FEMALE FACIAL AESTHETICS BASED ON SOFT BIOMETRICS AND PHOTO-QUALITY

*A. Dantcheva, J.-L. Dugelay**

Multimedia Communications Department, Eurecom, Sophia Antipolis, France
{Antitza.Dantcheva, Jean-Luc.Dugelay}@eurecom.fr

ABSTRACT

In this work we study the connection between subjective evaluation of facial aesthetics and selected objective parameters based on photo-quality and facial soft biometrics. The approach is novel in that it jointly considers both previous results on photo quality and beauty assessment, as well as it incorporates non-permanent facial characteristics and expressions in the context of female facial aesthetics. This study helps us understand the role of this specific set of features in affecting the way humans perceive facial images.

Based on the above objective parameters, we further construct a simple linear metric that hints modifiable parameters for aesthetics enhancement, as well as tunes soft biometric systems that would seek to predict the way humans perceive facial aesthetics.

Index Terms— Facial aesthetics, facial beauty, soft biometrics, image quality assessment.

1. INTRODUCTION

With millions of images appearing daily on Facebook, Picasa, Flickr, or on different social and dating sites, photographs are often seen as the carrier of the first and deciding impression of a person. At the same time though, human perception of facial aesthetics in images is a priori highly subjective. The nature of this perception has long been explored *separately* from psychological and photographical points of view, respectively focusing on the properties of the subject and of the image. The photographical point of view, corresponding to photo-quality assessment and enhancement, has recently attracted further attention, partly due to the vast amount of digital images that are now available, as well as due to the ease with which digital image manipulation can now be achieved.

1.1. Background

There are substantial amounts of works, both from psychological and sociological points of view, studying human perception of facial attractiveness and beauty. A general characteristic of such studies is that they often focus on particular face proportions and symmetries (see [1] and references therein).

From an image processing point of view, few attempts seek to exploit and validate some of the aforementioned psychological results and even introduce early methods for beauty prediction. In [2] for example, the authors present a multi-layer neuronal network for beauty learning and prediction regarding faces without landmarks. Such approaches often accept interesting applications, as the automatic forecast of beauty after a plastic surgery in [3]. The same work deals with beauty classification, considering facial measurements and ratios, such as ratios of distances from pupil to chin and from nose to lips (see also the work in [4] and [5]). Again from an image processing point of view, but incorporating classical photography considerations, the work in [6] and [7] focuses on photo-quality assessment and enhancement. Such methods have become increasingly relevant due to the prevalence of low price consumer electronic products.

1.2. Contribution

In this work we study the role of objective measures in modeling the way humans perceive facial images. In establishing the results, we incorporate a new broad spectrum of known aesthetical facial characteristics, as well as consider the role of basic image properties and photograph aesthetics. This allows us to draw different conclusions on the intertwined roles of facial features in defining the aesthetics in female head-and-shoulder-images, as well as allows for further insight on how aesthetics can be influenced by careful modifications.

Towards further quantifying such insights, we construct a basic linear metric that models the role of selected traits in affecting the way humans perceive such images. This model applies as a step towards an automatic and holistic prediction of facial aesthetics in images.

The study provides quantitative insight on how basic measures can be used to improve photographs for CVs or for different social and dating websites. This helps create an objective view on subjective efforts by experts / journalists when retouching images. The novelty in our work lies mainly in two aspects. The first is that we expand the pool of facial features to include non-permanent features such as make-up, presence of glasses, or hair-style. The second novelty comes from the fact that we seek to combine the results of both research areas, thus to jointly study and understand the role of facial features and of image processing states.

The paper is organized as follows. In Section 2 we introduce the employed database, as well as describe the basic

*This work was supported in part by the European Commission under contract FP7-215372 ACTIBIO.

features and methods used in the study. In Section 3 we proceed with numerical results, and provide intuition on the role of features, image quality and facial features, in human perception. In Section 4, we use these accumulated conclusions to construct a basic linear model that predicts attractiveness in facial photographs using different facial traits as well as image properties. Finally we examine and validate the designed metric.

