SCUT-FBP: A Benchmark Dataset for Facial Beauty Perception

Duorui Xie, Lingyu Liang, Lianwen Jin*, Jie Xu, Mengru Li
School of Electronic and Information Engineering
South China University of Technology, Guangzhou 510641, China
*Emails: lianwen.jin@gmail.com

***Abstract*—In this paper, a novel face dataset with attractiveness ratings, namely the SCUT-FBP dataset, is developed for automatic facial beauty perception. This dataset provides a benchmark to evaluate the performance of different methods for facial attractiveness prediction, including the state-of-the-art deep learning method. The SCUT-FBP dataset contains face portraits of 500 Asian female subjects with attractiveness ratings, all of which have been verified in terms of rating distribution, standard deviation, consistency, and self-consistency. Benchmark evaluations for facial attractiveness prediction were performed with different combinations of facial geometrical features and texture features using classical statistical learning methods and the deep learning method. The best Pearson correlation 0.8187 was achieved by the CNN model. The results of the experiments indicate that the SCUT-FBP dataset provides a reliable benchmark for facial beauty perception.**

***Index Terms*—Face dataset, facial attractiveness prediction, facial beauty assessment, facial beautification.**

I. Introduction

Assessing facial beauty is a challenging task that has been investigated by countless philosophers, artists, and scientists for many years. In particular, it has attracted considerable attention in the field of computer vision. Recent psychology research [1] has shown that the perception of beauty is consistent among different individuals. Another study [2] has indicated that facial beauty is a universal concept that can be learned by a machine. Research on facial beauty, which can serve as the basis for facial aesthetics, plastic surgery, and face image retouching, has contributed to the development of commercial systems for facial beauty enhancement, such as MeiTu [24] and Portraiture [25].

Most studies on facial beauty focus on designing facial beauty descriptors. Because facial symmetry, averageness, and secondary sex characteristics influence the perception of facial attractiveness [5, 6], data-driven facial beauty analysis based on geometric features [3, 4, 9] and skin texture features [7] has inspired many related studies in the fields of computer vision and machine learning. Although feature extraction for facial beauty analysis has been investigated extensively, little attention has been paid to data collection in this regard. A publicly available facial beauty dataset is expected to facilitate further research in this field. In particular, it can provide a unified benchmark for evaluating the performance of different algorithms, thereby promoting the development of new algorithms and applications for facial beauty analysis as well as selection criteria for facial beautification [32].

Fig. 1: Faces with different attractiveness in the SCUT-FBP dataset, which is publicly available at **http://www.hcii-lab.net/data/SCUT-FBP**.

Many studies on facial attractiveness prediction [8,19] have used existing face databases for evaluation, such as the databases for face recognition and smile detection [29]. Although these databases are suitable for some specific face analysis task, they may fail to meet the requirements of the facial beauty perception problem owing to the lack of attractiveness ratings.

Face datasets [12-13, 17, 33-34] for facial beauty assessment were built in a recent study. Fan et al. proposed a dataset [12] containing computer-generated face images with different facial proportions; however, it is limited for face structure analysis. Yan [13] proposed dataset gathering from social networks, but the resolution of the collected images was low. There are some large-scale databases for facial beauty analysis, such as the Northeast China database [4], the Shanghai database [9], the Hot or Not database [34] and the recent AVA database [15], which can be improved in certain aspects from the perspective of facial beauty perception. The Northeast China database [4] and the Shanghai database [9] are limited for geometric facial beauty analysis, which

978-1-4799-8697-2/15 $31.00 © 2015 IEEE
DOI 10.1109/SMC.2015.319

fail to capture the appearance features and the corresponding attractiveness ratings. The AVA database [15], a large-scale database for aesthetic visual analysis, contains a subset of portraits [14]. However, AVA is concerned with the aesthetic analysis of the entire image and not just the face. Therefore, the AVA ratings of a portrait reflect the quality of the image but not of the face itself. Thus, a portrait with a high rating may be influenced by the background or facial expressions. The main attributes of the representative dataset are summarized in Table I.

This paper proposes a benchmark dataset, namely the SCUT-FBP dataset, which can be used for different facial beauty analysis problems, including facial attractiveness prediction [33-34] and facial beautification [32].

