Expert Systems With Applications 82 (2017) 252–265

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Facial beauty analysis based on geometric feature: Toward attractiveness assessment application

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ARTICLE INFO

Article history:
Received 3 November 2015
Revised 28 March 2017
Accepted 7 April 2017
Available online 10 April 2017

Keywords:
Facial beauty analysis
Geometric feature
Semi-supervised learning
Facial aesthetic perceptron
Attractiveness assessment

ABSTRACT

Facial beauty analysis has been an emerging subject of multimedia and biometrics. This paper aims at exploring the essence of facial beauty from the viewpoint of geometric characteristic toward an interactive attractiveness assessment (IAA) application. As a result, a geometric facial beauty analysis method is proposed from the perspective of machine learning. Due to the troublesome and subjective beauty labeling, the accurately labeled data scarcity is caused, and result in very few labeled data. Additionally, facial beauty is related to several typical features such as texture, color, etc., which, however, can be easily deformed by *make-up*. For addressing these issues, a semi-supervised *facial beauty analysis* framework that is characterized by feeding geometric feature into the intelligent attractiveness assessment system is proposed. For experimental study, we have established a geometric facial beauty (GFB) dataset including Asian male and female faces. Moreover, an existing multi-modal beauty (M^2B) database including western and eastern female faces is also tested. Experiments demonstrate the effectiveness of the proposed method. Some new perspectives on the essence of beauty and the topic of facial aesthetic are revealed. The impact of this work lies in that it will attract more researchers in related areas for beauty exploration by using intelligent algorithms. Also, the significance lies in that it should well promote the diversity of expert and intelligent systems in addressing such challenging facial aesthetic perception and rating issue.

1. Introduction

Facial beauty is an everlasting topic of human society. Beauty perception has been studied for years, but scientists have not yet reached consensus on which factors are dominant in the perception and evaluation of facial attractiveness. In ancient times, researchers had discovered several rules for human beauty. For example, ancient Chinese and Greek scholars have proposed a set of general rules for beauty assessment by measuring the vertical and horizontal distances between organs on the faces and their ratios between these distances. They believe that the attractive human faces may follow the beauty and harmony rules in nature (e.g. golden ratio).

In modern times, facial beauty has been thoroughly studied and can be divided into several different approaches. One approach is to follow the rules of ancient scholars with more methodologies. A typical example is the Marquardt beauty analysis (http://www.beautyanalysis.com) in which a golden decagon matrix is constructed based on the traditional golden ratio. Marquardt beauty analysis is used as the geometric "source code" in producing a standard human face mask for facial beauty where the positions of each facial organs are well defined. The mask is also viewed as a perfect mask. The matching degree between a human face and the mask can be defined as the facial beauty score.

Evidences showed that many attractive faces, regardless of races, cultures and times, could match the mask fairly well. Similar work was also described in Jefferson (2004). Another approach in facial beauty studies was introduced by psychology and social scientists, who study the human's perception on facial beauty. In their research, several facial images were first collected and used to generate several simulated images. The raw and simulated images would be shown to several raters for a psychology experiment, and then the raters' perceptions about all images were collected and analyzed. Several interesting phenomena have been discovered in these experiments. For example, the average face of the whole set of faces is always considered to be more attractive than most of all individual faces (Langlois & Roggman, 1990), but may not be the most attractive face since the average face of a set of

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http://dx.doi.org/10.1016/j.eswa.2017.04.021
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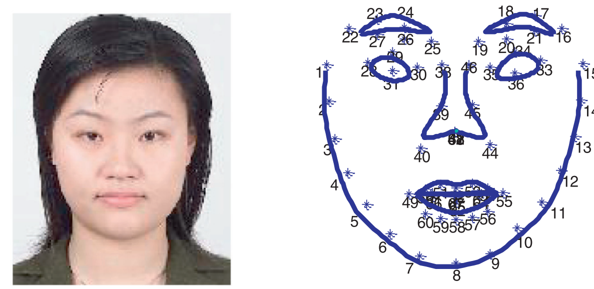
attractive faces is recognized to be more attractive than the average face of the whole set (Perrett, May, & Yoshikawa, 1994). Beyond the average face hypothesis, human perception on symmetrical faces (Perrett, Burt, Penton-Voak, Lee, Rowland, & Edwards, 1999; Rhodes, Proffitt, Grady, & Sumich, 1998; Swaddle & Cuthill, 1995) and other facial features (Johnston & Franklin, 1993; Penton-Voak et al., 2001; Slater, Rosenblatt, Penton-Voak, & Perrett, 2001) have also been studied.

With the rapid development of pattern analysis and machine learning techniques, computer aided approaches for beauty analysis are emerging in recent years which have brought several virtues. *First*, it gives us much more opportunity to construct large data sets with thousands of facial images (Davis & Lazebnik, 2008; Zhang, Zhao, & Chen, 2011; Gray et al., 2010) and discover new patterns relevant to beauty perception. *Second*, automatic pattern analysis techniques make it easier to discover implicit rules and knowledge in beauty. For example, feature selection techniques make us understand what kinds of features contribute more for attractive faces (Altwaijry & Belongie, 2013; Chang and Chou, 2009), and the mapping from facial features to beauty scores can explain how beauty perception varies with the change of facial appearance (Davis & Lazebnik, 2008). *Third*, automatic machines have been invented to predict the beauty score of a face (Kagian, Dror, Leyvand, Cohen-Or, & Ruppin, 2007) and beautify a facial image (Leyvand, Cohen-Or, Dror, & Lischinski, 2008), which is valuable for application in plastic surgery as well as other applications such as computer assisted beauty search of partners (Whitehill & Movellan, 2008), animation, advertising, computer games, video conferencing (Gunes, 2011), etc. Pattern analysis and machine learning based techniques, such as neural networks, support vector machines, K-nearest neighbor, linear regression, Ada-boost algorithms, and principal component analysis, have been proven to be promised supervised and unsupervised approaches for beauty analysis and application (Aarabi, Hughes, Mohajer, & Emami, 2001; Bottino & Laurentini, 2010; Eisenthal & Dror, 2006; Gray, Yu, Xu, & Gong, 2010; Mu, 2013; Sutić, Rešković, Huić, & Jukić, 2010).

Motivated by pattern analysis based approaches, this paper aims to make specialized investigation on the nature of facial beauty based on the geometric feature instead of facial texture and skin based features that may change with human aging and make up. For beauty perception of facial images, beauty analysis is handled as a regularized regression problem. The beauty model is defined as a beauty score function that maps a facial image into a score representing how attractive the face is. To fully explore the contribution of geometric feature in facial beauty, we focus on the geometric features (i.e. facial shape) such that the beauty score function can be modeled easily. This choice is made with consideration that the geometric features are essential and invariable, and closely related with facial beauty, while other features like texture, skin and hair color are easy to be changed by general makeup. Since the geometric features cannot represent the whole information of a face and the raters' decision on the attractiveness of a face may also be disturbed by those easily changed facial features (e.g. skin), thus constructing a computational beauty model directly on the geometric features is not suitable. To solve the problem, we define the geometric beauty score as the supremum of the all faces' beauty scores under the given geometric feature and other possible features. To learn the proposed geometric beauty score function, a Hessian energy based semi-supervised manifold weighted regression is presented in this paper. Additionally, a database of Chinese faces for facial beauty analysis has been established.

The contributions of this paper can be summarized as follows:

- This paper proposes a novel definition of facial beauty score function for studying facial attractiveness based on geometric feature, which reveals the fundamental cues of facial beauty, and avoids the impact of texture, skin, etc.
- A Hessian semi-supervised geometric beauty framework with random projection is proposed for modeling facial beauty score function, such that the attractiveness of a large number of real-world unlabeled faces can be automatically analyzed by the proposed method, which is labor free.
- The proposed work is less laborious due to that the labeling process of facial beauty score is unnecessary in training phase. For modeling, the attractive faces are of movie stars from Internet and the unattractive faces are generated by an existing deformation algorithm, while the real-world faces keeps unlabeled.
- Extensive experiments on two facial beauty databases are implemented for revealing the essence of beauty under the guide of geometric characteristics.



(a) raw face image (b) geometric face

Fig. 1. One example of geometric landmark representation.

The paper is organized as follows. In Section 2, the related works closely associated with this paper are presented. The proposed definition of facial beauty score function, the geometric beauty analysis framework, and the final algorithm for the proposed framework are described in Section 3. The established facial beauty dataset and the experiments including facial beauty modeling, testing and raters' verification are presented in Section 4. The experiment on an existing multi-modal facial beauty database is further studied for better evidence in Section 5. A discussion on the topic of facial beauty in terms of pros and cons is presented in Section 6. Finally, Section 7 concludes this paper.

2. Related work

2.1. Facial geometric representation

Geometric features are the most vital information of human beauty, which involve the distance between organs, the shape of face and organs, and so on. The complete geometric information of a face can be represented by a 3-D surface model. However, due to the complexity and difficulty to construct a 3-D face model, 2-D landmark features are used to characterize the geometric information of faces. Given a face image, the 2-D landmark features can be extracted by detecting the face region using Ada-boost or neural network based methods (Rowley & Baluja, 1998; Viola, 2004) first and then applying the ASM model (Cootes, 1995) to extract the n landmark points of the face in the detected region.