2. STUDY OF AESTHETICS IN FACIAL PHOTOGRAPHS

In our study we consider 37 different characteristics that include facial proportions and traits, facial expressions, as well as image properties. All these characteristics are, for the most part, manually extracted from a database of 325 facial images. The greater part of the database, 260 images, is used for training purposes and further 65 images are tested for the related validation. Each image is associated to human ratings for attractiveness, as explained in Section 2.1. The database forms the empirical base for the further study on how different features and properties relate to attractiveness.

We proceed with the details of the database and characteristics.

2.1. Database

The database consists of 325 randomly downloaded head-and-shoulders images from the web site HOTorNOT [8]. HOTorNOT has been previously used in image processing studies (cf. [2] [9]), due to the sufficiently large library of images, and the related ratings and demographic information.

Each image depicts a young female subject (see for example Fig. 1 and Fig. 2.) and was rated by a multitude of users of the web site. The rating, on a scale of one to ten, corresponds to the notion of attractiveness. The relevance and robustness of the provided ratings was confirmed in an experiment in [10], where subjects re-rated a collection of images. For increasing robustness, we consider only images that have received a sufficiently high number of ratings, specifically more than 70 ratings. We will henceforth refer to these ratings as the *Mean Opinion Score* (MOS). Among the chosen images of the database the mean MOS was 7.9, the standard deviation was 1.4, whereas the minimum value was 4.3 and the maximum value was 9.9.

The JPEG images in our database are of different resolutions and of different qualities.

We now proceed with the description of the two groups of considered features: the photograph-aesthetics (image properties), and the facial aesthetics. All characteristics, from both groups, are stated in Table 1.

2.2. Photograph Aesthetics

The considered photograph aesthetic features are here specifically chosen to be simple and objective. Firstly we include characteristics such as image resolution, image format (portrait or landscape) and illumination. Furthermore, we consider the relative angle of the face in the photograph (this angle is denoted as α in Fig. 1). We also incorporate the zoom-factor, specifically how large the face appears in comparison to the image height. Finally we also connect three novel image quality traits with facial aesthetics, which in previous work have been associated to photograph-aesthetics: the *relative foreground position*, the *BIQI* and the *JPEG quality measure*.

Regarding the *relative foreground position*, we essentially compute if the distance of the foreground's center of mass, (left eye, right eye or nose tip, respectively, cf. [11]) to one of the stress points (cf. [3]) is shorter than to the center of the image. For clarity Fig. 1 illustrates the stress points of the image, where each of the four stress points is in a distance of 1/3rd the image width and $1/3^{rd}$ the image height from the boundary of the image, an aspect derived from the "Rule of thirds". In case that the foreground's center of mass is equidistant to all stress points, which is the case in the image center, it has been shown, that subjects lose their attention and interest.

The *BIQI measure* is based on the distorted image statistics and it employs support vector machines for classification (cf. [12] and [13]). It is a blind quality measure; specifically it is a no-reference assessment measure on image quality.

The *JPEG quality measure* on the other hand considers artifacts caused by JPEG compression, such as blockiness and blurriness, evaluating again a no-reference score per image [14].

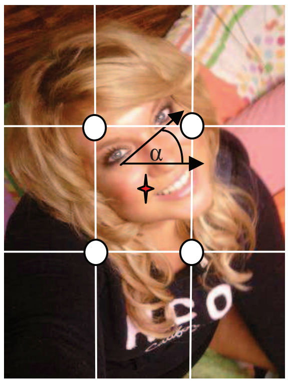

Fig. 1. Example image of the web site HOTorNOT, $MOS = 9.9$. The white disks represent the stress points, the red cross the image center.

2.3. Facial characteristics

Literature related to facial beauty (cf. [15]) identifies pertinent traits including the size of the face, the location and size of facial features like eyes, nose, and mouth, brows, lashes and lids, facial proportions, as well as the condition of the skin. Such literature confirms the role of these facial features in affecting human perception of beauty (cf. [15], [1]). Drawing from this previous work, we also consider ratios of facial features and/or their locations by relating a multitude of measures, specifically including known facial beauty ratios adhering to the golden ratio, e.g. x_{16} (see Table 1 for notations).