The main contributions of this paper can be summarized as follows:

1) **Dataset.** A large number of portraits with different levels of attractiveness are collected. To reduce the effects of irrelevant factors, SCUT-FBP contains high-resolution, front-on face portraits of Asian female subjects with neutral expressions, simple backgrounds, and minimal occlusion; these factors are conducive to facial beauty perception in both geometry and appearance.
2) **Beauty Rating Analysis.** Attractiveness ratings for all images are collected, and the final rating is determined according to the rating distribution. The average number of raters per image of the SCUT-FBP dataset is 70, which is greater than that of the datasets used in previous studies [9, 11, 12, 17]. We verify the ratings in terms of the rating distribution [14], standard deviation [14], consistency [2], and self-consistency [19].
3) **Feature Analysis.** We propose the use of an 18-dimensional geometrical featureand 2-dimensional Gabor texture features to predict facial attractiveness. The 18-dimensinal geometrical feature is based on traditional Chinese facial beauty standards. To extract texture features, we adopt two sampling methods which reduce the dimension and enhance the accuracy of the prediction. Experiments show that the above-mentioned features can represent facial beauty with sufficient accuracy.
4) **Beauty Prediction.** Both traditional machine-learning and deep learning methods are adopted to predict beauty. The best Pearson correlation for traditional machine learning and deep learning is 0.6482 and 0.8187, respectively, which indicates that the SCUT-FBP dataset provides a reliable benchmark for facial beauty analysis.

The remainder of the paper is organized as follows. Section II describes the creation of the SCUT-FBP dataset. Section III discusses the analysis of the dataset. Section IV and Section V present benchmark evaluations of the dataset using traditionally machine learning and the recent deep learning methods respectively. Section VI concludes the paper.

TABLE I: SOME REPRESENTATIVE DATASETS FOR FACIAL BEAUTY ANALYSIS

Dataset	Image Numbers	Raters per Image	Beauty Class	Publicly Available?
[2]	92/92	28/18	7	No
[4]	23412	unknown	2	No
[9]	1307	100	unknown	No
[17]	215	46	10	No
[12]	432	30	7	No
[14]	10141	78-549	10	Yes
SCUT-FBP	500	70	5	Yes

II. CREATION OF SCUT-FBP

A. Data Collection

We collected data to build a standard dataset that provides unified data for evaluating the performance of different algorithms. To reduce the effects of irrelevant factors such as age, gender, and facial expression, the SCUT-FBP dataset is confined to a unified form, i.e. it contains high-resolution, front-on face portraits of Asian female subjects with neutral expressions, simple backgrounds, no accessories, and minimal occlusion. A previous study [20] has shown that beautiful individuals constitute a small percentage of the population. The SCUT-FBP dataset contains a higher proportion of beautiful faces than that in the general population in order to facilitate effective learning of facial beauty. Specifically,it contains 500 portraits, some of which were captured by ourselves; others were licensed from different sources [26-28] or downloaded from the Internet. All the images were rated by numerous raters. Fig. 1 shows the faces with different attractiveness from the constructed dataset.

B. Rating Collection

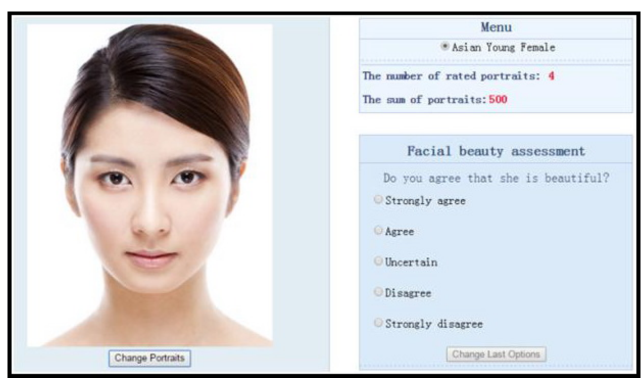


Fig. 2: Interface of the facial beauty assessment system.

We developed a web-based tool,namely, the facial beauty assessment system[1], to collect ratings. Images in the SCUT-FBP dataset were rated by 75 raters; the average number of

[1]The facial beauty assessment system can be accessed online at **http://202.38.194.248:8011/**.

raters per image was 70. Because the evaluation ground truth varied among individuals, we obtained raters opinions regarding the beauty of the portraits by asking them for answers to certain questions [10, 31]. The questions are listed in GUI of system, as shown in Fig 2. The portraits were randomly shown to the raters. The raters could change their ratings if they accidentally selected an incorrect option. Although facial beauty has been shown to be a universal concept [2], it is subjective to some extent. The procedure described above aims to eliminate unnecessary effects.

