

## Chapter 2

# Typical Facial Beauty Analysis

As an interdisciplinary research topic facial beauty can be investigated understood from many aspects. An important issue is to determine features closely associated with facial beauty. In this book after introducing conventional features for facial beauty analysis we also present typical facial beauty analysis methods. The literature shows that researchers favor different methods. Some researchers believe that facial beauty underlies in the golden ratio. Some are interested in the averageness symmetry hypotheses. Recently biometrics techniques are also utilized for facial beauty analysis. This chapter gives a review of the typical facial beauty analysis methods discusses the advantages limitations of them. After reading this chapter people can have preliminary knowledge on features methods for facial beauty analysis. With this knowledge people will easily understand the following chapters.

### 2.1 Introduction

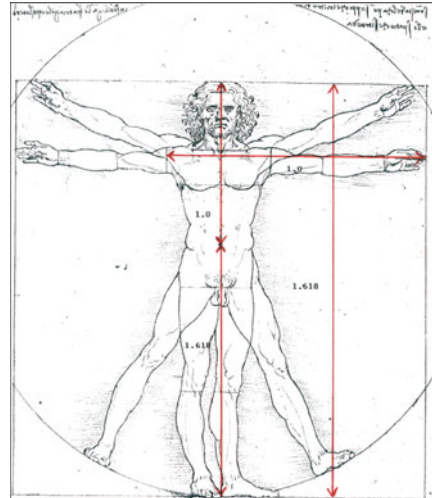
The secret of facial beauty has attracted the attention of artists and researchers for a long time. In ancient time, some sculptors and painters believed that the golden ratio is underlying beautiful faces. In ancient China, the vertical thirds and horizontal fifths rule was proposed. Since 1990s, the study of facial beauty perception has been popular in the psychology field. Some influential hypotheses, such as the averageness hypothesis, have been proposed and numerous studies have been reported and published. Facial beauty study has attracted the attention of computer scientists since 2000. Biometric techniques have been used for facial beauty modeling and developing real-life application systems.

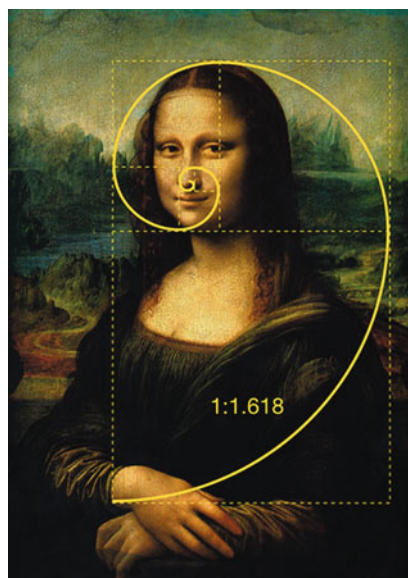
## 2.2 Golden Ratio Rules

The golden ratio (1.618), also called the divine proportion, can be seen in art, architecture, fashion, birds, insects, and flowers, etc. and has been believed to underlie the human body since the renaissance. Leonardo Da Vinci's drawing, Human Figure in a circle, is a great example of illustrating the golden ratio of the human body, see Fig. 2.1. The famous painting Mona Lisa also embodies the golden ratio, as shown in Fig. 2.2. The golden ratio is also believed to underlie beautiful faces. Marquardt proposed an 'ideal' face template based on the golden ratio, which is called the Phi mask, as shown in Fig. 2.3. It is exciting to set up a universal standard for facial beauty. However, many measurement-based studies showed that the golden ratio is not related with facial beauty, i.e., most beautiful faces do not conform to the golden ratio rules (Kiekens et al. 2008; Holland 2008; Peron et al. 2012). Also, in many cases the golden ratio exceeds the normal range of facial ratios. Fan et al. (2012) generated a 3D synthesized face model that conformed to as many golden ratio as possible, but only obtained a below average ratings in their perception experiment.