Moreover we proceed a step further and consider non permanent characteristics that carry low discriminative biometric information. Such characteristics are referred to as *soft biometrics*, and include eye-, hair- and skin-color, face- and brows-shape, as well as presence of glasses, make-up style and hair style. For more information on use and versatility of facial soft biometric features see for example [16]. It is to be noted that facial measures and ratios accept the definition of soft biometrics as well.

The full set of facial features is listed in Table 1 and can be categorized in the following four groups:

- Ratios of facial features and their locations
- Facial color soft biometrics
- Shapes of face and facial features
- Non-permanent traits and
- Expression.

Features related to the mouth and nose width were not exploited, due to the variety of expressions within the database, e.g. a mouth in a smiling face has sufficiently different measures than in a serious one. All selected traits are listed in

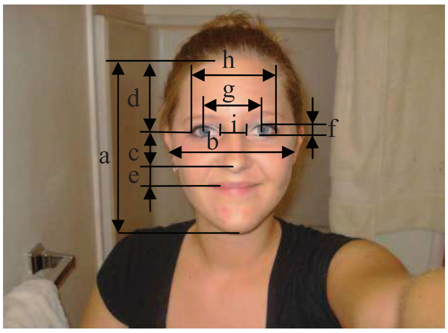

Fig. 2. Example image of the web site HOTorNOT, $MOS = 8.4$ with employed facial measures.

Table 1 (the photograph aesthetics are highlighted for a better overview). Table 2 and Table 3 in the Appendix exhibit the traits, trait instances and furthermore the range of magnitude for all photograph aesthetics and facial aesthetics respectively.

3. RESULTS

3.1. Effect of traits on the MOS rating

Our first goal is to find correlation measures for each of the 37 extracted traits and the MOS in order to observe the importance of each characteristic for human perception. The

Table 1. Characteristics listed in decreasing order with respect to the absolute Pearson's correlation coefficient, related Pearson's correlation coefficients and related $\widehat{MOS}$-model weights; see Fig.2 for notations of facial measures

Trait x_i	**Pearson's correlation coefficient** $r_{i,MOS}$	$\widehat{MOS}$-**Model weight** γ_i
x_1. Ratio (eye height / head length) **f/a**	*0.5111*	*18.3506*
x_2. Ratio (head width / head length) **b/a**	*0.4487*	*4.5780*
x_3. Eye make up	*0.3788*	*0.3055*
x_4. Face shape	*0.3521*	*0.1606*
x_5. Eye Brow shape	*0.2523*	*0.3337*
x_6. Fullness of Lips	*0.2242*	*0.2019*
x_7. Ratio (from top of head to nose / head length) **(d+c)/a**	*0.2198*	*-17.8277*
x_8. Glasses	*-0.2095*	*-0.6707*
x_9. Lipstick	*0.1997*	*0.0502*
x_{10}. Skin goodness	*-0.1856*	*-0.3930*
x_{11}. Hair Length / Style	*-0.1851*	*-0.0657*
x_{12}. Ratio (from top of head to mouth / head length) **(d+c+e)/a**	*0.1818*	*-4.1919*
x_{13}. Ratio (from top of head to eye / head length) **d/a**	*0.1774*	*49.3939*
x_{14}. Image format	*0.1682*	*0.1695*
x_{15}. Ratio (eye width / distance between eyes) **(h-i)/(2.i)**	*0.1336*	*0.8982*
x_{16}. Ratio (from nose to chin / eye to nose) **(a-d-c)/c**	*-0.1204*	*0.0970*
x_{17}. Left eye distance to middle of image or to mass point	*0.1183*	*0.4197*
x_{18}. Right eye distance to middle of image or to mass point	*0.1155*	*0.2042*
x_{19}. Ratio (from top of head eye / eye to nose) **d/c**	*-0.1012*	*-1.0091*
x_{20}. Image Resolution	*0.1012*	*-0.3493*
x_{21}. Expression	*-0.0913*	*-0.3176*
x_{22}. Ratio (outside distance between eyes / top of the head to eye) **h/d**	*-0.0833*	*-1.7261*
x_{23}. JPEG quality measure	*0.0802*	*0.9007*
x_{24}. Eyes symmetry, 0.93<(left eye width)/(right eye width)<1.06	*-0.0653*	*-0.0552*
x_{25}. Ratio (from eye to nose / nose to mouth) **c/e**	*0.0642*	*0.0462*
x_{26}. Nose distance to middle of image of mass point	*0.0537*	*0.0168*
x_{27}. Illumination	*0.0374*	*0.0127*
x_{28}. Skin Color	*-0.0368*	*-0.0549*
x_{29}. Ratio (from top of head to eye / eye to lip) **d/(c+e)**	*0.0328*	*-6.2474*
x_{30}. Ratio (eye-nose/head width) **c/b**	*0.0252*	*-0.6324*
x_{31}. Zoomfactor *a/Image resolution*	*-0.0201*	*-148.738*
x_{32}. Eye Color	*-0.0177*	*-0.0156*
x_{33}. Hair Color	*-0.0167*	*0.0312*
x_{34}. Angle of face	*-0.0137*	*-0.2688*
x_{35}. BIQI	*0.0121*	*-0.0053*
x_{36}. Ratio (from nose to chin / lips to chin) **(a-d-c)/(a-d-c-e)**	*-0.0057*	*-1.6907*
x_{37}. Ratio (Distance eyes/ head length) **g/a**	*-0.0028*	*13.9586*