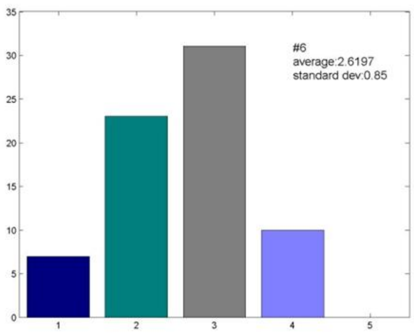


Fig. 3: Grade histogram for image 6 in the SCUT-FBP dataset.

The rating process is implemented as followings:

1) 75 raters were invited to use the facial beauty assessment system and rate the portraits;
2) The system displayed the portraits in a random manner;
3) The raters could rate a portrait or change the rating given to the last viewed portrait by clicking the Change Last Operation button. In addition, they could view the next portrait by clicking the Change portrait button, as shown in Fig. 2;
4) We analyzed the ratings, selected the appropriate data, and omitted the erroneous data. Then, we plotted a histogram for every portrait, as shown in Fig. 3. The average rating of all the raters was defined as the attractiveness rating label.

III. ANALYSIS OF SCUT-FBP

In this section, we describe the analysis of the SCUT-FBP dataset in terms of four aspects: rating distribution, standard deviation, consistency, and self-consistency.

A. Rating Distribution

We statistically analyzed the rating distribution for the dataset. The histogram of the rating distribution is shown in Fig. 4. It shows that the rating distribution is nearly Gaussian. The major part of the dataset consists of portraits having an average rating of around 2.5. This implies that average faces are more common than beautiful and unattractive faces, which reflects the real-world situation. In Figure 4, there is a small peak around 4.5 because the dataset contains a higher proportion of beautiful faces than the general population in order to facilitate effective learning of facial beauty. The rating distribution is consistent with our expectation.

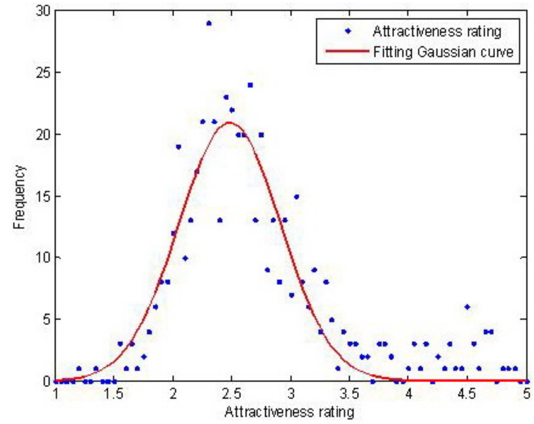


Fig. 4: Histogram of rating distribution.

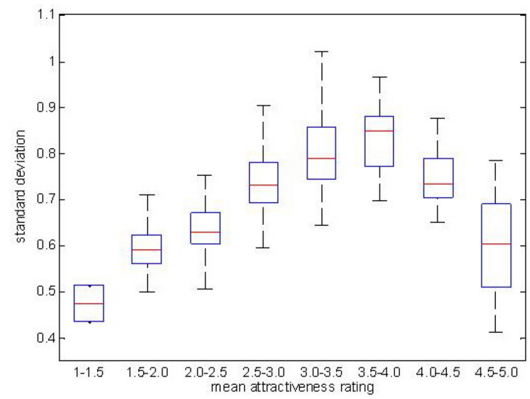


Fig. 5: Distribution of standard deviation for portraits with different mean ratings.

B. Standard Deviation

The standard deviation of the ratings indicates the rater consistency: a low standard deviation denotes high consistency. The standard deviation is concentrated between 0.6 and 0.8. The highest standard deviation is 1.07, the lowest standard deviation is 0.41, and the average standard deviation is 0.693. A small standard deviation indicates high consistency in the perception of facial beauty, thus verifying the rationality of our rating label set.