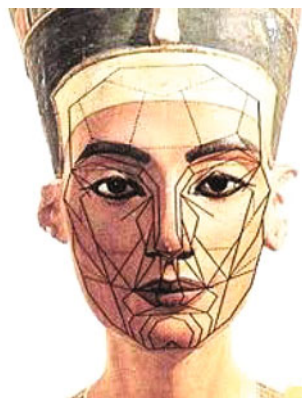
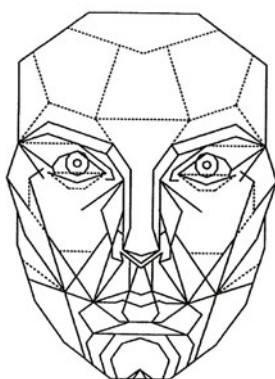
The golden ratio rules are an idealized description of facial beauty. Although they are not accurate, the idea of using ratios to understand facial beauty has been accepted. The ideal values of the ratios can be corrected according to the measurements on the target population. The corrected ratios still serve as references in today's aesthetic surgery plans. Moreover, the ratios are also taken as features for facial beauty modeling and automatic facial beauty prediction.

**Fig. 2.1** Human figure in a circle, illustrating divine proportion (by Leonardo Da Vinci)





**Fig. 2.2** Mona Lisa (by Leonardo Da Vinci)

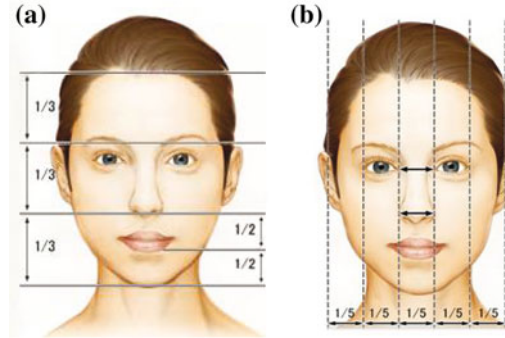


**Fig. 2.3** *Left* Marquardt's Phi mask (beauty analysis, Inc. <http://www.beautyanalysis.com/>). *Right* Egyptian queen Neferneferuaten Nefertiti (1370–1330 BC)

## 2.3 Vertical Thirds and Horizontal Fifths

The vertical thirds and horizontal fifths rules were proposed in ancient China. As shown in Fig. 2.4, the vertical thirds rules divide the length of the face into three parts of equal length: from hairline to eyebrow, from eyebrow to nasal floor, and from nasal floor to chin. The horizontal rules divide the width of the face into five

**Fig. 2.4** Sketch of vertical thirds and horizontal fifth rule. **a** Vertical thirds.  
**b** Horizontal fifths



parts of equal width, i.e., the width of one eye. Faces that conform to these rules are considered to be beautiful.

Similar to golden ratio rules, limited to the measuring techniques in ancient time, the vertical thirds and horizontal fifth rules are not accurate enough. Beautiful faces do not often conform to these rules. However, the ratios defined in these rules can be taken as features for facial beauty modeling.

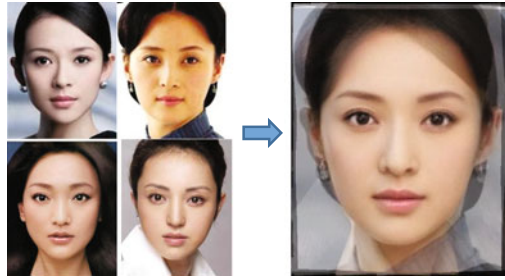
## 2.4 Averageness Hypothesis

In psychology, averageness is the most investigated general pattern of facial beauty. The averageness effect was first found by Francis Galton at the end of nineteenth century (Galton 1878). He overlaid multiple images of faces onto a single photographic plate and observed that the composite image was more attractive than the component faces.

Over a century later, Langlois and Roggman (1990) used computer-generated composite faces to examine the correlation between averageness and facial attractiveness. They found that both male and female composite faces were judged as more attractive than almost all the individual faces used to generate them, and that the composite faces became more attractive as more faces were entered. Similar results were obtained when examining faces from other cultures (Apicella et al. 2007). These studies suggested that averageness is positively correlated with facial attractiveness. Figure 2.5 shows four individual facial images and a computer-generated average face.