preprocessing step for the MOS related study includes the removal of about 5% of the images, due to their outlier character (i.e. $> 2\sigma_X$, given that x_i is each function of the described traits).

A direct way to find a relationship between the MOS and each of the 37 traits is using Pearson's correlation coefficient. We remind the reader that for two vectors, $X = x_1, x_2, , x_n$ and $Y = y_1, y_2, , y_n$, the Pearson's correlation coefficient is given by

$$r_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y)} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y)}, \quad (1)$$

where σ_X and σ_Y are being the standard deviations for X and Y, respectively. The coefficient ranges between -1 and 1, with the two extreme points being obtained when the variables are maximally linearly related.

Pearson's correlation coefficients are calculated for all 37 vectors, each vector corresponding to a feature. For each feature, the 260-length vector X describes the value of each feature for each training image, as denoted in Table 3, and the 260-length vector Y describes the MOS rating received by each image. Table 1 itemizes these coefficients in decreasing order of importance with respect to the absolute Pearson's correlation coefficient.

3.2. Insight provided from empirical data

The first surprising and eye catching result reveals the strong correlation between the best ranked traits and the MOS, which even exceeds a Pearson's correlation coefficient of 0.5 for the trait Ratio eye-height/face-height. Particularly in regard to an automatic MOS prediction image processing tool these results are very encouraging. Further we observe that photo-quality features play a less significant role than facial aesthetics, as expected, but they are not to be neglected, since they achieve an $r_{14,MOS} = 0.168$. Moreover we note that the high ranked traits x_1, x_2 and x_4 (the ratios (eye-height/face-height) and (head-width/head-height), and face shape) in Table 1 are features corresponding strongly to person's weight. This outcome brings to the fore the strong importance of low weight for aesthetics. Furthermore it is worth noting that Table 1 reveals the surprising fact among others, that non-permanent traits place a pivotal role in raising the MOS rating. Eye make-up, lipstick, glasses and hair-style are all among the top 11 of the obtained ranking. These results hint the high modifiability of facial aesthetics perception by simple means like make-up or hair styling. The relevance of eye make-up had been previously observed in [2]. Together with the different conclusions that one may draw from Table 1, it also becomes apparent that different questions are raised, on the interconnectedness of the different traits. This is addressed in Section 3.3. Finally we note that traits, such as x_1, x_7, x_{12} and x_{13} directly comply with the well known baby-faceness hypothesis (cf. [15]), which describes that childlike facial features in females increase attractiveness, such features include big eyes, cf. x_1 and a relative low location of facial elements, cf. x_7, x_{12} and x_{13}. One measure known for increasing attractiveness, if equal to the golden ratio $\phi = 1.618$, is x_{16}.

3.3. Interconnectedness of different traits

To get a better understanding of the role of the different traits in raising the MOS, it is helpful to understand the inter-relationship between these traits. This is addressed in Table 4 in the Appendix, which describes the correlation between selected traits. Due to lack of space we limit the correlation matrix to just a group of the first six traits. Table 4 can answer different questions such as for example the validity of the conclusion in Table 1 on the importance of the make-up feature. In this case, the question arises whether it is truly the make-up that affects the MOS or whether already attractive subjects use make-up more heavily. Table 4 suggests a low correlation between the facial proportions (representing beauty) and eye make-up, which validates the strong role of makeup in raising the MOS.