Fig. 5 shows the plot of standard deviation for portraits with mean ratings within a specific range. It can be seen that portraits with average ratings (ratings in the range $[2.5, 3.5]$) tend to have a higher standard deviation than portraits with ratings greater than 3.5 or less than 2.5. The closer the score to 1 or 5, the lower is the standard deviation. There same conclusion is reached in the case of AVA [15]. This indicates that there is a unified opinion regarding a beautiful face and an unattractive face, but the perception of an average face is rather subjective.

TABLE II: CORRELATIONS BETWEEN DIFFERENT SETS OF LABELS OF ATTRACTIVENESS

Rater No.	1^{st}–2^{nd} Correlation	2^{nd}–3^{rd} Correlation	1^{st}–3^{rd} Correlation	Average Correlation
female 1	0.68	0.74	0.69	0.70
female 2	0.64	0.68	0.69	0.67
female 3	0.70	0.68	0.61	0.67
female 4	0.73	0.73	0.71	0.72
female 5	0.71	0.73	0.87	0.77
female 6	0.73	0.68	0.72	0.71
female 7	0.78	0.80	0.81	0.80
female 8	0.78	0.80	0.81	0.80
female 9	0.85	0.86	0.85	0.85
female 10	0.66	0.67	0.72	0.69
Average correlation for female raters				**0.739**
male 1	0.77	0.76	0.78	0.77
male 2	0.77	0.76	0.78	0.77
male 3	0.72	0.73	0.75	0.73
male 4	0.69	0.66	0.69	0.68
male 5	0.71	0.71	0.85	0.76
male 6	0.68	0.72	0.76	0.72
male 7	0.71	0.67	0.64	0.67
male 8	0.67	0.66	0.61	0.65
male 9	0.67	0.66	0.61	0.65
male 10	0.76	0.78	0.81	0.78
Average correlation for male raters				**0.714**
Average correlation for all the raters				**0.727**

C. Self-consistency

Previous studies [2, 17, 11] divided ratings into two groups, calculated the mean rating of each group, and checked for consistency between the two mean ratings. We repeated this procedure numerous times. The correlation between the two mean ratings was found to be 0.96–0.97, which was higher than the correlations obtained previously 0.90–0.95 in [2] and 0.87–0.90 in [11].

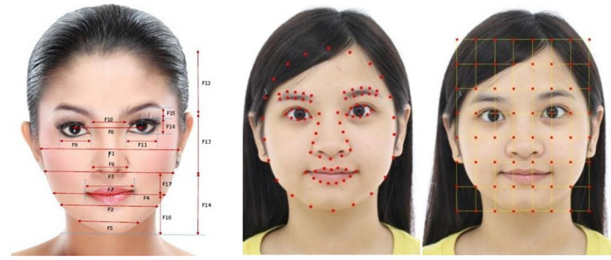
The t-test has also been used for dataset verification [2, 17]. We used the t-test in the experiment and found that the mean ratings of the two groups were not statistically different.

D. Consistency

Three sets of ratings were collected over different periods for consistency evaluation. Table II lists the self-consistency correlations for 20 raters (10 females and 10 males). The average correlation was 0.65–0.85. Furthermore, the self-consistency of females (0.739) was slightly higher than that of males (0.714). The average correlation for all 20 raters (0.727) is higher than that obtained previously (0.58) in [19].

For the entire dataset, the self-consistency correlations a-mong the three sets were 0.97, 0.97, and 0.98 respectively, which indicates a strong correlation.

In summary, the self-consistency of both the raters and the entire dataset was high, which confirms the reliability of the rating labels.



(a) (b) (c)

Fig. 6: Feature extraction used in the traditional ML methods. (a) shows the 18 dimensional facial geometric features. (b) and (c) illustrates two different sampling schemes for facial appearance features extraction.

IV. Facial Beauty Prediction via Traditional Machine Learning Methods

Using traditional machine learning, we aimed to develop a suitable feature extraction and machine-learning algorithm in order to learn and predict beauty automatically. The experiments are performed using 10-fold cross-validation.

A. Feature Extraction

We used the geometric features and skin texture features proposed in several previous studies [4, 9, 22].

Facial geometric features. As shown in Fig. 6(a), we extracted 18 features to abstractly represent each face based on [3]. The landmarks were automatic located (serious mistakes would be adjust manually). In addition to the 17 features in [3], the vertical distance from the hairline to the midpoint between the eyebrows is also used.