The coordinates $\{(x_1, y_1), (x_2, y_2), \cdots, (x_{68}, y_{68})\}$ of these landmark points can be used as the geometric feature of the face. For visualization, we present an example of a facial image and the geometric landmark coordinates in Fig. 1(a) and (b) which shows 68 landmark points as Zhang et al. (2011), respectively. However, the geometric feature simply uses the landmark coordinates which is defined in a coordinate system on the original image, thus the original geometric landmark features are sensitive to transformation of translation, rotation and scaling, and the original features must be pre-processed for invariance of such transformation. In previous work, Zhang et al. (2011) proposed a geometric feature space of human faces which is invariant with such transformation. Thus, for face alignment, the transformation of translation, scaling, rotation (Section 2.3 and 2.4 in Zhang et al., 2011) for different faces is used in this paper. Suppose $G = (x_1, y_1, \cdots, x_{68}, y_{68})^{\mathrm{T}}$ to be the geometric feature vector on a face formed by x- and y- coordinates of the landmarks. For translation invariant, we subtract from x- and y- coordinates by the average values of all landmark points, as $\tilde{x}_i = x_i - 1/68 \cdot \sum_{i=1}^{68} x_i$ and $\tilde{y}_i = y_i - 1/68 \cdot \sum_{i=1}^{68} y_i$. Then, the center of the landmarks is moved to the origin of the coordinate system. For scale invariance, we first normalize the geometric feature vector to unit length by dividing its components with its norm such that $\|\mathbf{g}\| = \sqrt{\sum_{i=1}^{136} g_i^2} = 1$. With such normalization, each face is mapped to a point in the following space $S_G = \{\mathbf{g}|\mathbf{g} \in \mathcal{R}^{136}, \sum_{i=1}^{68} g_{2i-1} = 0, \sum_{i=1}^{68} g_{2i} = 0, \|\mathbf{g}\| = 1\}$ (Zhang et al., 2011), which a 136 dimensional unit hypersphere. However, not all points in S_G are used to form a valid face shape, thus human face space is a sub-region of S_G, which can be termed as a nonlinear manifold. Furthermore, since the positions of organs in human faces are naturally regular, there is intrinsic low dimensional structure embedded in the geometric feature space. So, in this paper, we would like to build the beauty model on the basis of nonlinear geometric feature manifold.

For making representation of faces invariant to rotation, a rotation transformation $\mathbf{R}$ is applied on the landmarks of one face $\mathbf{g}_1$ such that it has the minimum Euclidean distance to the other face shape $\mathbf{g}_2$. Mathematically, the optimal rotation $\mathbf{R}^*$ between $\mathbf{g}_1$ and $\mathbf{g}_2$ can be obtained by solving the following optimization $\mathbf{R}^* = \mathrm{argmin}_{\mathbf{R}} \|\tilde{\mathbf{g}}_1 - \mathbf{g}_2\|^2$, in which $\tilde{\mathbf{g}}_1 = \mathbf{R} \circ \mathbf{g}_1$ denotes the result after rotation of $\mathbf{g}_1$. Interested readers can refer to Zhang et al. (2011) for specific solution of the optimization.

2.2. Supervised facial beauty model

Given a facial image Z, its beauty perception b of a person P is defined as a function $b = f(Z, P)$, where f is a beauty score function. Actually, we are always concerning the general beauty perception of Z over a population $\mathbb{Q}$, thus we aim to learn the expectation of b over all people in $\mathbb{Q}$, defined by

$$b_{\mathbb{Q}}(Z) = E_{P \in \mathbb{Q}}[f(Z, P)] \tag{1}$$

Generally, it is impossible to collect beauty perception of all people in a large population, therefore $b_{\mathbb{Q}}(Z)$ can be estimated by averaging the beauty perception of randomly selected N_P raters $\{P_1, P_2 \ldots, P_{N_p}\}$ as follow

$$\tilde{b}_{\mathbb{Q}}(Z) = \frac{1}{N_P} \sum_{i=1}^{N_P} f(Z, P_i) \tag{2}$$

Note that $b_{\mathbb{Q}}(Z)$ and $\tilde{b}_{\mathbb{Q}}(Z)$ can also be represented by $b_{\mathbb{Q}}(\mathbf{G}, \mathbf{T}, \mathbf{X})$ and $\tilde{b}_{\mathbb{Q}}(\mathbf{G}, \mathbf{T}, \mathbf{X})$, respectively, where $\mathbf{G}$, $\mathbf{T}$ and $\mathbf{X}$ denote the geometric, texture and other features.

Beauty analysis is to study a beauty score function $h_{\mathbb{Q}}(Z)$ which can approximate $\tilde{b}_{\mathbb{Q}}(Z)$ very well for a face Z. As a result, $h_{\mathbb{Q}}(Z)$ can be learned from a finite set $\{Z_1, Z_2, \ldots, Z_{N_s}\}$ of N_S uniformly selected faces by solving the following minimization problem

$$\min \frac{1}{N_s} \sum_{i=1}^{N_s} \left[h_{\mathbb{Q}}(Z_i) - \tilde{b}_{\mathbb{Q}}(Z_i) \right]^2 + \lambda \Omega(h_{\mathbb{Q}}) \tag{3}$$

where Ω denotes the regularizer imposed on $h_{\mathbb{Q}}$.

It is worth noting that our definition on beauty perception is restricted on a population $\mathbb{Q}$. For different population, the beauty perception may be different. For example, let $\mathbb{Q}_0$ denote the population of all people on the earth, $\mathbb{Q}_1$ denote the population of eastern people and $\mathbb{Q}_2$ denote the population of western people, then $b_{\mathbb{Q}_0}(Z)$, $b_{\mathbb{Q}_1}(Z)$ and $b_{\mathbb{Q}_2}(Z)$ may be different. However, researchers have confirmed that the beauty perception functions are highly correlated, and even consistent for very unattractive and very attractive faces.

For modeling the beauty score, we only consider binary beauty perception of a person in this paper, i.e. most attractive and most unattractive, because it is difficult to define multiple beauty levels accurately as beauty is an ill-defined concept and beauty perception is person specific. It is reliable to treat beauty as a binary perception issue for facial beauty analysis. That is, $b = f(Z, P)$ is a binary function with $b = 1$ if a person P recognizes a face Z to be attractive, and $b = -1$ otherwise. Thus, if most of the persons regard Z as attractive, $b_{\mathbb{Q}}(Z)$ is close to 1; on the contrary, if most of the persons regard Z as unattractive, $b_{\mathbb{Q}}(Z)$ is close to -1. Note that the binary definition does not mean that facial beauty analysis is a classification problem, instead, the principal task in this work is for facial beauty score regression and ranking. It can be understood that for a pair of unattractive facial images, the beauty score can be obtained by regression model, while only $b = -1$ is obtained after classification and the ranking cannot be achieved.

2.3. Facial attractiveness assessment

As mentioned in Introduction, the facial attractiveness assessment methods can be divided into three categories: ancient Chinese and Greek scholars based approaches, psychology and social scientists based approaches, and pattern analysis based approaches. In this paper, the proposed method is following the route of pattern analysis and machine learning. Therefore, a rigorous investigation on the existing pattern analysis based methods in terms of the feature extraction, machine learning strategy, human ratings, Internet labeling and generative labeling has been summarized in Table 1, for clarity. From the table, we observe that all other methods are supervised with human ratings as labels. Different from those previous methods, our method is semi-supervised. Additionally, the cost-ineffective and laborious human ratings are not necessary by leveraging a number of public Internet labeled “Most attractive” faces and our generated labeled “Most unattractive” faces.

3. Proposed geometric beauty analysis framework

3.1. Geometric beauty analysis

It is known that facial attractiveness depends on many factors of human faces. Three kinds of major features of a face Z are geometry feature $\mathbf{g}$, texture feature $\mathbf{t}$ and other feature $\mathbf{x}$ like skin color. So, a face y can be represented as $Z = \langle \mathbf{g}_Z, \mathbf{t}_Z, \mathbf{x}_Z \rangle$. Most of the current research focus on the geometric feature and texture feature. It is valuable to evaluate the contribution of these two types of features on the facial beauty quantitatively and independently. In this paper, we focus on the geometric features that are essential for facial beauty and have not been fully explored.

The geometric feature based beauty analysis is to find the contribution of the geometric shape to the beauty of faces. We define the beauty score function of geometric feature set $\mathbf{G}$ of faces $\mathbb{Q}$ as

$$b_{\mathbb{Q}}(\mathbf{G}) = \sup\ b_{\mathbb{Q}}(\mathbf{G}, \mathbf{T}, \mathbf{X}) \tag{4}$$

where symbol “sup” denotes the supremum of facial beauty score with geometric feature $\mathbf{G}$, texture features $\mathbf{T}$ and other features $\mathbf{X}$. To learn $b_{\mathbb{Q}}(\mathbf{G})$ from beauty perceptions on a set of faces, we need to know the human's perception on facial geometric features, we

Table 1
Comparisons of the existing pattern analysis and machine learning based approaches.