4. MODEL FOR FACIAL AESTHETICS

We choose a linear metric due to its simplicity and the linear character of the traits with increasing MOS. We perform multiple regression with the multivariate data and obtain a MOS estimation metric with following form:

$$\widehat{MOS} = \sum_{i=1}^{37} \gamma_i x_i. \quad (2)$$

The resulting weights γ_i corresponding to each trait are denoted in Table 1. We here note that the weights of the model are not normalized and do not give information about the importance of each characteristic. We did not normalize for the sake of reproducibility and usability of the results in further work. The importance of the characteristics is conveyed by the Pearson's correlation coefficients $r_{X_i,MOS}$.

4.1. Validation of the obtained metric

To validate our model we compute the following three parameters.

- Pearson's correlation coefficient. As described above, and it is computed to be

$$r_{\widehat{MOS},MOS} = 0.7690 \quad (3)$$

- Spearman's rank correlation coefficient, which is a measure of how well the relation between two variables can be described by a monotonic function. The coefficient ranges between -1 and 1, with the two extreme points being obtained when the variables are purely monotonic functions of each other. This coefficient takes the form

$$r_S = 1 - \frac{6 \sum_i d_i}{n(n^2-1)}, \quad (4)$$

where $d_i = rank(x_i) - rank(y_i)$ is the difference between the ranks of the i^{th} observation of the two variables. The variable n denotes the number of observations. The coefficient, which is often used due to its robustness to outliers, was calculated here to be

$$r_{S\widehat{MOS},MOS} = 0.7645 \quad (5)$$

- Mean standard error of the difference between the estimated objective $\widehat{MOS}$ and the actual subjective MOS.

$$MSE = 0.7398 \quad (6)$$

These results clearly outperform the outcomes from Eigenfaces of $r_{\widehat{MOS},MOS)} = 0.18$ (cf. [2]) and neural networks $r_{\widehat{MOS},MOS} = 0.458$ (cf. [2]), but the comparison is not very adequate as we would compare manual extraction with automatic extraction of facial aesthetics. Nevertheless the potential of our approach is evident and we proceed with the more robust validation of the facial aesthetics metric. For this purpose we annotated the 37 traits in a new testing set of 65 images. Once more we excluded outliers (3 images) and we computed the metric verification measures for the estimated $\widehat{MOS}$ and the according actual MOS.

- Pearson's correlation coefficient:

$$r_{\widehat{MOS},MOS} = 0.7794 \quad (7)$$

- Spearman's rank correlation coefficient:

$$r_{S\widehat{MOS},MOS} = 0.7860 \quad (8)$$

- Mean standard error:

$$MSE = 1.158 \quad (9)$$

The high Pearson's coefficient implies a robust prediction accuracy of the facial aesthetics metric. The Spearman's coefficient gives an indication about the correlation between estimated and real MOS, but without the restriction of linear dependence. It considers each monotonic function connecting the two vectors. In our case this coefficient is relatively high as well. The MSE on the other hand gives an idea about the absolute error between the predicted and actual values. It is interesting to observe that the testing set provides even higher correlation coefficients than the calibration set, but the MSE reveals that the absolute error increases for the testing set, and thus that the actual performance decreases.

5. CONCLUSIONS

We presented a study on facial aesthetics in photographs, where we opposed objective measures, namely photograph quality measures, facial beauty characteristics and non-permanent facial features with human subjective perception. The results of the correlation coefficients of the selected traits with the related MOS values, respectively are kind of surprising. Non-permanent features influence highly the MOS and we conclude that facial aesthetics in images is substantially modifiable. Simple image post-processing and traits like make-up, glasses and quality of the image cause a high effect on the MOS. In addition we built a linear metric based on the MOS and the selected traits for prediction of facial aesthetics, and provided promising results in the validation. This work builds a basis for further image processing work to fully automate prediction of aesthetics in facial images.