Facial appearance features. Facial appearance feature, such as skin texture, plays a significant role in the perception of female facial beauty [7]. A Gabor filter with 4 scales and 8 directions was applied to extract the appearance features. Two sampling methods schemes were adopted for appearance features extraction, as shown in Fig. 6.

Fig. 6(b) shows the first sampling scheme (denoted as KeyPointGabor), which extracts 84 points as sample points containing facial contour information and shape information of the eyebrow, eyes, mouth, and so on.

Fig. 6(c) shows the first sampling scheme (denoted as UniSampleGabor), which select the smallest rectangle that can include a face region. Then, 8×8 uniform sampling was conducted within this rectangle. The 64 points were collected as sample points.

B. Facial Beauty Assessment

We evaluated the prediction performance of different al-gorithms on the basis of several criteria such as Pearson correlation (PC) [30], mean absolute error (MAE) [10], and root mean squared error (RMSE) [10]. The machine learning methods used in the paper include SVM regression (SVR), linear regression, pace regression, and Gaussian regression.

TABLE III: PREDICTION PERFORMANCE USING GEOMETRIC FEATURES

	Linear Regression	Pace Regression	Gaussian Regression	SVR
PC	0.5921	0.5847	0.6057	0.608
MAE	0.4120	0.4139	0.4014	0.4021
RMSE	0.5389	0.5422	0.5316	0.5316

Performance for geometric features. From Table III, it can be seen that the best Pearson correlation (0.608) was achieved by SVR. Gaussian regression also showed good performance. Therefore, in the following experiments, we adopted Gaussian regression and SVR algorithms.

TABLE IV: PREDICTION PERFORMANCE USING GEOMETRIC FEATURES

	KeyPointGabor + PCA		UniSampleGabor + PCA	
	SVR	Gaussian Regres.	SVR	Gaussian Regres.
PC	0.5490	0.4591	0.5847	0.6347
MAE	0.5541	0.4724	0.4230	0.3969
RMSE	0.5606	0.6152	0.5452	0.5164

Performance for appearance features. Principal component analysis (PCA) was adopted to reduce the high dimension of the extracted Gabor features. From Table IV, we can see that the skin texture feature sampled in the second method showed better performance than that in the first method (Pearson correlation of 0.6347 based on Gaussian regression).

TABLE V: PREDICTION PERFORMANCE USING COMBINED FEATURES

	PC	MAE	RMSE
SVR	0.6433	0.3961	0.5120
Gaussian Regres.	0.6482	0.3931	0.5149

Performance for the combination features. We combined the geometric and UniSampleGabor features, referred as combined feature in order to improve prediction performance. The results are shown in Table V, which indicates that Gaussian regression achieves the best performance (Pearson correlation, 0.6482). The combined feature showed better performance than the individual features, which indicates that both geometric features and skin texture are important for the perception of facial beauty.

V. Facial Beauty Prediction via Deep Learning

Deep learning is an ever-growing realm in the machine learning community, whose network structure is inspired by the human brain for thinking and learning. A traditional approach to facial beauty prediction involves extracting features from images manually and adding them into a classifier for classification. Such an approach is inefficient and highly dependent on operator experience. In contrast, deep learning combines feature extraction and classification so that features can be learned automatically from the input data. Deep learning attempts to learn in multiple levels corresponding to different levels of abstraction. The levels in these learned statistical models correspond to distinct levels of concepts, where higher-level concepts are defined from lower-level concepts, and the same lower-level concepts can be used to define many higher-level concepts.

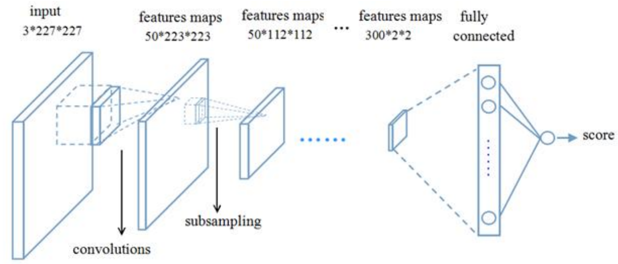


Fig. 7: The CNN architecture for facial beauty prediction.

