Enhancing the symmetry and proportion of 3D face geometry

Qiqi Liao, Xiaogang Jin, Wenting Zeng

Abstract—We present an engine for enhancing the geometry of a 3D face mesh model while making the enhanced version share close similarity with the original. After obtaining the feature points of a given scanned 3D face model, we first perform a local and global symmetrization on the key facial features. We then apply an overall proportion optimization to the frontal face based on Neoclassical Canons and golden ratios. A nonlinear least-squares solution is adopted to adjust the feature points so that the face profile complies with the aesthetic criteria, which are derived from the profile cosmetology. Through the above processes, we obtain the optimized feature points, which will lead to a more attractive face. According to the original feature points and the optimized ones, we perform Laplacian deformation to adjust the remaining points of the face in order to preserve the geometric details. The analysis of user study in this paper validates the effectiveness of our 3D face geometry enhancement engine.

Index Terms—facial attractiveness, facial symmetrization, facial proportion, facial profile, facial geometry.

1 Introduction

The human face plays an important role in making a first impression and conveying emotion. As a result, beautiful faces are more pleasurable to look upon, as they are interpreted as implying purity and goodness. Scientific studies have corroborated the advantages of attractive faces [1].

The question of what makes a face attractive has been studied by researchers for centuries. Recent work has shown that ingredients of beauty are neither arbitrary nor culturally bound. We can achieve a high cross-cultural agreement in attractiveness ratings from perceivers of different races. For example, new born infants prefer to look at faces that adults find attractive regardless of the faces' race, gender or age [2]. In addition, people from different cultures show considerable agreement about which faces are attractive [3]. These findings raise the possibility that some standards of beauty may be set by nature rather than culture convention. In this paper, we focus on three factors that have been deemed significant in previous work: symmetrization, frontal proportion and profile adjustment. By removing facial disharmonies and fitting faces into standard ratios, we explore the possibility of enhancing aesthetic appeal of human faces.

Recently, researchers have introduced a method to enhance facial attractiveness for 2D facial images [4]. Given an input facial image, their method can generate a more attractive version using supervised learning techniques. Their technique is image-based and thus can only deal with 2D facial images and it remains unclear how the warped image can be used to enhance the geometry of a 3D model. Enhancing the 3D geometry of a given face is a different challenge. To the best of our knowledge, no published work has dealt with the attractiveness enhancement of 3D face models. The attractiveness of a 3D face is more involved than image-space techniques. The attractiveness of face is not only determined by frontal portrait, but also by the profile view, and the combination of the two. Extending data driven methods to 3D is not a viable solution since collecting and setting up a 3D training set with proper geometric resolution is too technically involved. Therefore, our approach is unsupervised and based on geometric priors. The main

Fig. 1: An example of 3D face geometry enhancement by our method. The top three images are the left profile, the frontal face and the right profile of an input 3D face model. The bottom three images are their corresponding enhanced versions.

- *Qiqi Liao, Xiaogang Jin and Wenting Zeng are with the State Key Lab of CAD&CG, Zhejiang University, Hangzhou, 310027, China. E-mail: knightliao@gmail.com, jin@cad.zju.edu.cn, zengwenting@zjucadcg.cn*

challenge in this work is to enhance the 3D geometry of a face while keeping the local characteristics of human face.

Applications. Photo retouching has become commonplace in print journalism as it taps into the natural human instinct to pursue beautiful faces. With the fast development of humanoid avatar applications, a tool for 3D face enhancement has great potential. Our tool has applications in numerous diverse fields, such as following:

3D online virtual communities. Many online virtual 3D communities and games (e.g. Second Life [5]) provide users services to model avatars resembling their real selves. Enhancing the avatars' faces with the help of our tool could expand this market because an attractive face will receive more attention in virtual world, as it would in real life. Our tool can be integrated into games as an additional feature like virtual clothing, hair, make-up and fashion accessories which are sold in the virtual shops (e.g. marketplace [6] in Second Life).

3D interactive characters in e-commerce. Facial attractiveness is very important in e-commerce, as consumers prefer to deal with good looking sales people. Large companies such as IKEA and eBay are using automated online 3D assistants to offer online support to their customers. Our tool can be employed to retouch 3D avatars in these e-commerce systems, which can help to create positive feelings towards these companies, and potentially lead to a growth of sales.

Instant 3D communication. Our tool can be used as an interesting addition to instant 3D communication technologies like video conferencing [7] and talking heads [8]. By using our tool, not only the characteristics of the users face could be kept but also a more harmonious and pleasing aesthetic appeal would be presented. Users would enjoy a relatively higher self-confidence. These technologies are now populating not just web sites but desktops, e-learning centers and mobile phones. With the inevitable increase in popularity of these technologies, the popularity of a 3D face enhancement tool is expected.

Contributions. A novel geometric enhancement framework for 3D face models is proposed. We remove facial disharmonies by enhancing frontal faces and face profiles simultaneously. Profile proportion enhancement is formulated as a new energy function and solved by a nonlinear least-squares method. We also propose a novel method to calculate the facial attractiveness score for a 3D face. The weights for symmetry, frontal proportion and angular profile proportion are obtained via a user study.

2 Related Work

Research work related to faces has attracted lots of researchers in the computer graphics and computer vision communities. These researches include face modeling and animation [9], [10], face recognition [11] and face beautification [12], [13], [4], [14].

The most relevant work on facial attractiveness enhancement mainly deals with 2D face images. Tong et al. [12] proposed a cosmetic transfer method by which the cosmetic style captured in an example-pair can be realistically transferred to another person's face. Guo and Sim [13] advanced a program of creating face make-up upon a face image with the style example of another image. Since this method modifies the color and skin details of a face whose structure remains undamaged, it is parallel to the physical making up. However, these methods are used to transfigure and paint the original image in a way without altering the contour and geometry of the facial features.

Recently, Leyvand et al. [4] proposed a data-driven approach to aesthetic enhancement of human faces while maintaining close similarity between the original and the new version. However, this beautification engine is limited to 2D face images, and it cannot be applied to 3D face models directly.

Blanz and Vetter [15] proposed a morphable model for the synthesis of 3D faces from one or more photographs. Later, Blanz et al. [16] proposed a top-down approach to 3D data analysis by fitting a morphable model to scans of faces. Kim and Choi [17] proposed a method for enhancing the symmetry of a scanned 3D face.

Mesh editing approaches based on differential representation have been prevailing in recent years [18] because they can preserve the geometric details of the surface as much as possible. Different from the traditional global Cartesian coordinates, a differential surface representation encodes the information about the local shape of the surface, the size and the orientation of local details [19]. The main principle behind these deformation techniques is to use an intrinsic surface representation to achieve an intuitive and detail-preserving deformation result by putting the local differential properties under deformation.

Different from 2D face beautification approaches, our face attractiveness enhancement engine for 3D faces is based on the principles of Neoclassical Canons, symmetry, golden ratios and the definition of facial appeal standards in cosmetology. Our method adopts Laplacian surface deformation techniques to adjust the geometry of a 3D face model so as to keep its geometrical details. As a result, we obtain a more attractive 3D face model bearing close similarity with the input face.

3 Overview

Figure 2 illustrates the geometry enhancement process of our approach. All faces in our database are without makeup, accessories, and hair. Our method begins with a scanned 3D face with both geometry and texture information. We set up a left-handed coordinate

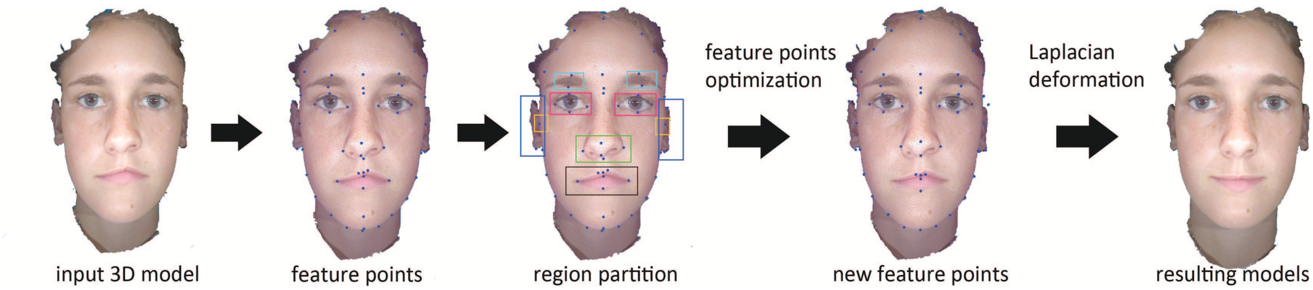


Fig. 2: Our 3D face geometry enhancement engine.

system in the face model where the positive x-axis points to the right and the positive y-axis points up. Then, we identify a set of facial landmarks (feature points) manually. According to these features, we partition the face into several facial feature regions and create symmetrical point-pairs for the face. Based on Neoclassical Canons, golden ratios, and the aesthetic criteria for face profile, we perform face symmetrization, frontal face proportion adjustment and facial angular profile proportion correction sequentially. After that, we get a set of modified feature points which will lead to a higher predicted attractiveness score than that of the input face model. We finally employ differential coordinates based deformation method to change the shape of the face model while keeping the geometric details. The effectiveness of our method is validated by a user study.