Methods	Geometric feature	Appearance feature	Machine learning	Human ratings	Internet labeling	Generative labeling
Gray et al., 2010	No	Yes	Supervised	Yes	No	No
Eisenthal and Dror, 2006	Yes	Yes	Supervised	Yes	No	No
Aarabi et al., 2001	Yes	No	Supervised	Yes	No	No
Kagian et al., 2007	Yes	Yes	Supervised	Yes	No	No
Mu, 2013	Yes	Yes	Supervised	Yes	No	No
Sutić et al., 2010	Yes	No	Supervised	Yes	No	No
Ours	**Yes**	**No**	**Semi-supervised**	**No**	**Yes**	**Yes**

define

$$\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i) = \max_{j,k} \tilde{b}_{\mathbb{Q}}\left(\mathbf{G}_i, \mathbf{T}_j, \mathbf{X}_k\right) \quad (5)$$

In this work, we define $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i)$ for only two specific types of faces:

- *Most attractive faces*: for the ith attractive face $\mathbf{Z}_i$, $\exists \mathbf{T}_i$, $\mathbf{X}_i$, $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i, \mathbf{T}_i, \mathbf{X}_i) = 1$, so $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i) = 1$;
- *Most geometrically unattractive faces*: for such faces, the geometric property severely violates the common beauty rules, so that there are no other features that can make such faces look attractive. So, $\forall \mathbf{T}, \mathbf{X}$, $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i, \mathbf{T}, \mathbf{X}) = -1$ and $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i) = -1$.

Since the amount of most attractive faces is relatively small, and there may be huge gap between the number of the most attractive faces and the most unattractive faces, it is very necessary to incorporate the unlabeled faces (i.e. *those faces that are controversial in beauty assessment*) into the geometric beauty model by leveraging the geometric prior knowledge of these unlabeled faces. Therefore, the facial beauty assessment system can be guaranteed to be more robust. Therefore, a semi-supervised regression model is more suitable to learn the geometric beauty score function $b_{\mathbb{Q}}(\mathbf{G})$:

$$\min \frac{1}{N_l} \sum_{i=1}^{N_l} \left[b_{\mathbb{Q}}(\mathbf{G}_i) - \tilde{b}_{\mathbb{Q}}(\mathbf{G}_i) \right]^2 + \lambda_1 \Psi(b_{\mathbb{Q}}) + \lambda_2 \mathcal{R}(b_{\mathbb{Q}}) \quad (6)$$

where N_l is the number of faces whose $\tilde{b}_{\mathbb{Q}}(\mathbf{G}_i)$ is known; $\mathcal{R}(b_{\mathbb{Q}})$ penalizes the complexity of $b_{\mathbb{Q}}$ in the functional space, $\Psi(b_{\mathbb{Q}})$ reflects the intrinsic geometric information of the facial manifold, λ_1 and λ_2 are the regularization parameters. With the semi-supervised regression problem proposed, the $b_{\mathbb{Q}}(\mathbf{G})$ of those faces with moderate beauty can be predicted.

3.2. Hessian regularization

Belkin, Niyogi, and Sindhwani (2006) proposed a general Laplacian regularized manifold regression, which seeks an optimal function f by minimizing the following objective function (Belkin et al., 2006).

$$J_g = \sum_{i=1}^{l} L(y_i, \ f(\mathbf{Z}_i, \mathbf{w})) + \gamma_A \parallel f \parallel_{\mathrm{F}}^2 + \gamma_I \parallel f \parallel_{\mathrm{I}}^2 \quad (7)$$

where $L(\cdot)$ denotes the loss function, y_i represents the beauty score *w.r.t.* the input $\mathbf{Z}_i$, $f(\mathbf{Z},\mathbf{w})$ denotes the learning function f with parameter $\mathbf{w}$, $\parallel f \parallel_{\mathrm{F}}^2$ penalizes the complexity of f in the functional space, $\parallel f \parallel_{\mathrm{I}}^2$ reflects the intrinsic geometric information of the marginal distribution $p(\mathrm{Z})$, γ_A and γ_I are the regularization parameters.

In the above framework, $\|f\|_{\mathrm{I}}$ plays a vital role. Belkin et al. (2006) proposed a Laplacian operator shown as

$$\parallel f \parallel_{\mathrm{I}}^2 = \int_M \parallel \nabla f \parallel^2 dV(\mathbf{Z}) \quad (8)$$

where ∇ is the Laplacian operator. The Laplacian operator is meaningful and effective in classification tasks. However, there are limitations in regression tasks due to that the null space of Laplacian operator contains only constant functions in which the learning function is not penalized. Thus, the operator will produce bias toward the constant function, and even when there exist functions that can produce isometric output along geodesic curves on manifolds (Kim, Steinke, & Hein, 2009). This means that the relationship between data points may not be thoroughly explored by the Laplacian method. To solve the problem, Kim et al. (2009) proposed a Hessian energy regularizer for semi-supervised regression which can be represented in the following form.

$$\parallel f \parallel_I^2 = \int_M \parallel \nabla_{\mathrm{a}} \nabla_{\mathrm{b}} f \parallel_{\mathbf{T}_{\mathbf{Z}}^* M \otimes \mathbf{T}_{\mathbf{Z}}^* M}^2 dV(\mathbf{Z}) \quad (9)$$

where $\nabla_{\mathrm{a}} \nabla_{\mathrm{b}} f$ is the second covariant derivative of f, $dV(\mathbf{Z})$ is the natural volume element, and $\mathbf{T}_{\mathbf{Z}}^* M$ denotes a local tangent space of data point x on the data sub-manifold M.

The details of the Hessian energy regularizer can be found in Steinke and Hein (2009). It shows that the null space of the Hessian energy regularizer contains functions that vary linearly with the geodesic distance. For a real-valued regression problem, a normal coordinate system is built on the manifold, and the term in Hessian energy regularizer can be computed as

$$\parallel \nabla_{\mathrm{a}} \nabla_{\mathrm{b}} f \parallel_{\mathbf{T}_{\mathbf{Z}}^* M \otimes \mathbf{T}_{\mathbf{Z}}^* M}^2 = \sum_{r,\ s=1}^{m} \left(\frac{\partial^2 f}{\partial \mathbf{Z}_r \partial \mathbf{Z}_s} |_p \right)^2 \quad (10)$$

where the right part of above equation can be computed by approximation.

$$\frac{\partial^2 f}{\partial \mathbf{Z}_r \partial \mathbf{Z}_s} |_{\mathbf{Z}_i} \approx \sum_j H_{i,j}^{r,s} f\left(\mathbf{Z}_j\right) \quad (11)$$

where H is an operator and $\mathbf{Z}_j$ denotes the data point in the neighborhood of $\mathbf{Z}_i$. The approximation is valid because in the neighborhood of $\mathbf{Z}_i$, f can be estimated by the second order Taylor expansion, in which the coefficients of the second order terms correspond to the elements of the Hessian matrix at $\mathbf{Z}_i$. Since the Taylor expansion is a least square regression problem, the coefficients can be used for the linear combination of $f(\mathbf{Z}_i)$ and $f(\mathbf{Z}_j)$ so that the above approximation is reasonable and $H_{i,j}^{r,s}$ can be computed as stated. Finally, the Hessian energy regularizer can be approximated using all points $\mathbf{Z}_i$ in the form of

$$\|f\|_I^2 = \langle f, \mathbf{\Omega} \cdot f \rangle \quad (12)$$

where $\mathbf{\Omega}$ is a matrix computed from all $H_{i,j}^{r,s}$ and $f_i = f(\mathbf{Z}_i)$.

Note that there are two parameters K and D in calculating the Hessian energy matrix Ω, where PCA is performed on the space $N_K(\mathbf{Z}_i)$ formed by K nearest neighbors of data point $\mathbf{Z}_i$, and the D leading eigenvectors correspond to an orthogonal basis of the local tangent space $\mathbf{T}_{\mathbf{Z}}^* M$. The total energy estimation is the summation from all points. As shown in Kim et al. (2009), the Hessian regression method obtains better performance than that of Laplacian method and kernel ridge regression method in various applications.

3.3. Hessian semi-supervised learning with random projection

Facial attractiveness assessment depends on the raters' evaluation which is person specific, so that the beauty score of one given face may be ambiguous sometimes. Additionally, evaluation on a large number of faces by raters for facial beauty scores (i.e. ground truth or labels) is very tedious and cost ineffective, so we recognize facial beauty analysis as a semi-supervised task in our work by leveraging Internet labeled faces (most attractive) and generated faces (most unattractive). Therefore, we propose a Hessian semi-supervised learning model, which is nominated as HSSL for modeling geometric facial beauty score in this paper.

In terms of regularized least square regression and the Hessian energy regularizer that shows better extrapolation capability, our proposed HSSL aims to solve the following optimization problem.

$$\min_{\mathbf{W},b,\mathbf{F}} \left\| \mathbf{HW} + \vec{1}_n b - \mathbf{F} \right\|_2^2 + \mu \|\mathbf{W}\|_2^2 + \mathrm{Tr}(\mathbf{F}-\mathbf{Y})^{\mathrm{T}}\mathbf{U}(\mathbf{F}-\mathbf{Y}) + \lambda \mathrm{Tr}\left(\mathbf{F}^{\mathrm{T}}\mathbf{\Omega}\mathbf{F}\right) \quad (13)$$

where $\mathbf{H} \in \Re^{n \times L}$ denotes the nonlinearly transformed geometric feature calculated as $\mathbf{H} = \mathrm{sigmoid}(\mathbf{ZP}^{\mathrm{T}} + \mathbf{B})$, $\mathbf{Z} \in \Re^{n \times d}$ denotes the landmark feature, $\mathbf{P} \in \Re^{L \times d}$ denotes the randomly generated matrix, $\mathbf{B} \in \Re^{L}$ is the randomly generated bias vector, $\mathbf{F} \in \Re^{n}$ denotes the predicted score vector, $\mathbf{Y} \in R^{n}$ denotes the ground truth score vector, $\mathbf{W} \in \Re^{L}$ denotes the prediction parameter, b is bias of model, $\vec{1}_n$ denotes a n-dimensional full one vector, n is the number of training samples, $\mathbf{\Omega}$ denotes the Hessian graph, and $\mathbf{U}$ is a diagonal matrix with the ith entry defined as a very large value (e.g. 10^6) if the ith sample is labeled, and 1 otherwise, which can make the predicted labels $\mathbf{F}$ consistent with the ground truth label $\mathbf{Y}$ as well as possible. Note that random projection has been successfully used in extreme learning machine (ELM) (Huang, Zhou, Ding, & Zhang, 2012; Huang, Zhu, & Siew, 2006) and its variants (Zhang & Zhang, 2015, 2016, 2017).