A convolutional neural network (CNN) is an important framework of deep learning. It consists of various combinations of convolutional layers, pooling layers, and fully connected layers. Such a structure allows a CNN to effectively exploit the two-dimensional structure of the input data. To avoid the existence of billions of parameters if all layers are fully connected, the concept of shared weight in convolutional layers has been introduced, whereby the same filter is used for each patch in the layer; this reduces the required memory capacity and improves performance. A CNN can be trained using a back-propagation algorithm [23]. Compared with other deep learning structures, a CNN gives better results in applications such as image and voice recognition.

In this study, a CNN was used to design a network for facial beauty prediction. We randomly selected 400 images from our SCUT-FBP dataset for training, and the remaining 100 images were used for testing. The network outputs a score for each test face. The correlation between the preset score and the predicted score was used to evaluate the network.

We designed a convolutional neural network for facial beauty prediction, as shown in Fig. 7. The network contained six convolution layers, each of which was followed by a max-pooling layer. The numbers of feature maps applied to the six convolution layers were 50, 100, 150, 200, 250, and 300; the sizes of the corresponding filters were are 55, 55, 44, 44, 44, and 22. Such a combination was found to give better results than networks with a greater number of feature maps or smaller filters. There were two fully connected layers at the top of the network: the first one had 500 neurons, whereas the second one had only one neuron because we wanted it to output the predicted score of the input image. To enhance the network, we used some tricks such as dropout. Finally, the Euclidean loss was selected as the loss function.

We conducted five experiments using five types of randomly

TABLE VI: PREDICTION PERFORMANCE USING CNN

Exp.	1	2	3	4	5	Average
PC	0.8509	0.8050	0.8112	0.7817	0.8446	**0.8187**

selected training and test sets, and we calculated the correlation coefficient for each of them. In addition, we calculated the average correlation coefficient. The results are listed in Table VI.

In the case of a single network, we obtained an average correlation coefficient of 0.8187, indicating a good correlation between the preset scores and the predicted scores obtained by CNN. This indicates that the CNN-based deep learning approach achieve better performance for facial beauty prediction comparing to the traditional ML methods with shallow architecture.

VI. Conclusions

We constructed a dataset of faces with attractiveness ratings, namely the SCUT-FBP dataset. This dataset contains 500 Asian female faces with different attractiveness ratings, which is publicly available online at **http://www.hcii-lab.net/data/SCUT-FBP/**.

We analyzed and verified the facial attractiveness ratings from many aspects, which indicates the reliability of the dataset. In addition, we presented a benchmark evaluation based on traditional machine learning and deep learning approaches. The best Pearson correlation 0.8187 is achieved by the CNN model. The SCUT-FBP dataset can be used to investigate different aspects of facial beauty analysis problems and promote further development in this field.

Acknowledgment

This research is supported in part by the National Natural Science Foundation of China (Grant No. 61472144), the National Science and Technology Support Plan (Grant No. 2013BAH65F01, 2013BAH65F03), Research Fund for the Doctoral Program of Higher Education of China (Grant No. 20120172110023) and China Postdoctoral Science Foundation.