4 3D Face Geometry Enhancement Engine

In this section, after defining the attractiveness score and the feature points of a 3D face, we propose three complementary techniques for the enhancement of a 3D face model: (1) a local and global symmetrization for the key facial features, (2) an overall frontal face proportion optimization for the facial outline and internal characteristics and (3) an optimized facial profile proportion correction.

4.1 Facial attractiveness score

To enhance the attractiveness of 3D faces, it is necessary to quantify the results in term of the changes we make. We believe that both beauty rules for frontal face and face profile are very important. Therefore, we take the symmetry, frontal proportion and angular profile proportion measure as the final factors influencing the attractiveness of a 3D face. The frontal proportion factor consists of Neoclassical Canons and golden ratios. Thus, we propose the following formula to calculate the attractiveness score for 3D faces:

$$Score = w_1 \times S_{symmetry} + \\ w_2 \times S_{proportion} + w_3 \times S_{profile}, \tag{1}$$

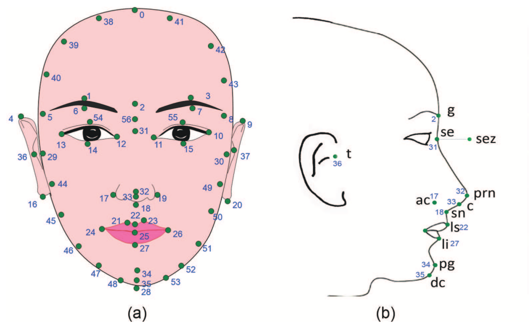


Fig. 3: Landmarks on the frontal face (left) and the right face profile (right). Sez is a point used to calculate profile angles and the line connecting Se and Sez is parallel with z-axis.

where $Score$ is the final facial attractiveness score for a 3D face, $S_{symmetry}$, $S_{proportion}$ and $S_{profile}$ are scores for symmetry, frontal proportion and angular profile proportion respectively, and w_1, w_2 and w_3 are the weights for them, $w_1 + w_2 + w_3 = 1$. To decide the values of w_i, we perform a user study to find how each step contributes to the degree of the final enhancement effect. We get the value w_1: w_2: w_3 = 0.374: 0.326: 0.300 through analyzing the results of our user study, which will be discussed in Section 5. In each step, we use the coefficient of variation instead of the standard derivation to measure the differences, as Schmid et al. did in [20]. The coefficient of variation is useful when comparing between data sets with different units or widely different means, which is necessary when we measure more than two differences.

4.2 Facial feature points

We manually identify 57 landmarks based on the existing literature [21], [20], [22], [23] and our own definitions. We suggest that the face models be well calibrated. Figure 3 shows the layout of the landmarks on the frontal face and the right face profile. Landmarks on the left and right profiles share similar positions. The sequence of the points starting from 0 have been marked.

Most of the feature points are defined in [21], [20], [22]. In literature [23], points 29 and 30 are the left

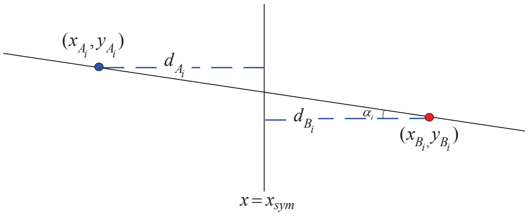


Fig. 4: Line of symmetry ($x = x_{sym}$) and a pair of symmetrical points.

and right zygions of the face respectively and point 56 is the nasion. In our own definition, landmarks from point 38 to point 53 are the facial outline points. Points 54 and 55 are the highest points on the upper margins of the left and right eyes respectively.

Except for point 5 and point 8, landmarks from point 0 to point 30 and points 36, 37, 54, 55, 56 are used for in proportion and symmetry operations. Points 2, 17, 18, 19, 22, 27, 31, 32, 33, 34, 35, 36, 37 are used for facial profile correction manipulation, and the rest are used for facial outline control.

Based on these feature points, we can obtain the point-pairs and calculate the values of Neoclassical Canons, symmetry, golden ratios and facial profile angular measures. The attractiveness score for the original face can then be computed.

4.3 Face symmetrization

Symmetry is an essential aspect of human faces and is considered to be an important factor for attractiveness [24]. We modify the point-pairs described in [21] and put them into our own symmetry analysis. We divide a face into six *local regions*. Each region has several feature pairs:

- Eyebrows (points 1 and 3; points 6 and 7)
- Eyes (points 10 and 13; points 11 and 12; points 14 and 15; points 54 and 55)
- Nose (points 17 and 19)
- Lips (points 21 and 23; points 24 and 26)
- Ears (points 4 and 9; points 16 and 20; points 36 and 37)
- Face (points 29 and 30)

We define *key facial points* as point-pairs in these regions for face symmetrization. Each of above regions belongs to the same feature except for the face region. To reduce the distortion caused by the translation of points 29 and 30, we adjust the landmarks identifying the facial outline according to the changes of points 29 and 30 in order to make all the changes uniform.

4.3.1 Computation of symmetrical score

In our implementation, we take the y-axis as the symmetry axis and we adopt the method proposed in [20] to compute face score, which uses horizontal distances and angles to compute the symmetry of a face.

Let (x_{A_i}, y_{A_i}) and (x_{B_i}, y_{B_i}) be the x-y coordinates of the i-th point-pair, as shown in Figure 4. The formulae of horizontal distances d_{A_i}, d_{B_i} and angle α_i can be described as follows:

$$\begin{aligned} d_{A_i} &= |x_{sym} - x_{A_i}|, \quad d_{B_i} = |x_{sym} - x_{B_i}|, \\ \alpha_i &= \tan^{-1}\left(\frac{|y_{A_i} - y_{B_i}|}{d_{A_i} + d_{B_i}}\right), \end{aligned} \tag{2}$$

where $x = x_{sym}$ represents the vertical line of symmetry.

We use the coefficient of variation cov_{H_i} to measure the differences between d_{A_i} and d_{B_i} while cov_{V_i} for differences between α_i and 0. The face score in symmetry can then be calculated as follows:

$$S_{symmetry} = \frac{1}{m}\sum_{i=1}^{m}(w_{H_i} \times S_{H_i} + w_{V_i} \times S_{V_i}), \tag{3}$$

$$S_{H_i} = \begin{cases} 0 & \mathrm{cov}_{H_i} > 1 \\ 1 - \sqrt{\mathrm{cov}_{H_i}} & \text{otherwise}, \end{cases} \tag{4}$$

$$S_{V_i} = \begin{cases} 0 & \mathrm{cov}_{V_i} > 1 \\ 1 - \sqrt{\mathrm{cov}_{V_i}} & \text{otherwise}, \end{cases} \tag{5}$$

where S_{H_i} and S_{V_i} are the scores of the horizontal and vertical symmetries for the i-th point-pair respectively, w_{H_i} and w_{V_i} are their corresponding weights, $w_{H_i} + w_{V_i} = 1$, and m represents the number of point-pairs in the face model. In our current implementation, $m = 13$, $w_{V_i} = w_{H_i} = 0.5$.

4.3.2 Symmetrical enhancement

The local and global symmetrization is based on the method proposed by Mitra et al. [25]. We show the symmetrization process in Figure 5. For each region, we conduct a local symmetrization according to its point-pairs. We take the yz-plane as the central plane of the human face model. Based on the difference and the local axes in each region, we perform corresponding translation and rotation globally for the feature points in all regions. Finally, we adjust the feature points conforming to the facial outline according to the changes of points 29 and 30. The detailed adjustment will be addressed in the distortion reduction of Section 4.4.2.

