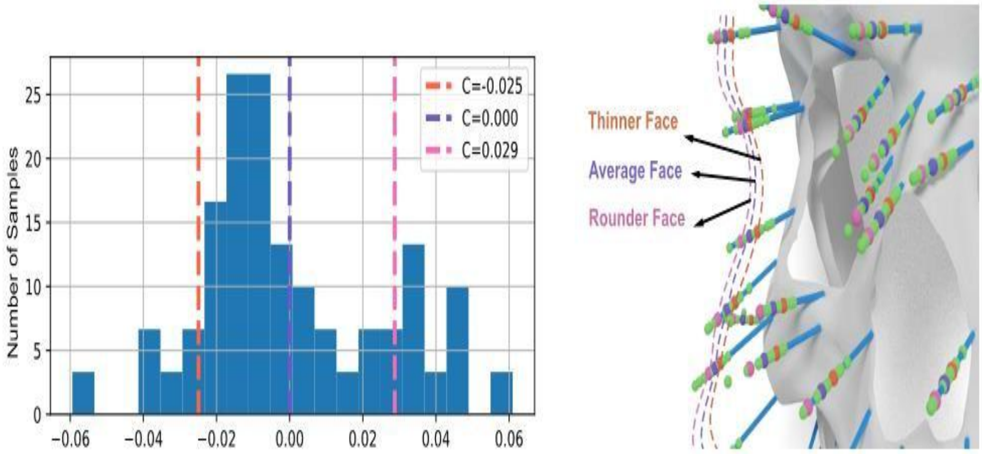

Figure 2
(a) Representative Values of the First Major Component Visualized; (b) Changes in Facial Shape (Liang et al., 2024).

Furthermore, the latent code (f) optimization is carried out by minimizing the objective function (L) which consists of three main components, namely: landmark loss (Llmk), projection loss (Lproj), and Symmetry Loss (Lsym) (Diao et al., 2024; La Cava et al., 2023).

Landmark Loss is used to measure the deviation between the aligned landmark (Pf) and the landmark of the resulting face. Projection Loss is used to improve the accuracy of registration from the face geometry to the target landmark by projecting the target landmark onto the reconstructed face and minimizing the Euclidean distance between these landmarks. (Mao et al., 2022). Symmetry Loss is used to encourage the resulting facial symmetry by dividing the facial landmark into three parts, namely left, center, and right, and measuring the Euclidean distance between the actual midpoint and the expected part of the reflected left and right landmarks. (Dong, 2024; Liang et al., 2024).

The Euclidean distance is one of the methods used to measure the distance between two points in Euclidean space. In the concept of geometry, this distance is the length of a straight line that will connect the two points. (Deng et al., 2024). The use of this euclidean distance is often used in computer graphics planes to render 3D images on 2D screens. At this stage, the face will be modified to the maximum so that a 3D image will be produced that is more by the specified facial landmarks. In addition, it ensures a good level of symmetry and geometric accuracy. (Gandhi et al., 2024).

The application of Artificial Intelligence in the 3D facial reconstruction of skull bones is very effective in helping forensic identification. The stages carried out in the reconstruction process include Tissue Depth Distribution (TDD), Initial Face Generation using Stable Diffusion XL and FLAME, and Anatomy-Guided Face Adaptation to improve the accuracy and symmetry of the face so that it gets more realistic results and can be an accurate and efficient solution in identifying victims. (Andersson & Valfridsson, 2005; Deng et al., 2024).

Despite its advancements, AI-based 3D facial reconstruction still faces challenges. One of the primary limitations is the accuracy of soft tissue prediction, which varies among individuals due to genetic and environmental factors. (Galzi & Mullins, 2016). Additionally, while CNNs and TDD methods have improved reconstruction precision, the lack of extensive forensic datasets limits their generalizability. Future research should focus on improving dataset diversity and developing hybrid AI models that integrate multiple approaches to enhance reconstruction accuracy. (Gandhi et al., 2024; Rinchon S et al., 2018)

Conclusion

AI-driven 3D facial reconstruction has emerged as a highly effective tool in forensic investigations, providing a more accurate and efficient method for identifying individuals from skeletal remains. Techniques such as Convolutional Neural Networks (CNNs) and Three-Dimensional Deep Learning (TDD) have significantly enhanced the precision of facial reconstructions by predicting tissue depth and facial morphology based on skeletal data. The integration of models like Stable Diffusion XL and FLAME further contributes to generating anatomically precise 3D faces, improving the accuracy of forensic identifications. While there are challenges, such as the variability in soft tissue prediction and the need for more extensive forensic datasets, the advancements in AI technologies offer great potential for overcoming these limitations. Future research should focus on enhancing dataset diversity and refining hybrid AI models to increase the generalizability and effectiveness of these methods in forensic applications. Ultimately, AI in forensic facial reconstruction provides a valuable solution for improving identification accuracy and supporting investigations across various fields such as anthropology, archaeology, and historical research.

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