References

[1] R. Thornhill and S. W. Gangestad, "Facial attractiveness," *Trends Cognit. Sci.*, vol. 3, no. 12, pp. 452C460, 1999.
[2] Y. Eisenthal, G. Dror, and E. Ruppin, "Facial attractiveness: Beauty and the machine," *Neural Computation*, vol. 18, pp. 119-142, 2006.
[3] H. Mao, L. Jin, and M. Du, "Automatic classification of Chinese female facial beauty using Support Vector Machine," in *Proc. SMC*, 2009.
[4] F. Chen and D. Zhang, "A benchmark for geometric facial beauty study," *Medical biometrics*, pp. 21-32, 2010.
[5] Etcoff, and L. Nancy, "Beauty and the beholder," *Nature*, vol.368, no. 6468, pp. 186C187, 1994.
[6] Langlois, H. Judith, and L.A.Roggman, "Attractive Faces are only Average," *Psychological Science*, vol. 1, pp. 115C121, 1990.
[7] H. Mao, "Feature Analysis and Machine Learning of Facial Beauty Attractiveness," *Ph.D Dissertation of South China Univ. of Tech.*, 2011.
[8] R. White, A. Eden, and M. Maire, "Automatic Prediction of Human Attractiveness," UC Berkley CS280A Project, vol. 1, pp. 2, 2004.
[9] D. Zhang, Q, Zhao, and F. Chen, "Quantitative analysis of human facial beauty using geometric features," *Pattern Recognition*, vol. 44, no. 4, pp. 940-950, 2011.
[10] B. Cohen, "Explaining psychological statistics," John Wiley & Sons, 2008.
[11] J. Gan, L. Li, Y. Zhai, and Y. Liu, "Deep self-taught learning for facial beauty prediction," *Neurocomputing*, vol. 144, pp. 295-303, 2014.
[12] J. Fan , K. Chau, X. Wan, L. Zhai and E. Lau, "Prediction of facial attractiveness from facial proportions," *Pattern Recognition*, vol. 45, no. 6, pp. 2326-2334, 2012.
[13] H.Yan, "Cost-sensitive ordinal regression for fully automatic facial beauty assessment," *Neurocomputing*, vol. 129, pp. 334-342, 2014.
[14] M. Redi, N. Rasiwasia, G. Aggarwal and A. Jaimes, "The Beauty of Capturing Faces: Rating the Quality of Digital Portraits," arXiv preprint arXiv:1501.07304, 2015.
[15] N. Murray, L. Marchesotti L, and F. Perronnin, "AVA: A large-scale database for aesthetic visual analysis," in *Proc. CVPR*, 2012.
[16] B. Davis and S. Lazebnik, "Analysis of human attractiveness using manifold kernel regression," in *Proc. ICIP*, 2008.
[17] H. Gunes and M. Piccardi, "Assessing facial beauty through proportion analysis by image processing and supervised learning," *International Journal of Human-Computer Studies*, vol. 64, no. 12, pp. 1184-1199, 2006.
[18] K. Schmid, D. Marx, and A Samal, "Computation of a face attractiveness index based on neoclassical canons, symmetry, and golden ratios," *Pattern Recognition*, vol. 41, no. 8, pp. 2710-2717, 2008.
[19] J. Whitehill and J.R. Movellan, "Personalized facial attractiveness prediction," in *Proc. AFGR*, 2008.
[20] B. Atiyeh and S. Hayek, "Numeric expression of aesthetics and beauty," *Aesthetic Plastic Surgery*, vol. 32, no. 2, pp. 209-216, 2008.
[21] A. Iliffe, "A study of preferences in feminine beauty," *British Journal of Psychology*, vol. 54, no. 3, pp. 267-273, 1960.
[22] G. Rhodes, "The evolutionary psychology of facial beauty," *Annu. Rev. Psychol.*, vol. 57, pp. 199-226, 2006.
[23] D. Rumelhart, G. Hinton, and R. Williams, "Learning representations by back-propagating errors," *Cognitive Modeling*, 1988.
[24] "Meitu," url: http://xiuxiu.web.meitu.com.
[25] "ArcSoft, PorTrait+," url: http://www.arcsoft.com/portraitplus.
[26] "ShutterStock," url: www.shutterstock.com/.
[27] "DataTang," url: http://datatang.com/.
[28] "Pixel Solutions," url: http://www.pixelall.com/.
[29] J. Whitehill, G. Littlewort, I. Fasel I, M. Bartlett, and J. Movellan, "Developing a practical smile detector," in *Proc. AFGR*, 2008.
[30] K. Pearson, "Notes on the history of correlation," Biometrika, pp. 25-45, 1920.
[31] R. Brown Beatty, "An Analysis of Racial Identity Attitudes and the Perception of Racial Climate on Job Satisfaction of African American Faculty at Historically White Institutions," Ohio University, 2012.
[32] L. Liang, L. Jin and X. Li, "Facial skin beautification using adaptive region-aware mask," *IEEE Trans. on Cybernetics*, vol.44, no.12, pp.2600-2612, 2014.
[33] S. Wang, M. Shao and Y. Fu, "Attractive or Not? : Beauty Prediction with Attractiveness-Aware Encoders and Robust Late Fusion," in *Proc. ACM Multimedia*, 2014.
[34] D. Gray, K. Yu, W. Xu and Y. Gong, "Predicting facial beauty without landmarks," in *Proc. ECCV*, 2010.