Let $\mathbf{T}$ be a reflective transformation which maps one point p to another point q. Given a set of point-pairs, we aim to find the optimal reflective symmetry transformation $\mathbf{T}$ which minimizes the symmetry cost caused by the corresponding displacements of these point pairs:

$$E = \sum_i \left(\|d_{p_i}\|^2 + \|d_{q_i}\|^2\right) = 2\sum_i \|d_{p_i}\|^2, \tag{6}$$

where d_{p_i} and d_{q_i} represent the vectors displaced from p and q respectively. The good pairs are updated

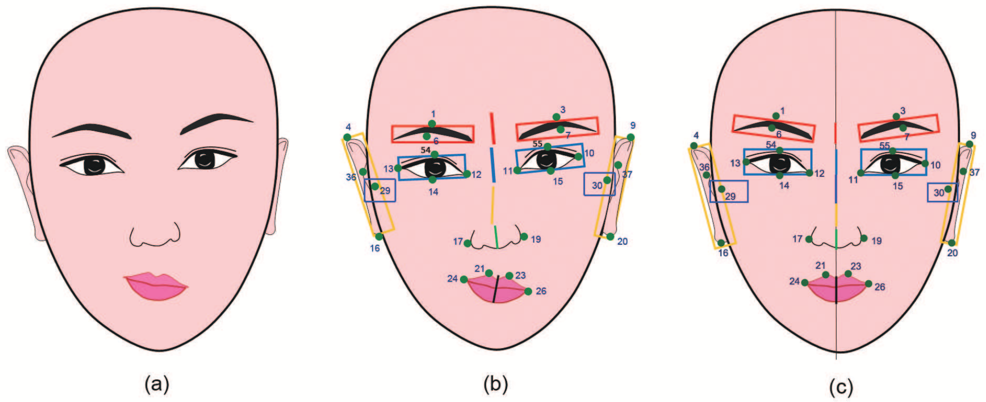


Fig. 5: Frontal face symmetrization. (a) Asymmetrical face model input. (b) Local symmetrization for every region. (c) Global symmetrization for the whole face.

Fig. 6: An example of symmetrization. Left: original model. Right: result after symmetrization.

iteratively until the change of the energy function E is less than a user-specified threshold.

A global symmetrization now can be performed by aligning the ideal symmetry of every local region with the fixed yz-plane. We apply matrix $\mathbf{T}_g$ to each of the local point-set L_i and $\mathbf{T}_g$ is

$$\mathbf{T}_g = \mathbf{R}\left(\mathbf{T}\left(L_i\right)\right), \tag{7}$$

where $\mathbf{T}$ is a translation matrix which transforms the point-set to make its symmetry line go through the origin of xy-plane resultantly, and $\mathbf{R}$ is a rotation matrix which rotates the translated points about z-axis and aligns the plane in which the points are set with the yz-plane.

Finally, we locate points 0, 2, 18, 22, 25, 27, 28, 31, 32, 33, 34, 35 and 56 in the symmetry axis (y-axis) and set the x-coordinates of these points as zero. Figure 6 demonstrates the comparison of models without and with symmetrization.

4.4 Frontal face proportion adjustment

Neoclassical Canons date back to the Renaissance when artists proposed them and regarded them as the direction to draw beautiful faces afterwards. These artists thought that the portions of an attractive face should follow certain ratio rules. Farkas et al. [26] summarized these rules in nine Neoclassical Canons and their variations. Popular literatures like [27] have reported that faces that have features with proportions or ratios close to golden ratios are thought to be aesthetically pleasing. According to these reports, faces tend to be more agreeable in the aesthetic point of view if they have features with ratios similar to the golden ratios.

TABLE 1: Canon formulae and golden ratios for proportion attractiveness.

Rater/face	Canon formulae	Ratio nos.
Female/female	6,8	5,6,7,14,17
Male/female	2,4,5,6,8	2,5,7,14,17
Female/male	2,6	5,6,7
Male/male	2,4,6,8	5,6,7

Schmid et al. [20] proposed six Neoclassical Canons and seventeen golden ratios as important principles to the judgment of frontal attractiveness. By clarifying the experimental results, the authors reached the conclusion that five Neoclassical Canons (including the 2nd, 4th, 5th, 6th and 8th ones) and six golden ratios (including the 2nd, 5th, 6th, 7th, 14th and 17th ones) are the most crucial factors in judging the attractiveness of a female frontal face, irrespective of whether the judger is male or female, while four Neoclassical Canons (including the 2nd, 4th, 6th, 8th ones) and three golden ratios (including the 5th, 6th, 7th ones) are the most influential for males, as shown in Table 1.

Therefore, we take the five Neoclassical Canons and the six golden ratios as the rules to decide whether the female facial proportions correspond with the aesthetic standards, and apply the four Neoclassical Canons and the three golden ratios to males. It should be noted that Schmid conducted his experiment for the purpose of finding factors most related to attractiveness, he made no attempt to use these principles to enhance faces, which we have done in this work.

4.4.1 *Computation of frontal proportion score*

In our work, we eclectically regard Neoclassical Canons and golden ratios as two principal factors influencing whether certain facial proportions are in line with the aesthetic rules. We use the coefficient of variation to measure how much the facial proportion agrees with Neoclassical Canons and golden ratios. For example, one of the Neoclassical Canons can be described as $A = B = C$ or $A = B$. Then, we can use the coefficient of variation to measure the difference between A, B and C (or A and B). In this way, we can obtain the correspondence degree between the facial proportion and this Neoclassical Canon. Similarly, one of the golden ratios can be described as $\frac{A}{B} = \frac{\sqrt{5}+1}{2}$. Then we can use the coefficient of variation to measure the difference between $\frac{A}{B}$ and $\frac{\sqrt{5}+1}{2}$, and the correspondence degree between the facial proportion and this golden ratio measurement.

Thus, the face score for proportion can be calculated as follows:

$$S_{proportion} = \frac{w_N}{m} \times \sum_{i=1}^{m} S_{N_i} + \frac{w_G}{n} \times \sum_{j=1}^{n} S_{G_j}, \tag{8}$$

$$\mathrm{S}_{N_i} = \begin{cases} 0, & \mathrm{cov}_{N_i} > 1 \\ 1 - \sqrt{\mathrm{cov}_{N_i}} & otherwise, \end{cases} \tag{9}$$

$$\mathrm{S}_{G_j} = \begin{cases} 0, & \mathrm{cov}_{G_j} > 1 \\ 1 - \sqrt{\mathrm{cov}_{G_j}} & \text{otherwise}, \end{cases} \tag{10}$$

where cov_{N_i} and cov_{G_j} represent the coefficient of variation values for the i-th neoclassical canon and the j-th golden ratio respectively, S_{N_i} and S_{G_j} represent facial scores for the i-th neoclassical canon and the j-th golden ratio respectively, w_N and w_G are the weights of Neoclassical Canons and golden ratios in the facial proportion grading, and $w_N + w_G = 1$. m and n are the numbers of Neoclassical Canons and golden ratios involved in the facial proportion scoring. We adopt five Neoclassical Canons and six golden ratios for female models, and four Neoclassical Canons and three golden ratios for male models as described in [20], which are the most influential in the attractiveness of human face. Here, we adopt $w_N = w_G = 0.5$.

4.4.2 Frontal proportion enhancement

In this subsection, we address how to make the frontal face proportion better fit the standards of Neoclassical Canons and golden ratios. In order to better elaborate the details of the algorithm, we use $P_i(x_i^P, y_i^P)$ and $P_i'(x_i^{P'}, y_i^{P'})$ to represent the i-th feature point before and after the transformation respectively, where x and y represent the x- and y- coordinates of the points in Figure 3. Meanwhile, we use $P_i^S(x_i^S, y_i^S)$ and $P_i^D(x_i^D, y_i^D)$ to represent the i-th source points (anchor points) and the destination points. During the frontal proportion enhancement process, a ratio (or a canon) always relates to two anchor points and two destination points. We set the anchor points unchanged and then calculate the coordinates of the destination points based on the anchor points and the ratios (or canons).

TABLE 2: Definitions and descriptions of feature points denotations.

Denotation	Feature descriptions	Feature points.
Fh	Forehead height	$\lvert y_0 - y_{56}\rvert$
Nl	Nose length	$\lvert y_{56} - y_{18}\rvert$
Lfh	Low face height	$\lvert y_{18} - y_{28}\rvert$
El	Ear length	$\lvert y_4 - y_{16}\rvert$ or $\lvert y_9 - y_{20}\rvert$
Fl	Face length	$\lvert y_0 - y_{28}\rvert$
Fw	Face width	$\lvert x_{29} - x_{30}\rvert$
Nw	Nose width	$\lvert x_{17} - x_{19}\rvert$
Id	Interocular distance	$\lvert x_{11} - x_{12}\rvert$
Efw	Right (or left) eye fissure width	$\lvert x_{13} - x_{12}\rvert$
Mw	Mouth width	$\lvert x_{24} - x_{26}\rvert$

According to the experimental results of Schmid et al, eleven principles have a significant relationship with female's attractiveness and seven principles with male (see Table 1). As some golden ratios are in correspondence with Neoclassical Canons, we eclectically employ five Neoclassical Canons and two golden ratios for females, four Neoclassical Canons and one golden ratio for males. Table 2 provides the definitions and the descriptions of feature points denotations we use in the frontal proportion enhancement steps.

