Face Symmentry

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July 5, 2025

Abstract

This study investigates the assessment of facial symmetry using advanced computer vision techniques. We employed MediaPipe to extract key facial landmarks, enabling precise measurement of facial asymmetry. By calculating the Euclidean distances between corresponding landmarks on the left and right halves of the face, we developed a quantitative symmetry score. Our findings indicate that quantifying facial symmetry through landmark analysis provides a reliable metric for assessing facial characteristics, paving the way for further research into its applications in various domains. This approach offers a computationally efficient method for facial symmetry evaluation, which can be utilized in real-time applications such as facial recognition and cosmetic analysis.

1 Introduction

Facial symmetry is widely regarded as a fundamental aspect of human attractiveness and plays a crucial role in social and psychological interactions. Numerous studies have demonstrated that symmetrical faces are often perceived as more beautiful. This has significant implications not only in fields like psychology and sociology but also in industries such as cosmetics, fashion, and entertainment, where appearance can impact success and opportunities.

In addition to its aesthetic significance, facial symmetry is linked to various health indicators. Symmetrical features are often associated with genetic fitness and overall well-being, making it a valuable area of study in medical and biological research. Understanding and quantifying facial symmetry can enhance the diagnostic capabilities in clinical settings, providing insights into developmental disorders or injuries that affect facial structure.

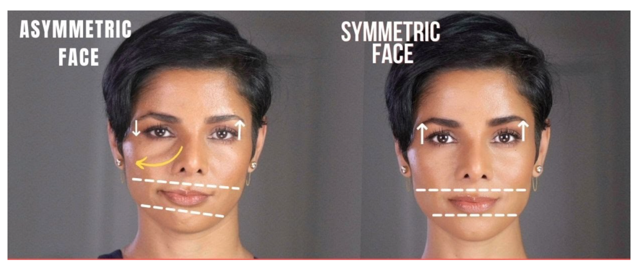

Figure 1: Symmetric and Asymmetric Face.

With advancements in computer vision technologies, quantifying facial symmetry has become more feasible. Traditional methods often rely on subjective assessments, introducing bias and variability. By utilizing automated techniques such as landmark detection and Euclidean distance calculations, this research aims to provide an objective and efficient method for assessing facial symmetry. The findings may enhance our understanding of the relationship between facial characteristics and human perception, with potential applications in facial recognition technology, cosmetic solutions, and psychological assessments.

2 Related Work

Facial symmetry analysis has been advanced by various computer vision techniques, with a significant focus on landmark detection models such as Dlib, Active Shape Models (ASM), and the more recent deep learning-based Mediapipe FaceMesh.

Dlib is a versatile library providing facial landmark detection through an ensemble of regression trees that predicts 68 landmarks on facial features. King's work in Dlib-ML highlights the library's efficiency in combining geometric relationships with machine learning to yield high landmarking accuracy on facial images [3]. However, despite its accuracy, Dlib's computational intensity and need for preprocessing limit its effectiveness in real-time applications.

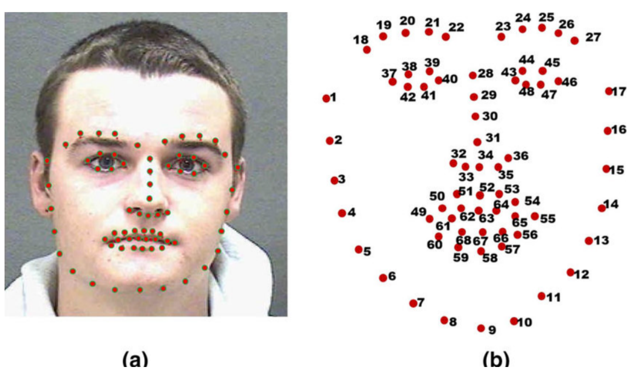

Figure 2: Dlib Landmarks.