To solve the minimization model (13), three steps are included. First, initialize $\mathbf{F}$ by setting the derivative of the following objective function w.r.t. $\mathbf{F}$ to be 0,

$$\min_{F} \mathrm{Tr}(\mathbf{F}-\mathbf{Y})^{\mathrm{T}}\mathbf{U}(\mathbf{F}-\mathbf{Y}) + \lambda \mathrm{Tr}\left(\mathbf{F}^{\mathrm{T}}\mathbf{\Omega}\mathbf{F}\right) \quad (14)$$

Then the initial value of $\mathbf{F}$ can be obtained as

$$\mathbf{F} = (\mathbf{U} + \lambda\mathbf{\Omega})^{-1}\mathbf{UY} \quad (15)$$

Second, compute $\mathbf{W}$ and b while fixing $\mathbf{F}$ by setting the derivative of the following objective function w.r.t. $\mathbf{W}$ and b to be 0, respectively,

$$\min_{\mathbf{W},b} \left\| \mathbf{HW} + \vec{1}_n b - \mathbf{F} \right\|_2^2 + \mu \|\mathbf{W}\|_2^2 \quad (16)$$

Then one can easily obtain the solutions of $\mathbf{W}$ and b as

$$\mathbf{W} = \left(\mathbf{H}^{\mathrm{T}}\mathbf{H} + \mu\mathbf{I}_d\right)^{-1}\left(\mathbf{H}^{\mathrm{T}}\mathbf{F} - \mathbf{H}^{\mathrm{T}}\vec{1}_n b\right) \quad (17)$$

$$b = \frac{1}{n}\left(\vec{1}_n^{\mathrm{T}}\mathbf{F} - \vec{1}_n^{\mathrm{T}}\mathbf{HW}\right) \quad (18)$$

where $\mathbf{I}_d$ denotes a d-dimensional identity matrix.

Third, calculate $\mathbf{F}$ while fixing $\mathbf{W}$ and b by setting the derivative of (13) w.r.t. $\mathbf{F}$ to be 0, we obtain

$$\mathbf{F} = (\mathbf{I}_n + \mathbf{U} + \lambda\mathbf{\Omega})^{-1}\left(\mathbf{HW} + \vec{1}_n b + \mathbf{UY}\right) \quad (19)$$

where $\mathbf{I}_d$ denotes a n-dimensional identity matrix.

Consequently, an efficient variable alternative optimization algorithm for semi-supervised geometric beauty analysis is proposed in Algorithm 1.

Algorithm 1 HSSL for semi-supervised human beauty analysis.

Input:
The training data $\mathbf{Z} = [\mathbf{Z}^l, \mathbf{Z}^u]$, where $\mathbf{Z}^l$ and $\mathbf{Z}^u$ are the labeled and unlabeled landmark sets;
Parameters K, D, λ and μ.
Output: $\mathbf{W}$ and b.
Procedure:
1. $\mathbf{W} \leftarrow 0$; $b \leftarrow 0$;
2. Compute $\mathbf{U}$;
3. Construct Hessian graph $\mathbf{\Omega}$;
4. Initial $\mathbf{F}$ using (15);
5. Randomly generate feature mapping matrix $\mathbf{P}$ and $\mathbf{B}$;
6. Calculate the nonlinear mapping $\mathbf{H} = \mathrm{sigmoid}(\mathbf{ZP}^{\mathrm{T}} + \mathbf{B})$;
7. **while** not converge **do**
   Calculate $\mathbf{W}$ and b using (17) and (18);
   Update $\mathbf{F}$ using (19);
   Until converge;
   end

3.4. Computational complexity

We briefly analyze the computational complexity of the HSSL involving T iterations. Before stepping into the learning phase, the complexity of computing the Hessian matrices is $O(n^3)$. In learning, each iteration involves two update steps with matrix multiplication and inverse operation, and the complexity in T iterations is $O(n^3T)$. Hence, the computational complexity of our method is $O(n^3)+O(n^3T)$. Note that the Hessian matrices are not involved during iterations and therefore the computational complexity of computing Laplacian matrix is $O(n^3)$.

3.5. Remarks on the convergence

In general, the proposed HSSL is non-convex with respect to the three variables $\mathbf{F}$, $\mathbf{W}$ and b. However, it is conditionally convex with respect to each of them, with the other two variables fixed. Therefore, the convergence of HSSL can be guaranteed by using the alternative optimization Algorithm 1. Specifically, for demonstrating the convergence of HSSL, one lemma is provided.

Lemma 1. *For alternative optimization, when update one variable with other variables fixed, it will not increase the objective function value J(F, W,b). Three claims with short proofs are given as follows*

Claim 1. $J(\mathbf{W}^{(t)}, b^{(t)}, \mathbf{F}^{(t)}) \geq J(\mathbf{W}^{(t+1)}, b^{(t)}, \mathbf{F}^{(t)})$

Proof. When fix $b^{(t)}$, $\mathbf{F}^{(t)}$ and update $\mathbf{W}^{(t+1)}$, the objective function is convex *w.r.t.* $\mathbf{W}$. By setting the derivative of the objective function (16) *w.r.t.* $\mathbf{W}$ to be 0, then it is clear that the expression of Claim 1 holds.

Claim 2. $J(\mathbf{W}^{(t+1)}, b^{(t)}, \mathbf{F}^{(t)}) \geq J(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t)})$

Proof. Similar to the proof of Claim 1, the objective function becomes convex *w.r.t.* b when fix $\mathbf{W}^{(t+1)}$, $\mathbf{F}^{(t)}$ and update $b^{(t+1)}$. Then, Claim 2 is proven.

Claim 3. $J(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t)}) \geq J(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t+1)})$

Proof. When $\mathbf{W}^{(t+1)}$, $b^{(t+1)}$ are fixed, and update $\mathbf{F}^{(t)}$, the optimization problem becomes (14) which is convex *w.r.t.* $\mathbf{F}$. By setting the derivative of the objective function (14) *w.r.t.* $\mathbf{F}$ to be 0, its solution in (15) makes Claim 3 hold.

With the provided three claims discussed above, we can obtain the following inequality

$$J\left(\mathbf{W}^{(t)}, b^{(t)}, \mathbf{F}^{(t)}\right) \geq J\left(\mathbf{W}^{(t+1)}, b^{(t)}, \mathbf{F}^{(t)}\right) \geq J\left(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t)}\right) \geq J\left(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t+1)}\right)$$

It clearly shows that $J(\mathbf{W}^{(t)}, b^{(t)}, \mathbf{F}^{(t)}) \geq J(\mathbf{W}^{(t+1)}, b^{(t+1)}, \mathbf{F}^{(t+1)})$, and the convergence is demonstrated.

4. Experiments on the proposed dataset

4.1. Our established dataset

In this section, we present a facial beauty study based on our established geometric facial beauty dataset (GFB), which consists of three parts.

First, the human faces in Shanghai database from China are used for real-world beauty analysis. In order to study the geometric beauty scores on a set of randomly selected faces, 711 female and 787 male faces are randomly selected as unlabeled samples whose geometric beauty scores would be studied in this paper.

Second, for learning the proposed geometric facial beauty model, we have also established labeled attractive faces. To find the attractive faces recognized by public, we have collected a list of artists including more than 1000 famous attractive actors and actresses in Eastern Asia from the Internet. For each actor or actress, we try to find those faces of a frontal facial image without obvious expression, poses variations and ages for beauty analysis, and those persons without shown frontal face will be automatically neglected. There are also some cases that a person is recognized to be attractive because of his excellent personal skills and popularity other than their real facial beauty, thus we invite raters to judge whether such a face is *a*) attractive, *b*) just common, or *c*) unattractive. Totally, 195 male faces and 191 female faces that are regarded as the Internet labeled attractive faces are obtained in this work.

Third, the labeled unattractive faces are then established. In this paper, considering the ethics, it is not suitable to label a face unattractive simply. Therefore, by following the principle of the psychology and social scientists in beauty analysis area, we have used the simulated faces on the real facial image as our unattractive faces. This strategy also complies with our pursuit on the common beauty perception study. The simulated unattractive dataset can be recognized accurately without ambiguous perception, such that the person-specific beauty perception issue can be omitted. In this way, a labor free facial beauty analysis method by using semi-supervised learning is proposed. Specifically, the geometrically unattractive faces are generated using MLSD face deformation and simulation method (Levin, 1998; Schaefer, McPhail, & Warren, 2006). The deformation is motivated by the findings that most faces will become more and more unattractive when moving far away from the average face (Zhang et al., 2011). In generation of unattractive faces, the unlabeled Shanghai dataset in the first part and the labeled attractive faces in the second part are used as references. For each face F in Shanghai dataset and attractive faces dataset, we generate four simulation faces $\{F_n,\ n=1,\ 2,\ 3,\ 4\}$ by driving it far away from the average face.

$$F_n = F + n \cdot d \cdot \frac{F - F_A}{\| F - F_A \|_2} \tag{20}$$

where F_A is the average face of Shanghai database, d is the average distance between samples and their nearest neighbors. With this approach, 4 simulated faces of each face are generated. The simulated faces with $n=3$ and 4 obviously violate basic geometric beauty rules so that they are automatically labeled as geometrically unattractive faces. For those simulated faces generated using $n=1$, 2, we randomly select a subset of faces and invite raters to select faces that obviously violates basic geometric beauty rules. Totally 65 female and 41 male faces were selected and manually labeled them as geometrically unattractive faces. Then, the remaining simulated faces with $n=1$ and 2 were automatically defined as unlabeled faces in experiments.