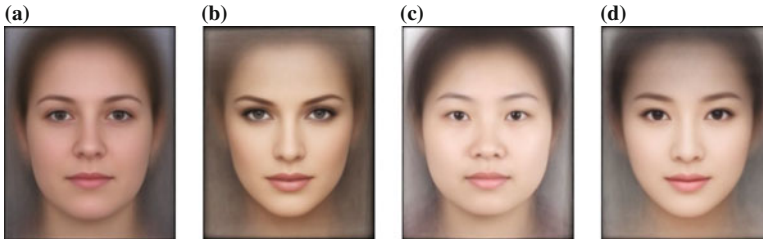
Studies on babies reveal that the preference of facial averageness is biological rather than cultural. New-born infants will gaze longer at attractive faces than at unattractive ones (Langlois et al. 1991; Slater et al. 1998; Kramer et al. 1995), and infants respond to average faces in the same way as they respond to attractive faces (Strauss 1979; Rubenstein et al. 1999). Moreover, the ability to extract the average from a set of realistic facial images operates from an early age, and it is almost instinctive.

**Fig. 2.5** Four individual face images and the computer-generated average face



Many researchers interpret the preference for facial averageness from the evolutionary perspective. Thornhill and Gangestad (1993) argued that average faces may be preferred to less-average faces because owners of average faces possess a more diverse set of genes, which may result in less common proteins to which pathogens are poorly adapted. Parasites are generally best adapted to proteins that are common in the host population, and hence, parasites are adapted to the genes that code for the production of these proteins. Another evolutionary theory for the preference of averageness in faces is that extreme genotypes are more likely to be homozygous for deleterious alleles. Rhodes et al. (2001b) showed that facial averageness is positively related to medical health as measured from actual medical records in both men and women. Facial averageness can then be potentially associated with both direct benefits in terms of associating with healthy, parasite- and/or disease-free partners and indirect benefits of heterozygous genes that can be passed onto offspring.

Despite these findings, the averageness hypothesis has to face many doubts and challenges. One challenge is that the attractiveness of average composite faces may be due to other factors co-varying with the averaging operation such as smoothed skin texture and the improved symmetry of the average composite faces (Alley and Cunningham 1991). In order to investigate the effect of individual factors on facial beauty, some researchers separately manipulated the averageness of shape and texture (O'Toole et al. 1999; Rhodes et al. 2001a). In their experiments, it was reported that individual faces warped into average face shapes were rated as more attractive than the original, and that decreasing averageness by moving the faces away from average face shapes decreased attractiveness. The results show that skin smoothness is not the only determinant of the attractiveness of average faces. Some researchers dissociated symmetry and averageness in facial beauty perception experiments and showed that symmetry positively contributes to facial beauty, but it cannot solely explain the attractiveness of average faces. Another challenge is whether all attractive faces satisfy the averageness hypothesis. Perrett et al. (1994) found that both men and women considered that a face averaged from a set of attractive faces was more appealing than one averaged from a wide range of women's faces, which implies that attractive faces have other types. Figure 2.6 shows the composite faces generated by common and attractive Caucasian and Asian, which agrees with Perrett's finding. Hence, average faces are attractive.



**Fig. 2.6** Average faces generated by **a** common Caucasians; **b** attractive Caucasians; **c** common Asians; **d** attractive Asians

However, these results do not mean that all attractive faces are average, or that average faces are optimally attractive (Rhodes 2006).

To summarize, averageness is positively correlated with facial beauty, but it is not the only determinant. Average faces are attractive but not optimally attractive. Facial beauty perception is complex. Although the averageness hypothesis is influential and has some evolutionary explanations, it is still very limited in defining facial beauty.