The process for females can be summarized as the following seven steps:

1) According to Neoclassical Canon 2, $\frac{Fh}{\alpha_1} = \frac{Nl}{\alpha_2} = \frac{Lfh}{\alpha_3}$, we have

$$\frac{\left|y_0^S - y_{56}^D\right|}{\alpha_1} = \frac{\left|y_{56}^D - y_{18}^D\right|}{\alpha_2} = \frac{\left|y_{18}^D - y_{28}^S\right|}{\alpha_3}, \tag{11}$$

where α_1, α_2, α_3 are user-control parameters for Fh, Nl and Lfh respectively, and $\alpha_1 + \alpha_2 + \alpha_3 = 1$. In our implementation, we set $\alpha_1 = \alpha_2 = \alpha_3 = 1/3$. Thus, we can calculate the coordinates of points 18 and 56 based on points 0 and 28 and the revised canon.

2) According to Neoclassical Canon 4, $Nl = El$, we have

$$\left|y_{56}^S - y_{18}^S\right| = \left|y_4^S - y_{16}^D\right| = \left|y_9^S - y_{20}^D\right|. \tag{12}$$

3) According to golden ratio 14, we have $\frac{Fl}{Fw} = \alpha$, where α is a user-control parameter and we set α to the golden ratio in our implementation. Since the face models we use are without hair, it is difficult to measure the length of the face. So we revise the definition of the length of the face in literature [20] according to literature [23], and use $Fl = \left|y_0^P - y_{28}^P\right| \times \beta,\ \beta > 1$ to represent it, where β is the ratio of the length of the face to the vertical distance between point 0 and point 28 and is close to 1.1 in our work. Moreover, we revise the definition of the width of the face in literature [16] to mark the feature points more accurately and use $Fw = \left|x_{29}^P - x_{30}^P\right|$. Therefore

we have

$$\left|y_0^S - y_{28}^S\right| \times \beta = \left|x_{29}^D - x_{30}^D\right| \times \alpha, \left|x_{29}^D\right| = \left|x_{30}^D\right|. \tag{13}$$

4) According to Neoclassical Canon 8, $\frac{Fw}{Nw} = \alpha$, we have

$$\left|x_{29}^S - x_{30}^S\right| = \left|x_{17}^D - x_{19}^D\right| \times \alpha, \left|x_{17}^D\right| = \left|x_{19}^D\right|, \tag{14}$$

where α is a user-control parameter, and we set α = 4 in our implementation.

5) According to Neoclassical Canon 5, $\frac{Id}{Nw} = \alpha$, we have

$$\left|x_{11}^D - x_{12}^D\right| = \left|x_{17}^S - x_{19}^S\right| \times \alpha, \left|x_{11}^D\right| = \left|x_{12}^D\right|, \tag{15}$$

where α is a user-control parameter, and we set α = 1 in our implementation.

6) According to Neoclassical Canon 6, $\frac{Efw}{Id} = \alpha$, we have

$$\left|x_{11}^S - x_{12}^S\right| \times \alpha = \left|x_{13}^D - x_{12}^D\right| = \left|x_{10}^D - x_{11}^D\right|, \tag{16}$$

where α is a user-control parameter, and we set α = 1 in our implementation.

7) According to golden ratio 17, $\frac{Mw}{Nw} = \alpha$, we have

$$\left|x_{24}^D - x_{26}^D\right| = \left|x_{17}^S - x_{19}^S\right| \times \alpha, \left|x_{24}^D\right| = \left|x_{26}^D\right|, \tag{17}$$

where α is a user-control parameter, and we set α to the golden ratio in our implementation.

Similarly, the process for males is summarized as the following five steps:

1) Identical to step 1 of females' enhancement process.
2) Identical to step 2 of females' enhancement process.
3) Identical to step 4 of females' enhancement process.
4) According to Neoclassical Canon 6, $\frac{Id}{Efw} = \alpha$, we have

$$\left|x_{11}^D - x_{12}^D\right| = \left|x_{13}^S - x_{12}^S\right| \times \alpha, \left|x_{11}^D\right| = \left|x_{12}^D\right|, \tag{18}$$

where α is a user-control parameter, and we set α = 1 in our implementation.

5) According to golden ratio 5, $\frac{Mw}{Id} = \alpha$, we have

$$\left|x_{24}^D - x_{26}^D\right| = \left|x_{11}^S - x_{12}^S\right| \times \alpha, \left|x_{24}^D\right| = \left|x_{26}^D\right|, \tag{19}$$

where α is a user-control parameter, and we set α to the golden ratio in our implementation.

Rather than simply make the frontal face proportion fit the standards of Neoclassical Canons and golden ratios, we revise several rules of Neoclassical Canons and golden ratios so that faces are likely to meet modern aesthetics. The study of Schmid et al. [20] shows that smaller noses, a larger distance between eyes, and smaller widths of mouth are desirable traits for female. So in our implementation, when one of above features in female models does not meet Neoclassical Canons or golden ratios, the feature remains unchanged. Moreover, golden ratios 6 and 7 in literature [20] are very important for point 22 to point 27 and could have been used in the last step of the above process for both females and males. However, we have found another golden ratio in literature [28] which is more effective in generating attractive lips. The new golden ratio is applied to the profile correction because it relates to point 32 which is adjusted in this process.

After solving all the equations, we obtain the displacement for each feature point $d_i(dx_i, dy_i) = P_i' - P_i,\ 0 \le i \le 56$. The final positions of the facial feature points are then represented as:

$$P_i' = P_i + d_i \cdot \alpha, \tag{20}$$

where α represents the extent of facial enhancement by proportion, and $0 \le \alpha \le 1$. $\alpha = 1$ indicates that the face completely corresponds to the aesthetic standard after the frontal proportion enhancement. Figure 7 demonstrates the comparison of models without and with frontal proportion enhancement, where $\alpha = 0.6$.

Distortion reduction. Since each principle will lead to the adjustment of feature points, we employ following two rules to reduce the distortion.

1) Equivalent adjustment. In general, the change of facial features' locations will lead to the equivalent change of other facial features. For example, Neoclassical canon 2 introduces the adjustments of points 18 and 56. To reduce distortion, facial features around point 56 (including eyes, eyebrows, ears) and point 18 (including nose, lips) will be adjusted identical to the way points 18 and 56 have been changed respectively. Similarly, the change of the face width in golden ratio 14 influences the location of ears. Specifically, Neoclassical canon 5 changes the interocular distance, which indicates the location change of eyes. So we adjust the location of eyes and eyebrows based on the change of points 11 and 12.
2) Proportional adjustment. To keep the shape of the facial features, we add local constraints on them. Points in ears, lips and eyes should remain in a proportional relationship. For example, when the length of ears is changed, as we have addressed in Neoclassical Canon 4, the positions of points 36 and points 37 will also be changed to reduce distortion. We adjust points 36 and 37 proportionally using the following formulae:

$$P_{36}' = P_{36} + \left(1 - \frac{y_4^P - y_{36}^P}{y_4^P - y_{16}^P}\right)\left(P_{16}' - P_{16}\right), \tag{21}$$

$$P_{37}' = P_{37} + \left(1 - \frac{y_9^P - y_{37}^P}{y_9^P - y_{20}^P}\right)\left(P_{20}' - P_{20}\right). \tag{22}$$

Similarly, golden ratio 17 introduces the change of points 24 and points 26, so we adjust points 21 and 23 based on the following formulae:

$$P'_{21} = P_{21} + \left(1 - \frac{x^P_{24} - x^P_{21}}{x^P_{24} - x^P_{22}}\right)(P'_{24} - P_{24}), \quad (23)$$

$$P'_{23} = P_{23} + \left(1 - \frac{x^P_{26} - x^P_{23}}{x^P_{26} - x^P_{22}}\right)(P'_{26} - P_{26}). \quad (24)$$