Table 2
Experimental data sets for facial beauty analysis.

Gender	Labeled		Unlabeled	Total
	Attractive	Unattractive		
Male	195	2005	2705 (787)	4905
Female	191	1869	2450 (711)	4510

In summary, the GFB dataset established in this paper is illustrated in Table 2. Note that the numbers in the brackets denote the number of Shanghai faces. Further, in order to easily understand the proposed dataset, we have provided the detailed description of the established dataset in Fig. 2 which shows the composition of attractive faces, unattractive faces and unlabeled faces, respectively. Several facial examples in the GFB dataset including attractive female and male faces, unattractive female and male faces, and Shanghai female and male faces are illustrated in Fig. 3. Additionally, several examples of geometric landmark feature points for female faces including attractive, unattractive, and unlabeled Shanghai faces are illustrated in Fig. 4.

Note that the unlabeled faces are also called as universal faces in this paper. As for the unattractive faces made by the simulation procedure, one may argue that some simulated facial images are impossible to be human faces in real life. In our opinion, the deformation principle is not arbitrary in this paper, instead, it is on the basis of Eq. (20) inspired by the popular "average face hypothesis" theory. The simulated unattractive dataset can be recognized to be accurate without ambiguous perception, which can avoid the person-specific issue of beauty perception. Therefore, they are still valuable prototypes of unattractive faces in pattern analysis. However, if the real world data is sufficient with accurate labels in the future through joint endeavor and effort, it can be better for facial beauty analysis as expected which is the ultimate pursuit of us.

4.2. Low-dimensional distribution visualization

The LLE algorithm (Roweis & Saul, 2000) is used for data visualization in low-dimensional representation. The 3-D visualizations of male and female faces including attractive faces, unattractive faces and unlabeled (universal) faces are shown in Fig. 5(a) and (b). We can see from Fig. 5 that the attractive faces and unattractive faces can be separated significantly. The universal faces are overlapped with attractive and unattractive faces in Fig. 5(b), which also demonstrates that the distribution of universal faces is uniform and lie in between attractive and unattractive faces.

4.3. Experimental results

There are three parameters to be determined in the proposed HSSL algorithm, i.e. the number K of neighbors for constructing the data manifolds, the dimension of the implicit manifold D, the size L of P, the regularization parameter μ and λ. In this work, the learned optimal parameters are $K=5$, $D=5$, $L=8000$, $\mu=1$, and $\lambda=1e-9$.

Notably, due to that the unattractive labeled samples are seriously deformed faces, thus each unlabeled face in Shanghai data set is far more attractive than the labeled unattractive faces, and the beauty scores of Shanghai faces may be positively shifted. Therefore, the predicted scores of Shanghai faces are rescaled into $[-1, 1]$.

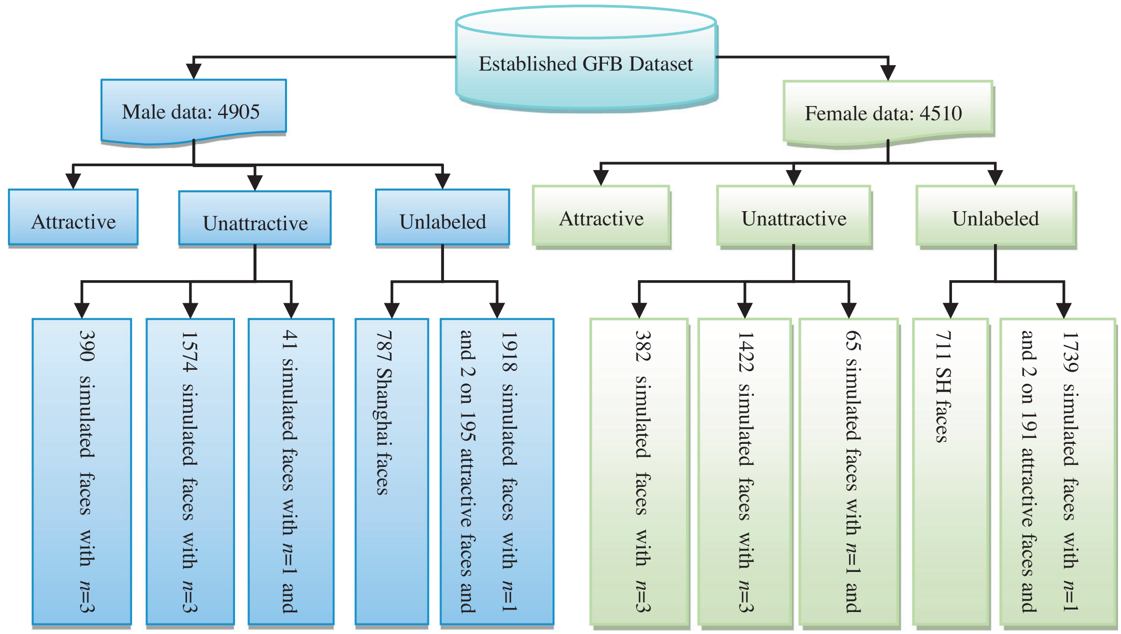
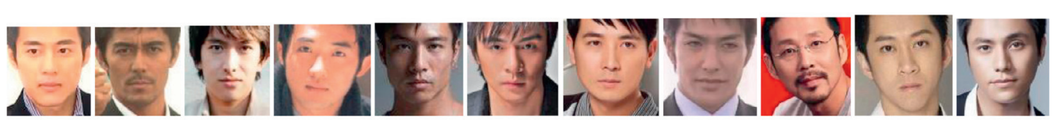


Fig. 2. Description of the established GFB dataset (SH denotes Shanghai faces).

(a) Attractive female faces

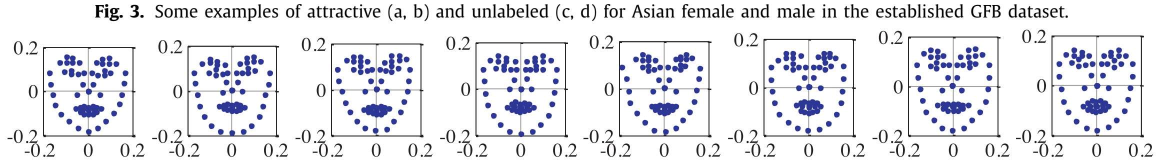


(b) Attractive male faces

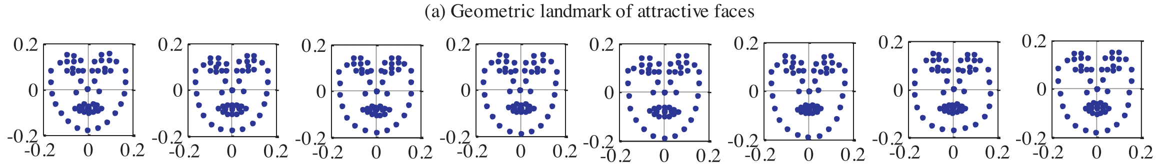
(c) Unlabeled female faces

(d) Unlabeled male faces

Fig. 3. Some examples of attractive (a, b) and unlabeled (c, d) for Asian female and male in the established GFB dataset.

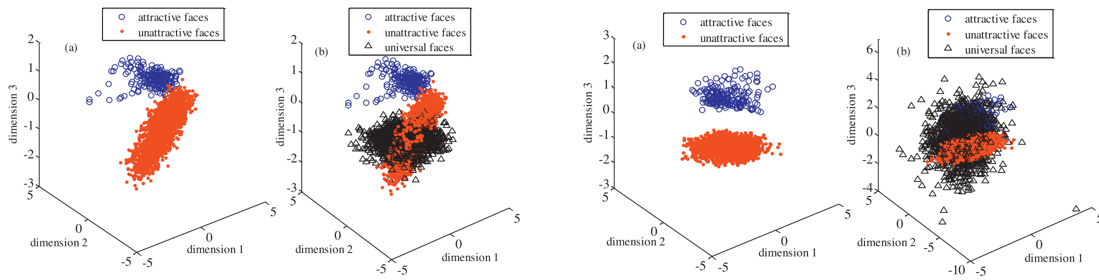


(a) Geometric landmark of attractive faces



(b) Geometric landmark of unlabeled faces (Shanghai faces)

Fig. 4. Several examples of geometric landmark points for female faces.



(a) (b)

Fig. 5. Visualized facial beauty data of male faces (a) and female faces (b) with dimension reduction using LLE algorithm: (a) two types with attractive and unattractive faces; (b) three types with attractive, unattractive and universal faces.

Table 3
Prediction performance of the proposed HSSL with ten splits of training and testing.

Gender	*MSEP* (%)										Average	Std
	1	2	3	4	5	6	7	8	9	10		
Female	15.3	15.7	14.8	15.4	15.3	14.5	14.7	14.6	14.6	14.4	14.9	0.429
Male	10.4	9.44	9.78	9.84	10.4	9.06	9.92	9.73	10.3	9.96	9.88	0.405

Table 4
Predictive error comparisons with existing facial beauty assessment methods.