## 2.5 Facial Symmetry and Beauty Perception

Facial symmetry is another well investigated trait of facial beauty. From an evolutionary perspective, symmetry may act as a marker of phenotypic and genetic quality and is preferred during mate selection in a variety of species (Perrett et al. 1999). Fluctuating asymmetries (FAs) are nondirectional (random) deviations from perfect symmetry in bilaterally paired traits. In nonhuman animals, FA in body traits reflects developmental instability, and increase with inbreeding, homozygosity, parasite load, poor nutrition, and pollution (Moller and Swaddle 1997; Parsons 1990; Polak 2003). In humans, body FAs increases with inbreeding, premature birth, psychosis, and mental retardation (Livshits and Kobylianski 1991). If similar relationships exist for facial FAs, then they could signal mate quality.

The methodology of symmetry hypothesis research is similar to that of the averageness hypothesis. Symmetric facial images are generated using image processing techniques, which serve as a group of stimuli, and the corresponding original facial images serve as the other group of stimuli. Participants are asked to compare and select the more attractive one between a pair of stimuli. The conclusion, i.e., whether symmetry positively correlates with facial beauty, is made according to the statistical analysis of the experimental results. However, conclusions on the symmetry hypothesis are controversial. Some studies suggested that normal faces with fluctuating asymmetries, FAs, are preferred to perfectly symmetric versions (Kowner 1996; Langlois et al. 1994; Samuels et al. 1994; Swaddle and Cuthill 1995), whereas some studies found that perfectly symmetric faces were

more attractive than the original slightly asymmetric faces (Perrett et al. 1999; Rhodes et al. 2001a). Another point of view is that even though symmetry is positively correlated with facial beauty, it is not the major determinant factor (Scheib et al. 1999), i.e., symmetric faces are not necessarily attractive.

Although the amount of effect of symmetry on facial attractiveness is still unclear, symmetry has been widely used as an additional feature in facial attractiveness calculation and modeling (Eisenthal et al. 2006; Schmid et al. 2008). The quantification of facial asymmetry based on 2D and 3D images has been investigated (Berlin et al. 2014; Berssenbrugge et al. 2014). For 2D images, horizontal distances from a vertical reference line (median sagittal plane), vertical distances from a horizontal reference line, and the horizontal direction between centers of bilateral points are used to measure facial asymmetry. The proper selection and identification of reference points is crucial. For highest accuracy, a sufficient number of evenly distributed and reproducible reference points should be used. If 3D point clouds are available, the point cloud representing the face is firstly mirrored at an initial plane which approximately corresponds to the median sagittal plane of the face. Subsequently, the mirrored copy is matched (registered) to the original version of the face using the Iterative Closest Point (ICP) algorithm (Besl and McKay 1992). The third step of the procedure consists in estimating a median sagittal plane. These three steps are repeated several times. The matching process is then repeated with the remaining surface parts. The best-fit plane of the last iteration is the desired estimate of the median sagittal symmetry plane. Local asymmetries are obtained as the distances between the original cloud and its repeatedly mirrored and registered copy.

2.6 Facial Beauty Analysis by Biometrics Technology

In computer science society, beauty is treated as a characteristic of a human face, such as identity, age, and expression, and biometrics techniques have been used for facial beauty analysis. A typical facial beauty analysis system contains four modules, as shown in Fig. 2.7.

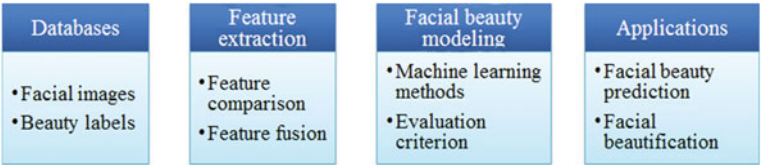


Fig. 2.7 Main modules of a typical facial beauty analysis system

The main issues in biometrics based facial beauty analysis include:

1. Build databases for facial beauty analysis and applications.
2. Decide which facial features work well for facial beauty analysis.
3. Build computational models that are able to map the facial features to a facial beauty score.
4. Develop applications using the results of facial beauty analysis.

The following subsections review the recent developments of the above issues and introduce the corresponding contents in the following chapters of this book.