Active Shape Models (ASM), introduced by Cootes et al. [2], provide a statistical approach for analyzing facial structures, creating a point distribution model based on a training set of annotated images. By iteratively aligning an average shape to target images, ASM effectively captures variations in facial geometry, allowing symmetry assessments. However, ASM requires extensive training data and is sensitive to variations in pose and lighting, which can impact its robustness across diverse settings.

Mediapipe FaceMesh, developed by Google, offers an advanced solution optimized for real-time landmark detection across 468 facial points. Mediapipe's deep learning architecture enables high precision and rapid processing, with applications extending to mobile and web environments where minimal latency is crucial [1]. The pipeline's efficiency makes it suitable for real-time analysis of facial symmetry, and its versatile API allows for seamless integration in various research and application contexts.

Recent deep learning methods have also expanded facial landmark detection and analysis. Zhang et al. explored a multi-task learning approach using CNNs for improved landmark precision, which combines facial alignment and feature extraction [4]. Similarly, Bulat and Tzimiropoulos investigated the use of 3D face alignment techniques to bridge the gap between 2D landmark detection and 3D facial analysis [6]. While these methods offer nuanced insights into facial geometry, they often demand high computational power and extensive datasets, limiting their applicability in real-time or mobile settings.

For a more comprehensive facial representation, 3D Morphable Models (3DMM) and deep volumetric CNNs have been employed in facial reconstruction tasks [7]. Although effective, these methods prioritize detailed geometry over computational efficiency and require robust datasets for reliable results.

Overall, while traditional models like Dlib and ASM laid the groundwork in facial symmetry analysis, Mediapipe FaceMesh emerges as a state-of-the-art tool due to its efficiency, versatility, and real-time capabilities. The implementation of Mediapipe FaceMesh in this research enables a robust framework for objective facial symmetry quantification, leveraging a codebase for streamlined analysis [8] and an extensive image dataset for validation [9]. This contributes to the ongoing advancements in automated facial analysis technologies.

3 Architecture of Mediapipe FaceMesh

3.1 Overview of Mediapipe

Mediapipe is an open-source framework designed for building efficient perception pipelines in machine learning applications. It provides a collection of customizable components for tasks such as face detection, hand tracking, and pose estimation, optimized for real-time performance across various platforms, including mobile devices and web applications.

3.2 FaceMesh Architecture

The FaceMesh module in Mediapipe employs a lightweight, convolutional neural network (CNN) architecture to detect and extract 468 facial landmarks in real time. The architecture consists of the following key components:

- **Landmark Detection Network:** The network processes input images to identify facial features, leveraging depth-wise separable convolutions to reduce computational complexity while maintaining high accuracy. The model is capable of functioning under varying conditions, including different head poses and facial expressions.

- **Facial Landmark Representation:** Each of the 468 landmarks represents specific facial features such as eyes, nose, and mouth, providing a comprehensive map of the face. This dense representation allows for detailed analyses, including facial symmetry assessments.

- **Modular Pipeline Structure:** Mediapipe's architecture is modular, enabling the seamless integration of different components such as face detection and landmark extraction. The pipeline is designed for efficient data processing, allowing for rapid inference times and minimal latency, which is critical for applications requiring real-time feedback.

3.3 Visualization Capabilities

Mediapipe FaceMesh includes built-in visualization utilities that facilitate the annotation of detected landmarks on input images. These utilities utilize connection specifications to draw facial contours, tessellations, and iris connections, providing intuitive visual feedback that enhances the interpretability of landmark positions.

3.4 Performance Optimizations

The FaceMesh architecture is optimized for mobile and edge devices, featuring model quantization and hardware acceleration options. These optimizations allow the framework to achieve high frame rates while minimizing resource consumption, making it suitable for use in real-time applications such as augmented reality and video conferencing.