Gender	*MSEP* (%)				
	KNN-based (Eisenthal & Dror, 2006)	RR-based (Mu, 2013)	ANN-based (Sutić et al., 2010)	SVR (Eisenthal & Dror, 2006)	HSSL (Proposed)
Female	30.1	27.3	20.9	17.8	14.9
Male	29.8	26.6	15.2	13.9	9.88

4.3.1. Overview of the distribution of geometric beauty score

For modeling, we randomly split the data set into training set, validation set and testing set 10 times with ratio 2:1:1. Then HSSL is learned on the training set and the best model parameters are found using the validation set. Finally, the performance is evaluated using the mean squared error of prediction (*MSEP*) calculated on the testing set. The performance with 10 random splits is shown in Table 3. Through the Table 3, we can see that the average *MSEP*s on the testing sets of female and male faces are 14.9% and 9.88% with standard deviations (Std) as 0.429 and 0.405, respectively. The results demonstrate that the proposed beauty model has almost equal and stable prediction ability for both female and male faces. For comparisons, the supervised methods that are commonly used in facial attractiveness prediction are also considered, such as the k-nearest neighbor (KNN) (Eisenthal & Dror, 2006), ridge regression (RR) (Mu, 2013), artificial neural network (ANN) (Sutić et al., 2010), and support vector regression (SVR) (Eisenthal & Dror, 2006). For fair comparison, the optimal results after running the algorithms 100 times have been reported. For KNN, the value of k varies from 1 to 100; for ANN, the number of hidden neurons is set as 25, the activation functions in hidden layer and output layer are "logsig" and "purelin", respectively; the kernel parameter σ^2 and regularization parameter γ in SVR are set as 0.002 and 1, respectively. The results of these methods have been shown in Table 4. From the comparisons, we can see that the HSSL is more competitive for facial beauty analysis.

To have an insight on the predicted beauty score of all faces, we present the predicted geometric beauty score using the proposed model as Fig. 6(a) with scatter points in which each point represents a face. An overview of the distribution of relative geometric beauty scores of universal male and female faces has also been shown in Fig. 6(b). We can see that the beauty scores of most Shanghai faces are lying between the attractive and unattractive faces. From the histogram of the relative geometric beauty scores, we can see that for most of the faces, the scores belong to the range of [0.2, 0.8], which accord with the fact that most universal persons are just with general beauty.

4.3.2. Discover top 5 attractive and unattractive faces

In order to observe the most geometrically attractive and unattractive faces, we present the faces with 5 highest beauty scores and 5 lowest beauty scores from Shanghai faces based on the proposed model. First, the faces in Shanghai data set are ranked by their geometric beauty scores, and the top 5 geometric attractive faces and the bottom 5 geometric unattractive faces are selected. Second, to give an intuitive understanding of the geometric beauty of the selected faces, we generate a beautified (simulated) face $B(Z)$ for each face Z in the following way.

$$B(Z) = \langle \mathbf{G}_Z, \mathbf{T}_{N_B}, \mathbf{X}_{N_B} \rangle \tag{21}$$

where N_B is the nearest attractive face of Z in the geometric feature space. In this way, the new face $B(Z)$ remains the same geometric feature $\mathbf{G}_F$ as Z, while both the texture feature $\mathbf{T}_{N_B}$ and other features $\mathbf{X}_{N_B}$ are from an attractive face N_B. This can remove the impact of the texture and other features like the skin that can be easily beautified by making up (e.g. face painting) in raters' assessment on facial beauty, which is only associated with geometric characteristic of faces.

From (21), we know that the texture and other features like skin can make the same effect to raters' assessment, and only geometric features are different between two faces. By viewing the face pair $\langle Z, B(Z)\rangle$, we can know how the geometric feature contributes to the beauty of a face. Based on the proposed facial beauty perceptron system, the facial images of face pairs $\langle Z, B(Z)\rangle$ of female and male faces with the top 5 and bottom 5 geometric beauty scores are shown in Fig. 7, in which Fig. 7(a) presents the top 5 geometric attractive faces of Shanghai faces and Fig. 7(b) presents the bottom 5 geometric unattractive faces. From the results, we can see that the simulated faces with top 5 beauty scores are indeed attractive, while those with bottom 5 beauty scores are

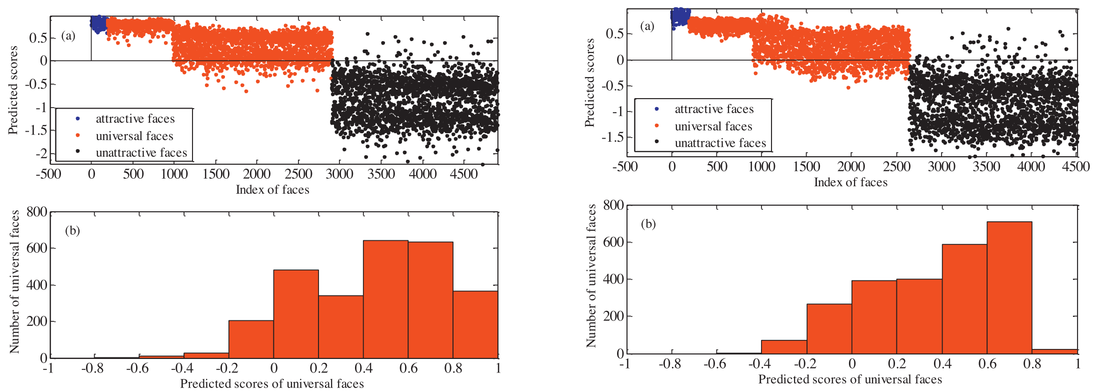


Fig. 6. Facial beauty score analysis of male faces (left) and female faces (right): (a) predicted score of attractive faces (blue points), universal faces (red points) and unattractive faces (black points); (b) Statistical results of predicted beauty scores of universal faces. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

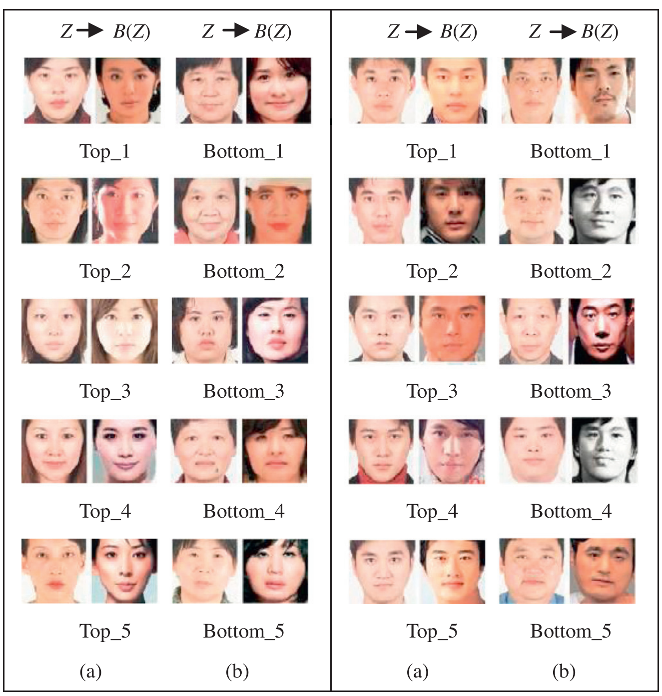


Fig. 7. Most attractive (a) and most unattractive faces (b) (female: left; male: right), and the beautified faces with original geometric features remained.

unattractive, even for their beautified faces $B(Z)$. It is worth noting that the original face Top_5 in Fig. 7(a) may be regarded to be unattractive because of the skin and the eye bag. However, this face is recognized to be attractive by our beauty model, and her simulated face is also attractive, which demonstrates that the geometric information contributes more in facial beauty. Therefore, the reasonability of the geometric beauty score definition based on the proposed beauty perceptron is confirmed.

4.4. Verification

To further verify the validity of the proposed method, we invite raters to evaluate the geometric beauty scores. First, we randomly select 100 pairs of faces with their beauty scores from Shanghai data set (50 pairs of female faces and 50 pairs of male faces) and then ask the raters to decide which one is geometrically more attractive. The decisions made by raters are then taken as the ground truth and the geometrical beauty scores of these faces produced using the proposed model will be evaluated in terms of the ground truth. To obtain reliable decisions of raters on the geometric beauty of a face Z without disturbance from texture and skin features, the beautified face $B(Z)$ is also used in verification experiments.

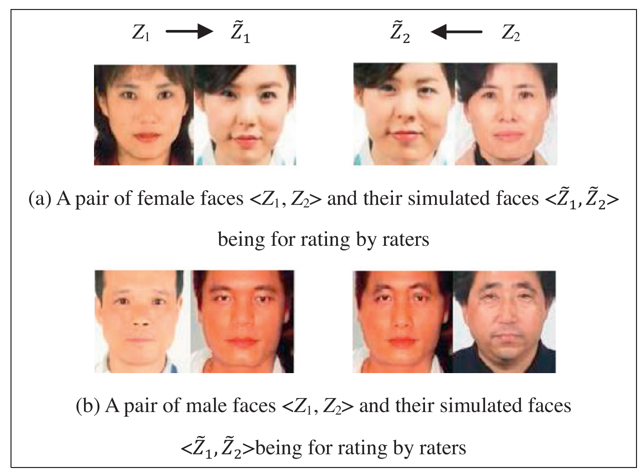


Fig. 8. Example of newly generated pair $(\tilde{Z}_1, \tilde{Z}_2)$ being evaluated by raters for verification of geometric beauty.