Since human perception of faces is extremely sensitive to the shape of the eyes, a restriction is imposed on the eyes when changing the width of the eyes – In Neoclassical canon 6, the landmarks identifying the height of the eyes will be adjusted at the same time:

$$P'_{14} = P_{14} + \left(\frac{|x^P_{12} - x^P_{14}|}{|x^P_{12} - x^P_{13}|}\right)(P'_{13} - P_{13}), \quad (25)$$

$$P'_{15} = P_{15} + \left(\frac{|x^P_{11} - x^P_{15}|}{|x^P_{11} - x^P_{10}|}\right)(P'_{10} - P_{10}). \quad (26)$$

Points 54 and 55 can be dealt with in a similar way. Moreover, we want to change the vertical length of the eye according to the variation of the horizontal width of the eye while keeping the enhanced version sharing the same ellipticity with the original. We adjust points 14 and 54 in the left eye and points 15 and 55 in the right eye using the following formulae:

$$y^{P'}_{14} = y^P_{14} - \Delta y_l/2, \quad y^{P'}_{54} = y^P_{54} + \Delta y_l/2, \quad (27)$$

$$y^{P'}_{15} = y^P_{14} - \Delta y_r/2, \quad y^{P'}_{55} = y^P_{54} + \Delta y_r/2, \quad (28)$$

where Δy_l and Δy_r are the vertical changes of the left and right eyes before and after adjustment respectively:

$$\Delta y_l = |y^P_{54} - y^P_{14}| \left(\frac{\left|x^{P'}_{13} - x^{P'}_{12}\right|}{|x^P_{13} - x^P_{12}|} - 1\right), \quad (29)$$

$$\Delta y_r = |y^P_{55} - y^P_{15}| \left(\frac{\left|x^{P'}_{11} - x^{P'}_{10}\right|}{|x^P_{11} - x^P_{10}|} - 1\right). \quad (30)$$

Specifically, keeping the shape the facial outline is necessary when we change the face width (points 29 and 30). We define the left and right facial outline point-sets as A={38, 39, 40, 5, 44, 45, 46, 47, 48} and B={41, 42, 43, 8, 49, 50, 51, 52, 53} respectively. From point $P_i = \{P_i(x^P_i, y^P_i)|P_i \in A\}$ we can obtain the adjusted point $P'_i(x^P_i, y^P_i)$ using the following formula:

$$P'_i = P_i + \left(\frac{|x^P_i - x^P_{31}|}{|x^P_{29} - x^P_{31}|}\right)(P'_{29} - P_{29}). \quad (31)$$

The new position for point $P_j = \{P_j(x^P_j, y^P_j)|P_j \in B\}$ can be computed similarly by:

$$P'_j = P_j + \left(\frac{|x^P_j - x^P_{31}|}{|x^P_{30} - x^P_{31}|}\right)(P'_{30} - P_{30}). \quad (32)$$

Fig. 7: An example of frontal proportion enhancement. Left: original model. Right: result after proportion enhancement.

4.5 Facial angular profile proportion correction

The attractiveness of a 3D face is determined not only by the frontal view, but also the profile view. To the best of our knowledge, there is no work on the profile enhancement. The research by Peck [29] shows that there is a universal standard for facial beauty in the profile view. Although the averageness hypothesis has been widely accepted, it can be further improved. Composites of beautiful people [30] were rated more appealing than those made from the larger, random population [3]. Therefore, we believe that the averageness of beautiful people' profiles identifies a more attractive profile. Park et al. [22] collected 71 profiles of famous beautiful female, and developed a photogrammetric profile analysis method to help clinicians perform appropriate aesthetic operations in facial plastic surgery. In this work we use the same data collection of profile angles collected by Park. As there has been no published facial angular profile proportion standard for male models, we currently adopt the same enhancement method both for male and female face models. Notice that Park et al. use profile analysis to offer aesthetic plastic surgeons reference while our intent here is to create a more attractive profile view.

4.5.1 *Computation of facial profile proportion score*

As shown in Figure 3, there are 11 anatomical landmarks (points 2, 17, 18, 22, 27, 31, 32, 33, 34, 35 and 36) in the face model. Park et al. [22] developed a

TABLE 3: Three new angular measures. RAMA and MPL represent recommended aesthetic mean angulars and maximum permissible limit respectively.

Calculated profile angles	RAMA	MPL
$\angle g - se - sez$	85.0	2.0
$\angle dc - g - pg$	2.5	1.0
$\angle t - dc - pg$	73.0	6.0

profile standard including 19 angular measures to determine whether a person's profile is agreeable. There are 19 recommended aesthetic mean angles (RAMA) and each of them has a standard deviation. The i-th measure can be represented as $R_i(\mu_i, \sigma_i)$, $1 \le i \le 19$, where μ_i and σ_i are the aesthetic mean angle and the standard deviation of the i-th measurement respectively. For an input model M, after we have calculated its 19 profile angle values $\{a_i,\ 1 \le i \le 19\}$, we divide the angles into two kinds. If the a_i is between $(\mu_i - \sigma_i, \mu_i + \sigma\ )$, we think it's the case that complies with the standards, so we set the score to 1.0. Otherwise, we calculate the coefficient of variation value between $|a_i - \mu_i|$and σ_i which means the distance with the standards. The beauty score of the profile can be computed as follows:

$$S_{profile} = \frac{1}{m}\sum_{i=1}^{m} S_{p_i}, \tag{33}$$

$$S_{p_i} = \begin{cases} 1 & |a_i - \mu_i| \le \sigma_i \\ 1 - \sqrt{\mathrm{cov}_i} & |a_i - \mu_i| > \sigma_i \text{ and } \mathrm{cov}_i < 1 \\ 0 & |a_i - \mu_i| > \sigma_i \text{ and } \mathrm{cov}_i > 1 \end{cases} \tag{34}$$

where S_{p_i} and cov_i represent the score and the coefficient of variation value for the i-th profile standard angular measure respectively. m is the number of standard angular measure and $m = 19$.

4.5.2 Profile proportion enhancement

Based on the 19 standardized reference data used in [22], we add three angular measures and two restrictive functions to solve some problems we found in the process, as shown in Table 3 and Table 4, where point tags are derived from Figure 3. The first new angular measure is added in order to avoid point se protruding point g. The 2nd and 3rd new angular measures are used to adjust point dc in vertical and horizontal directions respectively. The first new restrictive function f_1 is derived from literature [28] and used to generate more attractive lips. In order to make as little change to the length of the lips in profile adjustment, we add the 2nd new restrictive function. Therefore, we can have 24 measurements including recommended aesthetic mean angle and corresponding standard deviation which can be represented as $R_i(\mu_i, \sigma_i)$, $1 \le i \le 24$ in the profile proportion enhancement process.

Our rule in the profile proportion enhancement can be succinctly stated as follow: *Make the profile correspond with aesthetic standards while the feature points should move as less as possible to avoid the face being out of proportion.* We fix points of soft tissue profile (points 2 and 36) in order to normalize variable facial profile angles. In addition, we adjust profile feature points in yz-planes without altering their x-coordinates. Therefore, we have only nine feature points and their related 18 variables unknown. We define the profile face point set as $\Omega = \{2, 17, 18, 22, 27, 31, 32, 33, 34, 35, 36\}$, and the goal of our profile proportion enhancement is to find the optimal displacements of the nine feature points that minimize the cost E:

TABLE 4: Two new restrictive functions. RAMV and MPL represent recommended aesthetic mean value and maximum permissible limit of the restrictive functions respectively. f_1 represents ratio of the distance of nosetip to chin to the distance of lips to chin. G represents the golden ratio. Lh and f_2 represent the lengths of the lips before and after profile correction respectively.

Restrictive functions	RAMV	MPL
$f_1 = \frac{y^P_{32} - y^P_{28}}{y^P_{22} - y^y_{28}}$	G	$G \times 2\%$
$f_2 = y^P_{22} - y^P_{27}$	Lh	$Lh \times 5\%$

$$E = \left(\sum_i E_i\right) + E', \tag{35}$$

where E_i is the i-th measurement, for example, the first measurement can be expressed as the following formula:

$$E_1 = \frac{1}{\sigma_1}\left(\arccos\left(\frac{(P_2 - P_{31}) \bullet (P_{36} - P_{31})}{\|P_2 - P_{31}\|\ \|P_{36} - P_{31}\|}\right) - \mu_1\right), \tag{36}$$

where μ_1 and σ_1 are the aesthetic mean angle and the standard deviation of the 1-th measurement.