### ***2.6.1 Databases Used in Existing Works***

To the best of our knowledge, there has been no public database established for facial beauty study. Most of the databases used in existing works were collected by the authors. A database for facial beauty study requires two types of data: facial images and their corresponding beauty scores. The facial images can be obtained from three sources: (1) Frontal portraits captured by a photographer. These images are often captured in a controlled environment with similar illumination conditions and image qualities. However, the number of images is limited, and very beautiful faces are scarce. (2) Facial images collected from the Internet, which can provide not only plenty of facial images but also those of well-known beautiful faces. A major challenge is related to the large variability and low quality (i.e., different resolutions, orientations, illuminations and expressions) of the images collected. (3) Synthesized facial images. The advantage is that data generation can be controlled, but these images are unrealistic. The beauty score of the collected facial images are usually measured by the average of human ratings. Obtaining human ratings is labor-intensive and time-consuming work. This problem is not obvious for small databases. However, when the size of the database increases, it is difficult to obtain enough human ratings. To solve this problem, researchers often relied on images taken from hotornot.com, a site that allows users to rate, on a 10 point scale, the attractiveness of photos voluntarily submitted by others. Most of databases contain only female images. Table 2.1 is a summary of the databases used in existing works.

### ***2.6.2 Facial Feature Extraction***

The core of facial beauty analysis is to discovering the relationship between low-level visual features and high-level perceived attractiveness. Effective features can promote the performance of facial beauty analysis, such as facial beauty assessment and facial beauty manipulation.



**Table 2.1** Review of the databases used in existing works

Work	Size	Gender	Rating	Source
Eisenthal et al. (2006)	92	F	7-scale	Captured
Gunes and Piccardi (2006)	215	F	10-scale	Captured
Schmid et al. (2008)	452	F/M	10-scale	Captured
Kagian et al. (2008)	91	F	7-scale	Captured
Whitehill and Movellan (2008)	2000	F/M	4-scale	Internet
Gray et al. (2010)	2056	F	10-scale	Internet
Fan et al. (2012)	545	F	9-scale	Synthesized
Leyvand et al. (2008)	92	F	7-scale	Captured
Melacci et al. (2010)	60	F/M	N/A	Internet

Many types of features have been adopted in existing works. According to the embedded information, the features can be divided into geometric features and appearance features. The ratios suggested by putative rules (e.g., the golden ratio rule, the neoclassical canons, horizontal fifths, and vertical thirds) are typical geometric features, which are often used to assess facial beauty (Gunes and Piccardi 2006; Schmid et al. 2008; Fan et al. 2012). Given a training data set, the authors build computational models using the ratio features as dependent variables. It was found that although ratio based models are capable of reproducing the average human judgment to some extent, only a small subset of ratio features is important for prediction of facial attractiveness (Schmid et al. 2008) and the putative ideal ratio values are not accurate (Fan et al. 2012). Shape is another type of geometric feature, which is represented by the concatenated x- and y-coordinates of a series of facial landmarks (Melacci et al. 2010). The ratio features can be calculated given the shape feature, and hence, the shape feature contains more information than the ratios. In addition, averageness and symmetry are also adopted as supplementary features in facial beauty assessment (Eisenthal et al. 2006; Schmid et al. 2008). Appearance features contains the information of the whole image. Most of them are inspired from face recognition studies, including eigenface, Gabor filter responses (Liu and Wechsler 2002), and local binary patterns (LBP) (Ahonen et al. 2006). According to the characteristics, the features can be divided into holistic features and local features. Shape, eigenface, averageness and symmetry are holistic features, whereas ratios, Gabor filter responses, and LBP are local features.

Researchers also combine multiple types of facial features to build facial beauty models. For example, Eisenthal et al. (2006) and Kagian et al. (2008) combine geometric features, hair color, and skin smoothness into the regression model. Nguyen et al. (2013) concatenated LBP, Gabor filter responses, color moment, shape context, and shape parameters as a feature vector and applied principle component analysis (PCA) (Duda et al. 2000) to reduce the dimensionality.