4.4.1. Analysis of rates' agreement (RA)

Given a pair of faces Z_1 and Z_2 from Shanghai faces, we generate a pair of simulated faces $\tilde{Z}_1$ and $\tilde{Z}_2$ according to (21), which preserves the geometric information of Z_1 and Z_2 respectively, but borrow all other features like texture and skin from the same attractive face N_B. In this way, the fairness in beauty selection can be guaranteed, where N_B is selected as the attractive face nearest to Z_1 and Z_2, such that the beauty of $\tilde{Z}_1$ and $\tilde{Z}_2$ does only reflect the geometric beauty. With this approach, the raters are guaranteed to focus on geometric features and cannot be disturbed by other artificial facial features in raters' subjective evaluation process. In this way, the raters will be invited to decide which one is more attractive between $\tilde{Z}_1$ and $\tilde{Z}_2$.

Two instances of female and male faces involved in this strategy have been described in Fig. 8, in which the simulated images $\tilde{Z}_1$ and $\tilde{Z}_2$ will be presented to the raters for decision. Furthermore, to avoid random decisions when given a pair of faces with similar geometric beauty to the raters, we select those face pairs with difference between the relative geometric beauty scores of two faces larger than 0.4 for this experiment. This strategy can make the raters produce reliable decision between faces $\tilde{Z}_1$ and $\tilde{Z}_2$, and

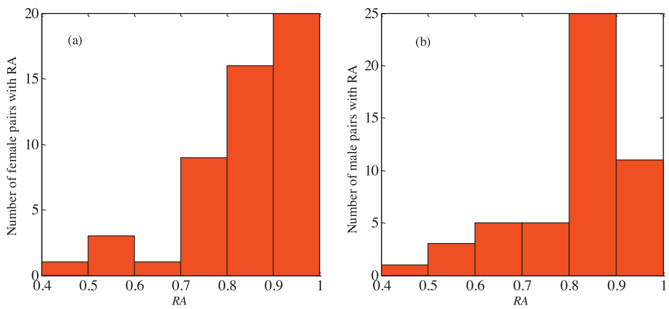


Fig. 9. Statistical results of Raters' Agreement (*RA*) on 50 female face pairs (a) and 50 male face pairs (b).

reduce the ambiguity. Totally, 100 pairs of faces $\langle \tilde{Z}_1, \tilde{Z}_2 \rangle$ including 50 pairs of female faces and 50 pairs of male faces are exploited for evaluation by 87 raters in experiment. Let $P_i = (\tilde{Z}_1^i, \tilde{Z}_2^i)$ denote the ith face pair being evaluated, $M(P_i)$ denote the decision of the proposed model on P_i, and $D(P_i, R_j)$ denote the rating made by the jth rater on P_i. Note that both $M(P_i)$ and $D(P_i, R_j)$ are binary functions with output as 1 if $\tilde{Z}_1^i$ is recognized (by the model or the rater) to be more attractive than $\tilde{Z}_2^i$, and -1 otherwise.

Let n_P and n_R denote the number of face pairs and raters involved in the experiment, respectively. For full respect of each rater's rating, the accuracy of the proposed facial beauty model approximating the raters' ratings can be computed as

$$Accuracy = \frac{\sum_{i=1}^{n_P} \sum_{j=1}^{n_R} I\Big(M(P_i) = D\big(P_i, R_j\big)\Big)}{n_P \times n_R} \tag{22}$$

where $I(\cdot)$ is the binary indicator function.

Through analysis, we can obtain that the accuracies for female and male faces are 84.21% and 81.47%, respectively, which verify the validity of the proposed model effectively. To further investigate the correlation and the uniformity of perception to facial beauty between all raters' ratings and the decisions of the proposed model on each face pair P_i, we define the Raters' Agreement (*RA*) as

$$RA_i = \frac{1}{n_R} \sum_{j=1}^{n_R} I\Big(M(P_i) = D\big(P_i, R_j\big)\Big) \tag{23}$$

From the calculation of *RA*, we know that if $RA_i = 0.5$, it denotes that 50% raters have the same decisions on P_i. The statistic results of *RA* on 50 pairs of female faces and 50 pairs of male faces have been presented in Fig. 9(a) and (b), respectively.

From Fig. 9, we can see that a majority of raters are coincided with the proposed beauty model. However, there are also still some cases that have low agreement. This is consistent with the fact that people hold different opinion in beauty perception.

4.4.2. Analysis of raters' agreement between each-others (RABE)

To investigate the reasons of such disagreement, we define the Raters' Agreement Between Each-others (*RABE*) as follows

$$RABE_{i,j} = \frac{1}{n_R - 1} \sum_{k=1, k \neq j}^{n_R} I\Big(D(P_i, R_k) = D\big(P_i, R_j\big)\Big) \tag{24}$$

Note that *RABE* is a matrix of $n_P \times n_R$, which can be used to measure the consistency between decisions of one rater and those of all other raters' decisions.

For quantitative analysis of the agreement, given a pair P_i and a threshold α of *RABE*, we can say that one rater agrees with all other raters at level α $(0 < \alpha < 1)$. The proportions $PRABE_j(\alpha)$ of the n_P pairs for the jth rater that agree with all other raters at level α can be represented as

$$PRABE_j(\alpha) = \frac{1}{n_P} \sum_{i=1}^{n_P} I\big(RABE_{i,j} > \alpha\big) \tag{25}$$

Table 5
Statistics of *PRABE* (α).

α	*PRABE* (α) of 50 female pairs				*PRABE* (α) of 50 male pairs			
	Min	*Max*	*Mean*	*Std*	*Min*	*Max*	*Mean*	*Std*
0.5	0.28	1.00	0.85	0.1510	0.10	0.98	0.82	0.1542
0.6	0.22	0.92	0.80	0.1458	0.06	0.92	0.77	0.1493
0.7	0.22	0.90	0.79	0.1424	0.02	0.82	0.71	0.1379
0.8	0.16	0.72	0.65	0.1127	0	0.72	0.63	0.1215
0.9	0.12	0.40	0.37	0.0545	0	0.22	0.20	0.0400

The statistics of *PRABE*(α) with five different values of α are shown in Table 5. Obviously, the results demonstrate that the raters have different perceptions of beauty, so their decisions on a facial image may not be highly consistent. Therefore, it is impossible for the proposed method to produce results with high consistency with all raters. We also observe that the proposed method almost achieves the maximum consistency with all raters (for female data with $\alpha = 0.5$). This means that the proposed method captures the most uniformity of facial beauty perception.

4.5. Insightful implications

In this section, we take the phenomenon of raters' disagreement on beauty perception as a potential research subject and give some preliminary analysis. However, in previous research, such disagreements are never seriously considered. For example, in the experiments of Chang and Chou (2009), the results of raters whose beauty score has low correlation to the average score are omitted to get a highly consistent ground truth. In our opinion, the cognition of people's brain to beauty is an important topic in beauty analysis and should not be neglected. However, it does not contradict the human's common perception of beauty since there are also different tastes of beauty by different people.

Additionally, according to our experimental analysis and verification, the results demonstrate that our proposed semi-supervised method with very positive data (most attractive faces from public Internet) and very negative data (most unattractive faces generated by us) is effective for beauty assessment on the general faces (unlabeled moderate attractive faces). This demonstrates that the beauty labeling process of faces for beauty study is not necessary. On one hand, it is time-consuming and laborious by inviting a number of raters for labeling. On the other hand, due to the ill-conditioned essence of beauty that is person-specific, it is difficult to achieve some consensus for consistent beauty perception. To this end, in this paper, during the model training process, the labeling process on the facial dataset is discarded. Also, for verifying the proposed method, we have conducted the verification experiments by comparing the results of the proposed method with that of human scores. The results demonstrate that our proposed method comply with human's evaluation, which also prove that it is not necessary to label the faces during training process by using the proposed beauty score function defined in Section 3.1.

The findings of this paper reveal that it is also feasible to use deep learning and large-scale facial data in the future for facial beauty analysis, because a number of most attractive faces can be easily acquired from Internet and a number of most unattractive faces can be easily generated (simulated) by using some deformable method, without any extra human labeling procedure.

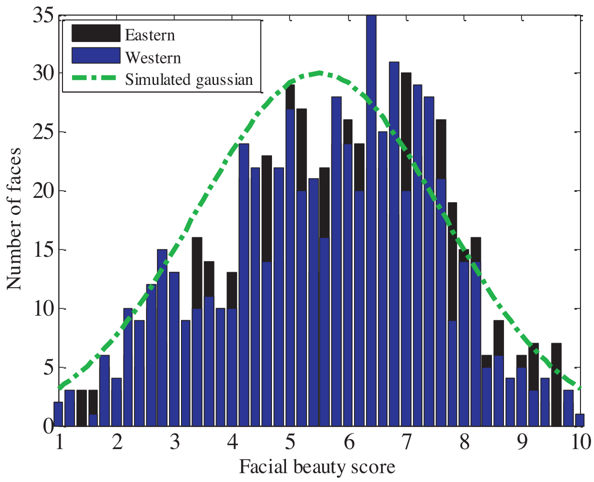


Fig. 10. Statistic histogram of facial beauty scores.