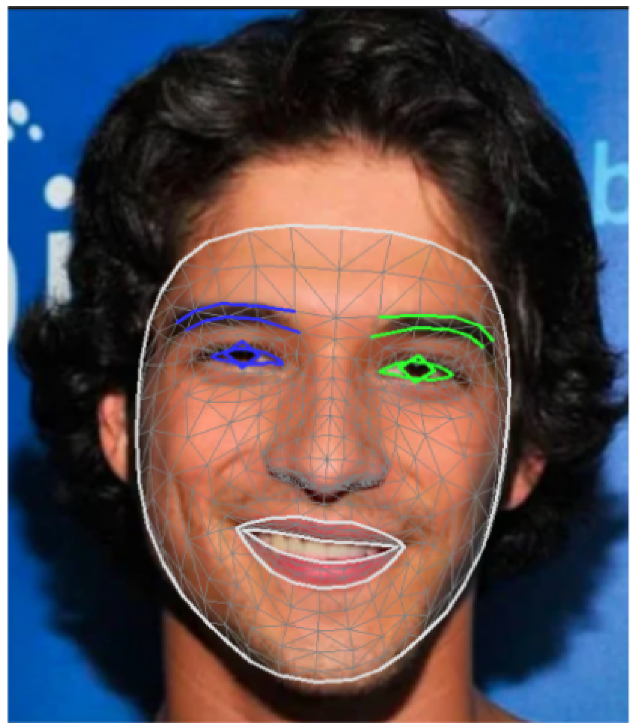

Figure 3: Facial Landmarks using MediaPipe Facemesh.

4 Methodology

In this study, we employed the Mediapipe FaceMesh framework to analyze facial symmetry through landmark detection and Euclidean distance calculations. The methodology consists of the following steps:

4.1 Data Acquisition

We utilized a set of images containing human faces, selected to include various expressions and orientations. The images were processed to extract facial landmarks, which serve as key points for symmetry analysis.

4.2 Facial Landmark Detection

Using Mediapipe's FaceMesh module, we initialized the face mesh model in static image mode with the capability to detect up to one face at a time. For each input image, we converted the color space from BGR to RGB and processed the image to detect facial landmarks. The output, which includes a list of detected landmarks, was stored for subsequent analysis.

4.3 Landmark Visualization

To facilitate the analysis, we employed a function to draw the detected facial landmarks and highlight the symmetry-related pairs. The drawing utility provided by Mediapipe allows for visualizing the tessellation and contours of the face.

4.4 Symmetrical Pair Definition

We defined specific pairs of landmarks that correspond to symmetrical features of the face, such as the outer corners of the eyes and the mouth corners. The symmetrical pairs were utilized to compute the symmetry score. The identified pairs are as follows:

- Outer corners of eyes
- Cheeks
- Jawline
- Mouth corners
- Inner eye corners
- Nostril corners
- Jaw angles
- Outer eye end

Figure 4: Symmetric Pairs.

4.5 Symmetry Score Calculation

To quantify facial symmetry, we employed a systematic approach to evaluate the spatial relationship between selected pairs of facial landmarks. Symmetrical pairs were chosen based on their anatomical significance and common facial features, which include:

- Outer corners of the eyes - Cheeks - Jawline - Mouth corners - Inner eye corners - Nostril corners - Jaw angles - Outer eye ends

These pairs were specifically selected because they are representative of key facial features that contribute to the overall aesthetic perception of symmetry. By focusing on these landmarks, we aimed to ensure that our analysis accurately reflects the facial characteristics that are typically associated with symmetric appearances.

The symmetry score was calculated by measuring the Euclidean distance between corresponding points of each symmetrical pair. The Euclidean distance is defined as:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

where (x_1, y_1) and (x_2, y_2) are the coordinates of the points being compared. In our implementation, we first determined the coordinates of each landmark from the Mediapipe output, converting normalized coordinates into pixel values based on the image dimensions.

For each symmetrical pair, we computed the distance between the left-side landmark and its corresponding right-side landmark. Additionally, we calculated the mirrored position of the right landmark across the vertical midline of the face, which is assumed to be the line of symmetry. This mirrored approach allowed us to assess the deviation of each landmark from its expected position, thereby providing a more accurate measure of asymmetry.