Although very many handcrafted features have been used in facial beauty analysis, few works compared the discriminative power of different types of features and optimized the feature set. In this book, Chap. 7 focuses on facial feature

extraction, comparison, and fusion strategy for facial beauty analysis. Extensive experiments are carried out, new features are tested and compared, and an optimal feature set is obtained.

### 2.6.3 *Modeling Methods*

To build a computational model of facial beauty, the general approach is: (1) prepare a training data set, including facial images and their corresponding beauty scores, (2) extract facial features from the facial images, which are supposed to be related to facial beauty, and (3) build a model by supervised learning techniques.

The first two steps were introduced in Sects. 2.6.1 and 2.6.2. Given a set of feature vectors and beauty scores, multivariate linear regression (LR) and support vector regression (SVR) (Vapnik 1995) have often been used to learn the beauty model (Eisenthal et al. 2006; Schmid et al. 2008; Kagian et al. 2008; Whitehill and Movellan 2008; Leyvand et al. 2008). The LR method can obtain a beauty model in an explicit form. With radial basis function (RBF) kernels, SVR can model non-linear structures, but the model cannot be explicitly expressed. LibSVM (Chang and Lin 2011) can be used to train the SVR model, and the parameters can be optimized by grid search. More recently, with the development of the machine learning field, new methods have been proposed for facial beauty modeling. For example, Gray et al. (2014) designed a multi-scale feature model by local filters and down-sampling, which is a form of the convolutional neural network. Gan et al. (2014) applied deep self-taught learning for facial beauty prediction.

Facial beauty models are evaluated by Pearson correlation between machine-predicted beauty scores and human-rated beauty scores. Due to different databases, features, and learning methods used, the reported performances of the models are different, in a range from 0.45 to 0.8. In this book, Chap. 7 optimizes the feature set for facial beauty modeling, which significantly promotes the performance of the model. Except for the Pearson correlation criterion, Chap. 11 proposes a causal effect criterion for model evaluation, which is essential for models used in facial beauty manipulation.

### 2.6.4 *Applications*

As presented in Chap. 1, facial beauty analysis has many applications, such as social networks, image editing software, animation design and arts, and plastic aesthetic surgery and cosmetic industries.

Facial beauty assessment and automatic face beautification are the key problems in the real applications. The former is a straight application of facial beauty models. For face beautification, there are two representative works. Leyvand et al. (2008) proposed a SVR-based method to beautify facial geometry, which first trained a

beauty model and then modified geometric features to increase the beauty score predicted by the model. Melacci et al. (2010) prepared a set of beautiful faces and proposed beautifying the geometry of a query face by the weighted average of its  $k$  nearest-neighbors (KNN) in the training set.

Chapters 12 and 13 study facial beauty prediction and face beautification using the learned facial beauty models. By using the optimized feature set, facial beauty prediction accuracy has been significantly improved. By using the Active Appearance Models (AAMs) feature to build the facial beauty model, Chap. 13 realizes facial texture beatification.

## 2.7 Summary

This chapter surveys typical research methods of facial beauty analysis. First, the studies of golden ratio rules, the averageness hypothesis, and the symmetry hypothesis are reviewed, the main conclusions of these studies are summarized, and the limitations of these methods are discussed. Then, we survey biometric-based facial beauty analysis methods, which contain our key issues: databases, feature extraction, modeling, and applications. Recent progress on these issues is reviewed. Despite the progress, the studies on biometric-based facial beauty analysis are still at a primary stage. A number of issues require further effort. Building a large-scale public database for fair comparison of different methods is necessary. Comprehensive comparison of different types of features, feature selection, and feature fusion strategy needs more research. New machine learning techniques are expected to be applied to the topic of facial beauty analysis. Also, facial geometry beautification, and facial appearance beautification should be more interesting.

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Computer Models for Facial Beauty Analysis

Zhang, D.; Chen, F.; Xu, Y.

2016, XV, 268 p. 141 illus., Hardcover

ISBN: 978-3-319-32596-5