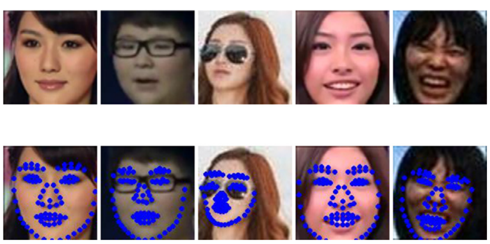


Fig. 11. Examples of eastern female faces in M^{2}B database.

5. Experiment on M^{2}B dataset

5.1. M^{2}B dataset

In this section, we will conduct the experiments using another dataset which is a newly public multi-modality beauty (M^{2}B) database developed by Nguyen, Liu, Ni, Tan, Rui, and Yan (2012, 2013). This database was collected from YouTuBe website, which contains faces, dresses and voices of female persons from different races. Totally, there are 620 females from eastern countries and 620 females from western countries. Note that the facial images in M^{2}B are with different expressions, poses, and illumination, which are different from our constructed Shanghai database that only the frontal images without expression and other interferences are considered. The attractiveness score i.e. the ground-truth of each face has also been well defined by raters using k-wise ratings in M^{2}B database, and therefore the subjective evaluation experiments are not conducted in this paper. The attractiveness scores, which have been statistically presented as histogram in Fig. 10, are finally scaled between 1 and 10. Fig. 10 clearly shows that the histogram of facial beauty scores complies with Gaussian distribution. To focus on the study of three beauty levels of unattractive (−1), universal (0) and attractive (1), three attractiveness score ranges [1, 3.5], [3.5, 7.5] and [7.5, 10] are divided in experiments.

In this paper, the facial beauty dataset of geometrical landmark features in M^{2}B database are used for verifying the proposed facial beauty model. Some facial images such as eastern females in M^{2}B database are shown in Fig. 11, in which the first row denotes the raw images and the second row denotes the images with 87 geometrical landmark points. Similarly, some examples of western female faces and their geometrical landmark points have been shown in Fig. 12.

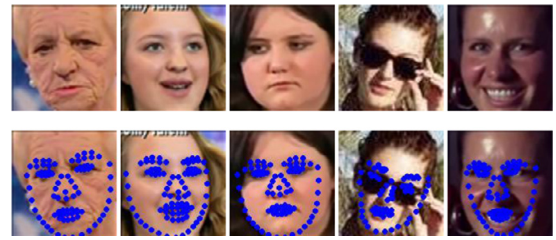


Fig. 12. Examples of western female faces in M^{2}B database.

5.2. Beauty score prediction

In terms of the existing ground truth (beauty score), we only conduct the experiments of facial beauty score prediction in this section. The eastern and western facial beauty score prediction experiments will be employed separately. For each race, the data is randomly split into training and testing with a proportion 3:1. For parameter setting, the optimal K and D for Hessian energy matrix calculation are selected from 1 to 100 alternatively. For eastern data set, the optimal parameters are $K=4$, $D=4$, $\lambda=1e-3$; for western data set, the optimal parameters are $K=6$, $D=6$, $\lambda=1e-3$. Considering that the M^{2}B is a complete database including the features and ground truth beauty scores, so this dataset is directly used to show the effectiveness of the proposed beauty analysis model.

The prediction performance *MSEP* (%) of the proposed facial beauty analysis model with 10 random splits of training and testing samples is shown in Table 6. We can see that the proposed beauty score model can achieve 82.5% and 88.7% average estimation accuracy for eastern and western female facial beauty, respectively. Both the deviations for two races are near 1%.

For comparisons with the relevant work in beauty score prediction analysis using KNN, ridge regression (RR), ANN and SVR, we run each program 100 times and the best result is presented in Table 7. For KNN, the number k of nearest neighbors varies from 1 to 100; for RR, the ridge parameter is set as 1; for ANN, the number of hidden neurons is 25, the “logsig” and “purelin” functions are used in the hidden and output layer, respectively; for SVR, the regularization and kernel parameters are set as 10 and 0.2, respectively.

As denoted in this challenging dataset, expression is a typical feature and the expression will change the facial geometric shape (e.g. mouth). Generally, facial attractiveness and the model maybe impacted by obvious expression, however, slight smile can also promote the attractiveness in the raters’ heart, because it can make people more comfortable in psychology. This dataset is used for validation of the proposed model in more complicated and actual conditions.

6. Discussion

This paper explores the facial beauty modeling based on facial geometric representation and semi-supervised learning, which aims to conduct potential application in attractiveness assessment. Motivated by the fairness in beauty assessment, the variable facial appearance features such as texture and skin color are not considered, because some slight changes (e.g. facial makeup) may cause different beauty perception from raters. In contrast, the facial geometric information cannot be easily self-deformed. Thus, in this paper, we exclusively use original coordinates of landmark points as the feature and reveal its intrinsic relationship with beauty. The geometric features are the coordinates of 2-D landmark points and can only represent frontal facial geometric information. Since a face can also be represented as a 3-D surface, it may have

Table 6
Prediction performance of the proposed method with ten times of learning.

Race	1	2	3	4	5	6	7	8	9	10	Average
Eastern	16.5	18.1	17.3	18.2	18.3	17.0	18.6	15.4	18.8	16.7	17.5 ± 1.04
Western	11.2	11.7	12.4	12.2	9.96	11.1	11.5	9.96	9.81	12.8	11.3 ± 1.01

Table 7
Predictive error comparisons with existing facial beauty assessment methods.

Race	KNN-based (Eisenthal & Dror, 2006)	RR-based (Mu, 2013)	ANN-based (Sutić et al., 2010)	SVR (Eisenthal & Dror, 2006)	HSSL (Proposed)
Eastern	31.5	25.4	26.5	24.9	17.5
Western	28.9	26.3	27.3	23.0	11.3

different contributions to facial beauty perception. Recently, there was a great progress in 3D reconstruction techniques from a single image (Biswas, Aggarwal, & Chellappa, 2009; Wang et al., 2009), and thus it becomes possible to reconstruct a large 3-D face image set from facial images. With 3-D geometric features, the proposed framework in this paper still works and tends to make a more accurate facial geometric score predictor.

In experiments, we can see that different types of beauty perception may exist among all individuals. This phenomenon reveals that although there are advanced rules about beauty perception, people may also have personalized favor of beauty. For example, it may disagree with each other when two closely attractive faces are shown to them for assessment. In our opinion, it is very challenging to study the slight difference in beauty perception, especially for those faces with moderate beauty. In this paper, we do not concern this problem too much, as beauty is still an ill-defined concept. That is, beauty is in the eye of beholder, which is person specific and different persons have different beauty cognition. Golden ratio is a common concept in facial beauty, which holds an assumption that those faces satisfying with the golden ratio can be recognized to be attractive faces. In addition to golden ratio, average face hypothesis and symmetric face hypothesis are also popular concepts which represent a beautiful face intuitively. However, it is a complicated task for facial beauty assessment using golden ratio, average face hypothesis as well as symmetric face hypothesis. This is due to that they depend on a precise distance measurement. Therefore, it is very meaningful to develop a computational model which can be used to predict the beautiful faces objectively and automatically by leveraging machine learning techniques, such as the proposed HSSL method.

The proposed HSSL method is semi-supervised, by using public labeled attractive faces and unattractive faces (geometric simulated face), in which the moderately attractive faces are recognized to be unlabeled. Therefore, one advantage of the proposed method is that we do not cost much labor for labeling a number of faces, which is well suitable for large-scale facial beauty analysis. This is because beauty labeling is more difficult than identity labeling, which is caused by the subjective nature of beauty. For other methods, to achieve some consensus, more persons should be invited for rating each face, which is time-consuming and unnecessary. One disadvantage and limitation of the proposed method is that the accurate beauty score of the moderately attractive faces may not be achieved, because of the modeling mechanism. However, a beauty rating of the faces can be given. To this end, the proposed method can be applied for geometric beauty rating in Internet or public shows.

Cognition of people's brain to beauty is an important topic in psychology, but it is out of our research in computer science. Clustering of persons according to their beauty perception is a vital task in beauty analysis, and it can help to make further understanding for ourselves. In our experiments, we found that it costs so much to invite raters, introduce standard and process the voting results, etc. These difficulties seriously restrict the accuracy of the labeling results. Clustering of persons according to their beauty perception may need tens of thousands of raters to produce a meaningful result, indeed. We believe that this problem also bothers other researchers in this field. We also consider provide a game-like experience for current rating workflow and make it online on a SNS site by using the power of gamers, which is similar with the conditions in solving the problem about DNA (Khatib et al., 2011).

7. Conclusion

In this paper, we aim to study facial aesthetic perceptron and explore the essence of beauty from the viewpoint of geometric characteristic toward an interactive attractiveness assessment application. A geometric beauty score function is proposed for attractiveness assessment quantitatively, modeled via the proposed semi-supervised HSSL learning method, by leveraging Internet labeled attractive faces and generated labeled unattractive faces. For experimental study, we established a facial beauty dataset (GFB) with geometric landmark features annotated. Additionally, an existing multi-modal facial beauty dataset (M^2B) is also used in experiments. Experimental results demonstrate the effectiveness of our proposed facial aesthetic perceptron method based on geometric feature for human beauty analysis.

In our future work, we shall investigate the facial attractiveness with the variation of facial expression, which will also be interesting clinical topics with psychological concept that smiling faces are more beautiful than angry faces.

Acknowledgments

We would like to express our sincere appreciation to the anonymous reviewers for their insightful comments, which may greatly improve the quality of the paper in the future. This work was supported by National Natural Science Foundation of China under Grant 61401048, and the Fundmental Research Funds for the Central Universities.

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