E' is a new energy function added by us in order to attain the slightest move of feature points in the profile face point set,

$$E' = \frac{1}{\sigma_g}\left(\sum_i \|Q'_i - Q_i\|^2 - \mu_g\right), \tag{37}$$

where $Q_i \in \Omega$ represents a feature point before face profile adjustment and Q'_i is its corresponding adjusted point. μ_g and σ_g represent the average value and the variation of coefficient of the displacement distance of profile feature points respectively. In our implementation, exhaustive searching is used to determine the value of μ_g and σ_g. When E is minimized, σ_g and μ_g with smaller E' will generate better results and smaller distortion simultaneously. Note that users can also modify these parameters.

We adopt a nonlinear least square method to solve this optimal system and obtain nine optimized coordinates of profile feature points. Figure 8 demonstrates

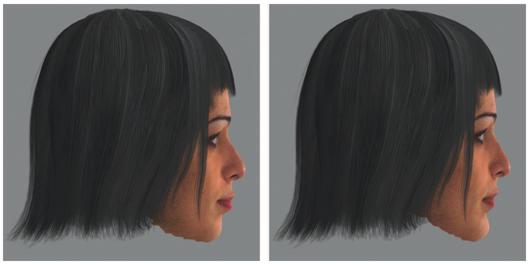


Fig. 8: An example of profile angular enhancement. Left: original model. Right: result after profile angular enhancement.

the comparison of models without and with profile angular enhancement.

4.6 3D Face Deformation

Given the displacements of the facial feature points, Noh and Neumann [31] proposed to use Radial Basis Functions (RBF) to calculate the displacements of the non-feature points for expression cloning. It is well known that there is a wide variety of geometric details in a human face and human perception is extremely sensitive to facial distortion. We should keep the information of local characteristics of the human face when we deform the face. This is in line with the detail-preserving property of the differential representation-based approach. Therefore, we employ Laplacian deformation method which is based on differential surface representation [18] as it can preserve geometric details as much as possible. By utilizing Laplacian deformation, local feature details can be retained effectively when we adjust the human face. In this way, the deformed face still shares some similarities with the original one.

To deform the original face mesh, we use 57 feature points v_i as handles which are illustrated in Figure 3. These handles are moved to new positions c_i which are calculated by our facial geometry enhancement engine. The solution is better if the handle constraints are satisfied in a least square sense rather than solved exactly [18]. With the following 57 constraints

$$x_i = c_i, i \in 0 \dots 56, \tag{38}$$

we can calculate the x-coordinates of all face points $\tilde{\mathbf{x}}$ by solving the following quadratic minimization problem:

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}}(\|L\mathbf{x} - \delta_x\|^2 + \sum_{i=0}^{56} |x_i - c_i|^2) \tag{39}$$

where matrix L is the topological Laplacian of the face mesh, $\mathbf{x}$ is the vector of the x-coordinate of all the vertices, δ is the Laplacian coordinate matrix. The same goes for y and z coordinate vectors. As a result, we have enhanced the attractiveness of the face models so that they look more pleasing while preserving their original details.

Fig. 11: An example of different degrees of enhancement. Left: original model. Middle: result with $\alpha = 0.6$. Right: result with $\alpha = 1.0$.

5 Results and Discussion

We have implemented our face geometry enhancement prototype system on a 64bit 2.83GHz Intel(R) Core(TM)2 Quad Q9550 CPU with 8GB RAM. All the face models but the hair are scanned from real persons. The color information of a face is stored in each scanned model. We clean the raw scanned point cloud data of a face and triangulate them into a triangular mesh. The mesh encoding both the geometry and color information is used as the input of our system. We have enhanced the attractiveness of 19 face models using our enhancement system and 10 of them are shown in Figure 9 and Figure 10. In each example, we show the left profile, the frontal face, the right profile and their enhanced versions. The statistics for the results are shown in Table 5.

There are two reasons for the attractiveness score of the enhanced version not being close to one. The first is that we adopt the revised principles in Neoclassical Canons and golden ratios in the frontal proportion enhancement process. The second is that we expect the profile angle values after profile proportion enhancement vary between $(\mu_i - \sigma_i, \mu_i + \sigma_i)$, where μ_i and σ_i are the aesthetic mean angle and the standard deviation of the i-th measurement respectively, and the model will not get full score unless all 19 angles are equal to their corresponding aesthetic mean angles.

As mentioned in Section 4.4.2, the user can enhance the frontal proportion by specifying the desired degree using α, as shown in Figure 11. The result with $\alpha = 0$ corresponds to the original face without the frontal proportional enhancement. When $\alpha = 1$, the enhanced face complies with aesthetic standard completely in the frontal proportion enhancement. To keep the similarity between the original model and the enhanced one, the degrees of the results shown in Figure 9 and Figure 10 are set roughly between 0.4 and 0.6.

Empirical Validation. To assess our facial attractiveness enhancement technique objectively, we perform an empirical user study to validate the enhancement effect. By using this tool, human raters can observe the original model and the enhanced one side by side freely with camera synchronized. Our 3D viewer presented 19 pairs of faces (original and beautified)

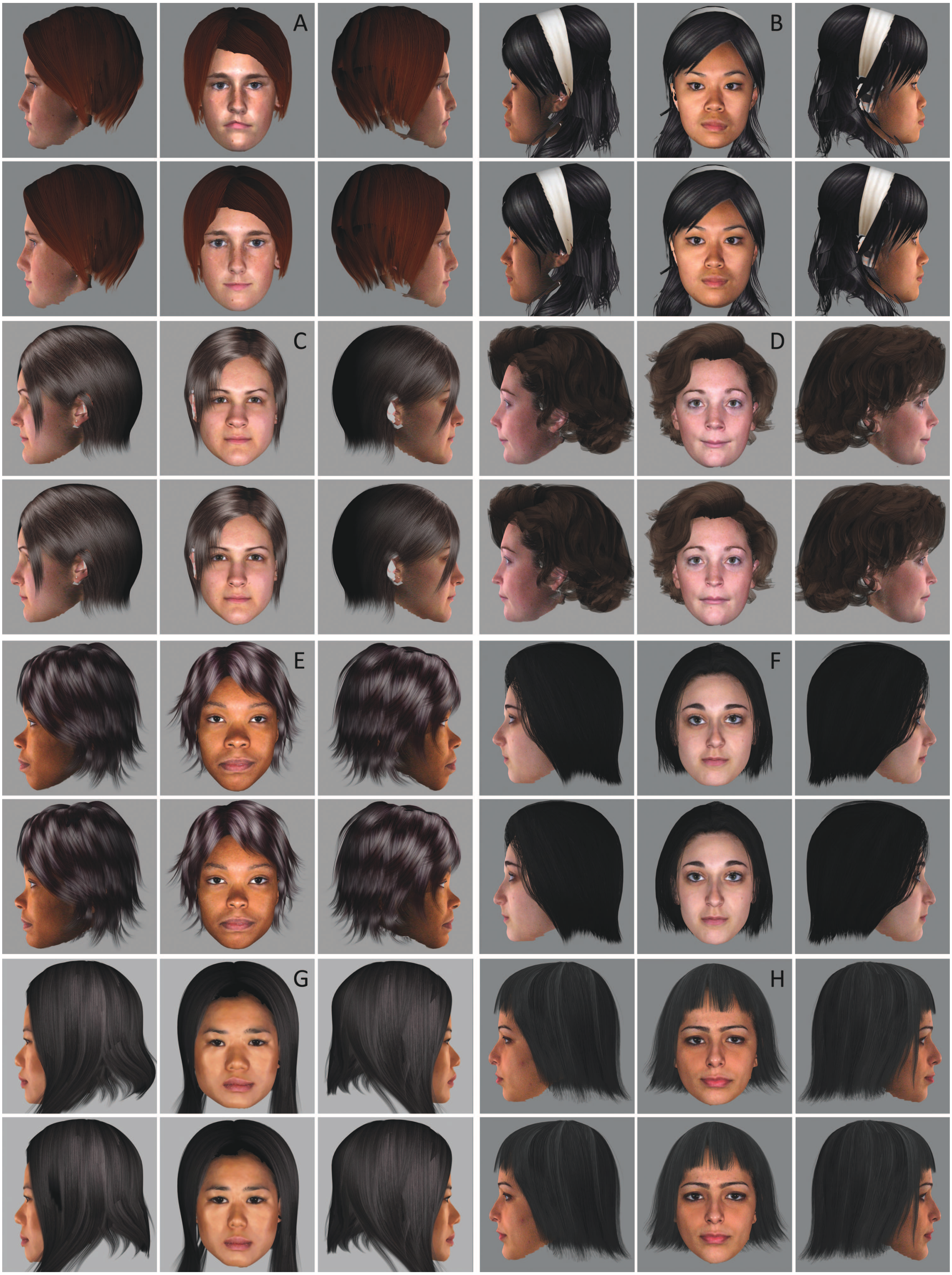


Fig. 9: Eight 3D face geometry enhancement examples of females.