The symmetry score for each image was then derived as the average of the distances calculated for all defined symmetrical pairs. A lower symmetry score indicates a closer alignment of the landmarks, reflecting a more symmetrical facial structure. This scoring system not only quantifies facial symmetry but also facilitates comparisons across different images, allowing for a comprehensive analysis of symmetrical features within diverse facial structures.

Through this methodological framework, we aimed to create a robust quantitative measure of facial symmetry that can be applied in various fields, including aesthetics, psychology, and even facial recognition technologies.

4.6 Interpretation of the Symmetry Score

In our symmetry analysis, a lower symmetry score represents a higher degree of facial symmetry. This is based on the premise that symmetry is characterized by minimal deviation between corresponding features on the left and right sides of the face. By calculating the Euclidean distance between each pair of symmetrical landmarks, we obtain a measure of how closely aligned these points are with respect to an ideal vertical midline that divides the face.

The symmetry score is derived as the average of these distances, capturing the overall deviation across multiple landmark pairs. A lower score indicates that the distances between corresponding points are small, suggesting a closer alignment of facial features. Conversely, a higher symmetry score signifies greater distances between the symmetrical landmarks, which points to more pronounced asymmetries in the facial structure.

This approach aligns with the well-established notion in aesthetics and psychology that symmetrical faces are generally perceived as more attractive and harmonious. Small deviations between paired landmarks imply a balanced and proportionate face, characteristics often associated with favorable visual appeal. Thus, the symmetry score provides a quantitative way to capture these subtle differences, making it a valuable metric for objective facial symmetry assessment.

Ultimately, this low-score interpretation is advantageous because it directly corresponds to visual symmetry, offering an intuitive and robust measure for comparing facial symmetry across individuals or expressions.

4.7 Results Visualization

Finally, we displayed the processed images with the annotated facial landmarks and the calculated symmetry scores using a plotting function. The symmetry scores were printed and superimposed on the images for easy interpretation, facilitating a visual assessment of the symmetry:

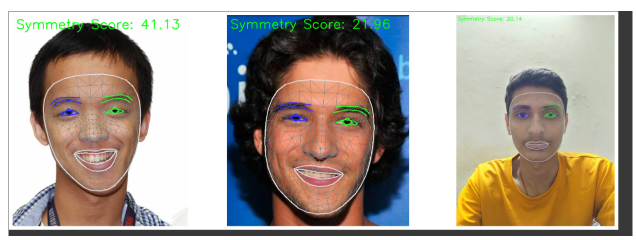

Figure 5: Final Symmetry Score.

- Rightmost face has **Symmetry Score of 41.13**
- Middle face has **Symmetry Score of 21.96**
- Leftmost face has **Symmetry Score of 20.14**

As can be seen the rightmost face in figure 5 seems to be more symmetric than the leftmost face which can be confirmed from their symmetry score. More the symmetric score , more asymmetric the face is.

5 Conclusion

This research presents a novel approach for quantifying facial symmetry using MediaPipe's FaceMesh framework and Euclidean distance calculations across selected symmetrical landmark pairs. By leveraging MediaPipe's efficiency in landmark detection and employing specific, anatomically relevant facial landmarks, we developed a robust method for assessing facial symmetry through a calculated symmetry score. Our method yields a straightforward yet effective metric, where a lower score indicates higher symmetry.

The approach has potential applications in a wide range of fields, from aesthetic evaluation to psychological studies and biometric systems, providing a quantitative framework for analyzing facial symmetry objectively. Future work could extend this research by exploring dynamic facial symmetry in real-time applications, incorporating more complex symmetry metrics, or evaluating the method's efficacy across diverse facial datasets. Overall, our findings contribute a scalable and reliable approach to facial symmetry assessment, paving the way for further exploration and refinement in computer vision and symmetry analysis.

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