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A. APPENDIX

Table 2. Photograph aesthetic traits, according trait instances and annotations

Trait x_i	**Trait instance**
x_{14}. Image format	1:Portrait, 2:Landscape
x_{17}. Left eye distance to middle of image or to mass point	1: shorter distance to middle of image 2: shorter distance to mass point
x_{18}. Right eye distance to middle of image or to mass point	1: shorter distance to middle of image 2: shorter distance to mass point
x_{20}. Image Resolution	Normalized from 0 to 1; Discrete
x_{23}. JPEG quality measure [14]	Continuous
x_{26}. Nose distance to middle of image of mass point	1: shorter distance to middle of image 2: shorter distance to mass point
x_{27}. Illumination	0: poor; 0,5: medium; 1: excellent
x_{31}. Zoomfactor *a/Image resolution*	Continuous
x_{34}. Angle of face	Continuous
x_{35}. BIQI (cf. [12][13])	Continuous

Table 3. Facial aesthetic traits, according trait instances and annotations

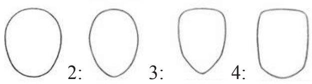
Trait x_i	**Trait instance**
x_1. Ratio (Eye height / head length) **f/a**	Continuous
x_2. Ratio (Head width / Head length) **b/a**	Continuous
x_3. Eye make up	0:No make up, 0.5: light make-up, 1:strong make-up
x_4. Face shape	1: 2: 3: 4:  5:2&3, 6:1&3, 7:1&2
x_5. Eye Brow shape	1: 2: 3: 
x_6. Fullness of Lips	0:Thin lips, 0.5:medium, 1:full lips
x_7. Ratio (from top of head to nose)/head length **(d+c)/a**	Continuous
x_8. Glasses	0:No glasses, 1:glasses
x_9. Lipstick	0:No lipstick, 1:bright lipstick, 2:flashy lipstick
x_{10}. Skin goodness	1:Clear skin, 2:not clear skin (pimples)
x_{11}. Hair Length / Style	1:Short, 2:shoulder, 3:long, 4:half tied back, 5:tied back
x_{12}. Ratio (from top of head to mouth)/head length **(d+c+e)/a**	Continuous
x_{13}. Ratio (from top of head to eye/head length) **d/a**	Continuous
x_{15}. Ratio (eye width / distance between eyes) **(h-i)/(2.i)**	Continuous
x_{16}. Ratio (from nose to chin / eye to nose) **(a-d-c)/c**	Continuous
x_{19}. Ratio (from top of head eye / eye to nose) **d/c**	Continuous
x_{21}. Expression	1:Smile + teeth, 2:smile, 3:neutral, 4:corner of the mouth facing down, 5:non of all
x_{22}. Ratio (outside distance between eyes/ top of the head to eye) **h/d**	Continuous
x_{24}. Eyes symmetry	0.93<(left eye width)/(right eye width) <1.06
x_{25}. Ratio (from eye to nose / nose to mouth) **c/e**	Continuous
x_{28}. Skin Color	1, 2, 3 (from light to dark)
x_{29}. Ratio (from top of head to eye / eye to lip) **d/(c+e)**	Continuous
x_{30}. Ratio (eye-nose/head width) **c/b**	Continuous
x_{32}. Eye Color	1:blue, 2:green, 3:brown, 4:black, 5:mix
x_{33}. Hair Color	1:blond, 2:brown, 3:black, 4:red, 5:dark blond
x_{36}. Ratio (from nose to chin / lips to chin) **(a-d-c)/(a-d-c-e)**	Continuous
x_{37}. Ratio (Distance eyes/ head length) **g/a**	Continuous

Table 4. Correlation matrix of selected non permanent and permanent traits, see Table 1 for notations of x_i

	x_1	x_2	x_3	x_4	x_5	x_6
x_1	1	0.317	0.308	0.153	0.151	0.161
x_2	0.317	1	0.132	0.268	0.034	0.092
x_3	0.308	0.132	1	0.140	0.158	0.108
x_4	0.153	0.268	0.140	1	-0.0036	0.122
x_5	0.151	0.034	0.158	-0.0036	1	0.155
x_6	0.092	0.092	0.108	0.122	0.155	1