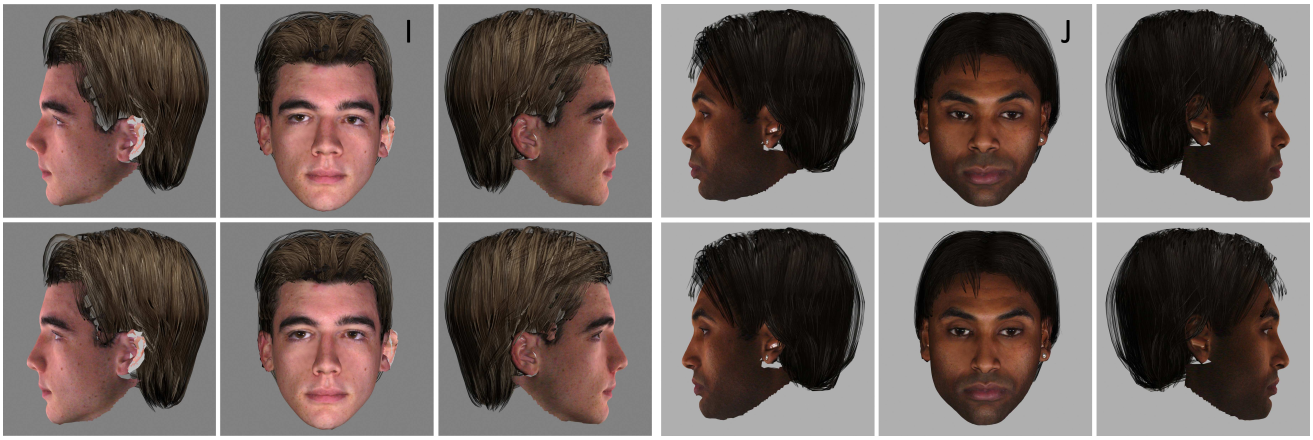


Fig. 10: Two 3D face geometry enhancement examples of males.

TABLE 5: Statistics of attractiveness score for the ten examples in Figure 9 and Figure 10 .

	Symmetry Score		Proportion Score		Profile Score		Attractiveness Score	
Model	Original	Enhanced	Original	Enhanced	Original	Enhanced	Original	Enhanced
A	0.759	0.998	0.725	0.783	0.665	0.802	0.720	0.869
B	0.788	0.997	0.651	0.707	0.655	0.887	0.703	0.869
C	0.828	0.999	0.656	0.754	0.799	0.874	0.763	0.882
D	0.805	0.998	0.707	0.784	0.693	0.979	0.740	0.922
E	0.815	0.999	0.648	0.778	0.654	1.000	0.712	0.927
F	0.746	0.997	0.711	0.742	0.437	0.613	0.654	0.813
G	0.701	0.995	0.621	0.697	0.843	0.984	0.721	0.868
H	0.738	0.998	0.747	0.775	0.786	0.970	0.755	0.917
I	0.778	0.986	0.701	0.798	0.701	0.722	0.715	0.846
J	0.697	0.987	0.661	0.785	0.786	1.000	0.712	0.925

of females (15 faces) and males (4 faces). The position (left or right) of each pair is determined randomly Thirty-two participants (16 males and 16 females) were chosen aged from 18 to 40 years. Each rater was required to give an overall consideration to each pair and choose the more attractive face in each pair. They were also asked to rate the more attractive face on a scale from 1 to 100 indicating how much the results were improved based on his or her opinion.

The results show that 78.33% of the raters chose the enhanced version $(P-value = 3.055\times10^{-27})$ and the average improved scale was 35.39 $(P-value = 9.670\times10^{-19})$. Note that these findings are both statistically significant. Our results indicate that our method is capable of enhancing the facial attractiveness of the faces we experimented with. In addition, we did a Pearson's product moment correlational analysis on the average rating and the scale of each model, which is used to find how two variables are related. The result showed that average ratings achieved a pretty high correlation of 0.819 with the scales. Since random two variables has a correlation of zero, the result indicated that the models that were chose for most of users generally got a high scale identifying the degree of enhancement. It further proved that our tool was capable of enhancing the facial attractiveness regardless of the size and difference of rater samples and face model samples.

We have also performed an experiment to determine the contribution of three factors, symmetry, frontal proportion and angular profile proportion toward attractiveness of a face. Using the 3D viewer, three groups of faces (57 faces) were presented to 32 raters. In each group, one face was the original model while the other was the enhanced version by certain step operation (symmetry, frontal proportion or angular profile proportion). The raters were asked to choose the more attractive one. As we can expect, each step's contribution to the degree of final enhancement effects is not the same. In the experiment of symmetry, 75.26% of the raters chose our version, and 65.56% in the experiment of frontal proportion while 60.35% in the experiment of angular profile proportion. The reason for the symmetry step's large proportion may be that raters are more sensitive to the symmetry of a face even though these differences were quite subtle. This observation has been proved by an experiment conducted by Rhodes et al [32]. Therefore, we set the weights for symmetry, frontal proportion and angular profile proportion as 0.374, 0.326 and 0.300.

Comparisons. As far as we know, there is no published work on the attractive enhancement of 3D face models. One relevant attempt is made by Blanz [14] in his homepage to manipulate the facial attractiveness for 3D face models. Based on a set of faces with manually assigned labels describing the markedness of attractiveness, Blanz computes the weighted sum of differences, which can be added or subtracted from an input face to make it more attractive or more unattractive. However, as facial attractiveness is a highly non-linear attribute [4], the similarity between the original face model and its enhanced version cannot be guaranteed for this approach. On the contrary, our method can enhance the attractive of 3D faces while keeping close similarity with the input face.

Leyvand et al. [4] proposed a data-driven approach to enhance the attractive of 2D face images. This is the most relevant state-of-the-art method we have found so far. However, their beautification engine is limited to 2D face images with no enhancement to the profiles. As we have found in the empirical validation, profiles also play an important role in determining the attractiveness of a face. Although Leyvand et al. mentioned that their 2D enhancement method can be extended by fitting a 3D morphable model to the 2D enhanced result, no results are presented. Moreover, such an extension does not use the geometry of the input face, therefore the geometry similarity between the original face model and its enhanced version cannot be preserved. Since we perform the enhancement directly on the 3D faces, our method applies not least to the applications with 3D face inputs.

6 Conclusions and Future Work

We have developed a 3D face geometry enhancement method based on the revised Neoclassical Canons, symmetry, golden ratios and revised facial profile measurements. In order to preserve the facial feature details, we use Laplacian editing tools to deform face models. In addition, we propose a new method to grade the attractiveness of a human face. As a result, our method enhances the attractiveness of a 3D face model while keeping similarity between the input model and the new version.

There is still much work to be done, both in improving the presented method and investigating other approaches. Here are some directions we would like to explore in the future.

Automatic facial feature points extraction. In our current implementation, facial feature points are specified manually. This is a limitation of our approach as we focus on the process of enhancing the facial attractiveness. To make our method more usable, automatic facial feature points extraction algorithms are desirable.

3D face models with more general expressions. Our method is limited to 3D face models with a neutral expression. Attractiveness enhancement for faces with more general expressions is part of our future work. We believe that with no limitation on the expression, the application of our method will be more extensive.

Data-driven profile enhancement. The profile proportion enhancement method for male models can be updated as soon as facial profile measurements for males are published. Moreover, it would be interesting to enhance our profile view by employing a data-driven method. As the beauty enhancement can be computed using the landmark set which is independent of the representation of a face model, we can use a collection of human profile images as a training set and establish the corresponding ratings to enhance the profiles of 3D face models.

Facial enhancement for non-frontal views. Most of the state-of-the-art 2D facial enhancement methods are designed for frontal views. By generating a 3D face from a non-frontal image and enhancing the model with our framework, our method provides the possibility to enhance facial images for non-frontal views.

Employing more factors. There are lots of other factors which may affect the attractiveness of a human face, such as the color of skin, skin textures, eyes, eyelashes, mouths, noses, fatness, hair styles, and even emotions. Currently we are investigating how to integrate other factors into our attractiveness enhancement engine. Machine learning may provide some solutions to our problem. We believe that even better results can be achieved if we take more factors into consideration.

Acknowledgments

The models used in this paper were collected from the BU-3D Facial Expression (BU3DFE) database [33]. The authors would like to thank Prof. Daniel Cohen-Or for his constructive suggestions in improving the presentation and the revision of the paper. This paper was supported by the National Key Basic Research Foundation of China under Grant 2009CB320801, the NSFC-MSRA Joint Funding under Grant 60970159, the Zhejiang Provincial Natural Science Foundation of China under Grant Z1110154, the National Natural Science Foundation of China under Grant 60933007, and the NSFC-RS international joint project under Grant 61111130209.

References

[1] D. I. Perrett, K. J. Lee, I. Penton-Voak, D. Rowland, S. Yoshikawa, D. M. Burt, S. P. Henzi, D. L. Castles, and S. Akamatsu, "Effects of sexual dimorphism on facial attractiveness," *Nature*, vol. 394, no. 6696, pp. 884–887, 1998.

[2] A. Slater, C. V. der Schulenburg, E. Brown, M. Badenoch, G. Butterworth, and S. Parsons, "Newborn infants prefer attractive faces," *Infant Behavior and Development*, vol. 21, no. 2, pp. 345–354, 1998.

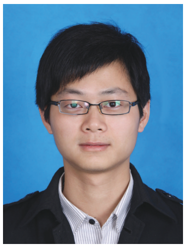
[3] D. Perrett, K. May, and S. Yoshikawa, "Facial shape and judgements of female attractiveness," *Nature*, vol. 368, no. 6468, pp. 239–242, 1994.

[4] T. Leyvand, D. Cohen-Or, G. Dror, and D. Lischinski, "Data-driven enhancement of facial attractiveness," *ACM Transactions on Graphics*, vol. 27, no. 3, p. 38, 2008.

[5] I. Linden Research, "An example of 3d communities and games," Availiable at http://secondlife.com/, 2011.

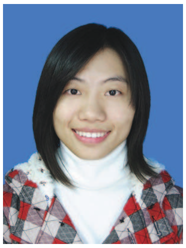
[6] ——, "An example of virtual shops," Availiable at https://marketplace.secondlife.com/?lang=en, 2011.

[7] P. Eisert and B. Girod, "Analyzing Facial Expressions for Virtual Conferencing," *IEEE Computer Graphics and Applications*, vol. 18, pp. 70–78, 1998.
[8] Y. Xiao, M. H. Garzon, and M. Nolan, "Using Talking Heads for Real-Time Virtual Videophone in Wireless Networks," *IEEE MultiMedia*, vol. 13, pp. 78–84, 2006.
[9] B. Guenter, C. Grimm, D. Wood, H. Malvar, and F. Pighin, "Making faces," in *Proceedings of the 25th annual conference on Computer graphics and interactive techniques*. ACM New York, NY, USA, 1998, pp. 55–66.
[10] X. Ma, B. Le, and Z. Deng, "Style learning and transferring for facial animation editing," in *Proceedings of the 2009 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*. ACM, 2009, pp. 123–132.
[11] W. Zhao, R. Chellappa, P. Phillips, and A. Rosenfeld, "Face recognition: a literature survey," *ACM Computing Surveys*, vol. 35, no. 4, pp. 399–458, 2003.
[12] W. S. Tong, C. K. Tang, M. S. Brown, and Y. Q. Xu, "Example-based cosmetic transfer," in *Proceedings of the 15th Pacific Conference on Computer Graphics and Applications*. IEEE Computer Society, 2007, pp. 211–218.
[13] D. Guo and T. Sim, "Digital face makeup by example," in *CVPR*, 2009.
[14] V. Blanz, "Manipulation of facial attractiveness," Availiable at http://www.mpi-inf.mpg.de/ blanz/data/attractiveness/, 2003.
[15] V. Blanz and T. Vetter, "A morphable model for the synthesis of 3D faces," in *Proceedings of the 26th annual conference on Computer graphics and interactive techniques*. ACM Press/Addison-Wesley Publishing Co. New York, NY, USA, 1999, pp. 187–194.
[16] V. Blanz, K. Scherbaum, and H. P. Seidel, "Fitting a morphable model to 3D scans of faces," in *IEEE ICCV*, 2007, pp. 1–8.
[17] J. S. Kim and S. M. Choi, "Symmetric deformation of 3D face scans using facial features and curvatures," *Computer Animation and Virtual Worlds*, vol. 2, no. 3, pp. 289–300, 2009.
[18] O. Sorkine, Y. Lipman, D. Cohen-Or, M. Alexa, C. Rössl, and H.-P. Seidel, "Laplacian surface editing," in *Proceedings of the Eurographics/ACM SIGGRAPH Symposium on Geometry Processing*. Eurographics Association, 2004, pp. 179–188.
[19] O. Sorkine, "Laplacian mesh processing," in *Eurographics State-of-the-Art Report*, 2005.
[20] K. Schmid, D. Marx, and A. Samal, "Computation of a face attractiveness index based on neoclassical canons, symmetry, and golden ratios," *Pattern Recognition*, vol. 41, no. 8, pp. 2710–2717, 2008.
[21] J. Shi, A. Samal, and D. Marx, "How effective are landmarks and their geometry for face recognition?" *Computer Vision and Image Understanding*, vol. 102, no. 2, pp. 117–133, 2006.
[22] H. S. Park, S. C. Rhee, S. R. Kang, and J. H. Lee, "Harmonized profiloplasty using balanced angular profile analysis," *Aesthetic Plastic Surgery*, vol. 28, no. 2, pp. 89–97, 2004.
[23] M. Cvicelova, R. Benus, L. Lysakova, A. Molnarova, and Z. Borovska, "Occurrence of neoclassical facial canons in Caucasian primary school pupils and university students." *Bratislavské lekárske listy*, vol. 108, no. 10-11, p. 480, 2007.
[24] D. W. Zaidel, S. M. Aarde, and K. Baig, "Appearance of symmetry, beauty, and health in human faces," *Brain and Cognition*, vol. 57, no. 3, pp. 261–263, 2005.
[25] N. J. Mitra, L. J. Guibas, and M. Pauly, "Symmetrization," *ACM Transactions on Graphics*, vol. 26, no. 3, pp. #63, 1–8, 2007.
[26] L. G. Farkas, T. A. Hreczko, J. C. Kolar, and I. R. Munro, "Vertical and horizontal proportions of the face in young adult North American Caucasians: revision of neoclassical canons," *Plastic and Reconstructive Surgery*, vol. 75, no. 3, p. 328, 1985.
[27] G. Meisner, "The human face," Availiable at http://goldennumber.net/face.htm, 2006.
[28] D. L. Narain, "The perfect face," Availiable at http://cuip.uchicago.edu/ dlnarain/golden/activity8.htm, 2003.
[29] H. Peck and S. Peck, "A concept of facial esthetics," *Angle Orthod*, vol. 40, no. 4, pp. 284–318, 1970.
[30] S. C. Rhee, "The average Korean attractive face," *Aesthetic Plastic Surgery*, vol. 30, no. 6, pp. 729–730, 2006.
[31] J.-Y. Noh and U. Neumann, "Expression cloning," in *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, ser. SIGGRAPH '01. ACM, 2001, pp. 277–288.
[32] G. Rhodes, F. G. Proffitt, and A. J. M. Sumich, "Facial Symmetry and the Perception of Beauty," *PSYCHONOMIC BULLETIN AND REVIEW, 20*, vol. 5, no. 4, pp. 659–669, 1998.
[33] L. Yin, X. Wei, Y. Sun, J. Wang, and M. Rosato, "A 3D facial expression database for facial behavior research," in *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition*, 2006, pp. 211–216.



Qiqi Liao received the BSc degree in computer science and technology in 2008 from Xiamen University, Xiamen, P. R. China and the MSc degree in computer science and technology in 2011 from Zhejiang University, Hangzhou, P. R. China. His research interests include mesh editing, facial animation and real-time rendering.

Xiaogang Jin received the BSc degree in computer science and the MSc and PhD degrees in applied mathematics from Zhejiang University, Hangzhou, P. R. China, in 1989, 1992, and 1995, respectively. He is a professor in the State Key Laboratory of CAD & CG, Zhejiang University. His current research interests include implicit surface computing, special effects simulation, digital geometry processing, texture synthesis, crowd animation, cloth animation, computer-generated marbling, and non-photorealistic rendering.



Wenting Zeng received the BSc degree in computer science and technology in 2010 from Xiamen University, Xiamen, P. R. China. She is currently a graduate student in the State Key Laboratory of CAD & CG, Zhejiang University. Her research interests include mesh editing, facial animation, non-photorealistic rendering and image processing.