A Survey of Perception and Computation of Human Beauty

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ABSTRACT

Perception of (facial or bodily) beauty has long been debated amongst philosophers, artists, psychologists and anthropologists. Ancient philosophers claimed that there is a timeless, aesthetic ideal concept of beauty based on proportions, symmetry, harmony, and geometry, that goes well beyond the observer. Modern philosophers, on the other hand, have commonly suggested that beauty is in the eye of the beholder, and that beauty canons depend on culture. Despite the continuous interest and extensive research in cognitive, evolutionary and social sciences, modeling and analysis of human beauty and aesthetic canons remains open. Therefore, this paper aims to put the beauty trait under the spotlight by investigating various aspects involved in its perception and computation.

Categories and Subject Descriptors: A.1 Introductory & Survey: [Survey]; H.1.2 User / Machine systems: [Human information processing] ; I.5.4 Pattern Recognition Applications: [Models, Learning]

General Terms: Algorithms, Human Factors, Performance, Theory.

Keywords: Human beauty, theories of attractiveness, computation and analysis of beauty, enhancement of attractiveness.

1. INTRODUCTION

Physical personality comprises those aspects of appearance, which, at zero acquaintance, give rise to an initial impression of personality and a concomitant set of reactions and expectations in others [37]. Models of physical personality aim to attribute certain personality traits to various physical characteristics. Human beauty or attractiveness is a dominant aspect (trait) of the physical personality [37]. When we meet others, we attempt to incorporate information about them into our framework of intentions, motives, and causal relations, all of which are used to compose a model of the other and can be used to predict how the other may act. Attractiveness therefore plays an important role in meeting people, and in determining which social relationships will be pursued [27]. According to the evolutionary perspective, attractiveness preferences are deeply rooted in the origins of evolution. This theory suggests that there is a preference for various facial and bodily traits due to the fact that they signal mate quality and imply success in reproduction and parasite resistance. Additionally, contemporary research findings on attitudes and personality revealed that people respond positively to attractiveness and associate it with positive character traits (e.g., socially competent, potent, intellectually capable and psychologically more adapted) [37]. These in turn bring to mind the question of what (morphological) characteristics make a human (face / body / voice) attractive? Are there any universally accepted and recognized aesthetic canons? Such questions have long been debated amongst philosophers, artists, psychologists and anthropologists. The Greek philosophers, namely Plato and Aristotle, were arguably the first ones to focus on studying the concept of human beauty. More specifically, ancient philosophers believed that there is a timeless, aesthetic ideal concept of beauty based on proportions, symmetry, harmony, and geometry, independent of the observers themselves. The Renaissance artists popularized this view by formulating the ideal proportions of the human form (e.g., ideal facial proportions were defined with the theory of equal thirds). Until the nineteenth century these views had a major influence on the Western perception of beauty and use of certain artistic canons. In the twentieth century anthropometrists started challenging these claims and canons by conducting a number of experiments (e.g., [10] - [13]). Modern view of beauty thus has been based on the idea that it is variable and subjective to race, culture or era. For instance, it has been reported that in general faces that are more familiar are considered more attractive [32], and there is evidence that moral judgments influence opinions of beauty. A number of studies, however, found evidence supporting the claim that perception of beauty is somewhat universal and hard-wired into our brain, cross-culturally, cross-racially, and across age groups [36].

Overall, the psychologist and anthropometrists have not reached a consensus yet on whether beauty is a social, cultural and learned concept or it is *hard-wired* into our brain from birth, and which facial/bodily/vocal qualities and characteristics appear to make a human being *appealing*.

Despite the lack of a theory of attractiveness that is generally accepted, recently automatic attractiveness analysis and enhancement research fields have emerged based on the

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notion that it is possible to analyze and classify human physical cues (facial cues, bodily cues, vocal cues, etc.) along the attractiveness trait (dimension). There also exists research suggesting that attractiveness is a notion that should be implemented in the design of social agents (e.g., recommender systems) [27]. If agents are equipped with the capability of perceiving and classifying the physical personality of other agents and humans, they can function as social mirrors for others [27]. For instance, in the virtual world, agents designed to enforce rules or command could be less attractive and more mature-faced, while agents designed to assist others could adopt a baby-faced appearance.

In order to shed an interdisciplinary light on the issue, this paper aims to put the beauty trait under the spotlight by investigating various aspects involved in its perception and computation.

2. THEORIES OF ATTRACTIVENESS

2.1 Facial attractiveness

Researchers suggested that the frontoparallelness of the face, precisely controlled symmetry, height of the internal features, relative luminance of different facial features, and the quality and the characteristics of the skin play an important role in the perception and assessment of facial attractiveness. An overview of the existing major theories is provided in the following sections.

The composite faces theory. Studies of reactions to average (composite) faces show that the more faces added to the composite, the greater the perceived beauty. Moreover, an average face (created from a set of random faces) is perceived as more attractive than the original ones [23]. We illustrate this in Figure 1 where twelve images of famous female faces were selected and cropped, and the composite facial image was obtained. Morphing the facial shape of a face towards the mean facial shape of a set of images appears to enhance attractiveness, whereas morphing the facial shape further from the mean appears to reduce attractiveness [34]. However, Cunningham et al. [2] proved that, although averaged faces are perceived as attractive, a very beautiful face is not close to this average.

(a) (b)

Figure 1: Illustration of the composite faces theory: (a) images of 12 famous female faces and (b) the composite (average) face obtained.

The symmetry theory. There are various hypotheses regarding the role of symmetry in perception of attractiveness. The fact that human faces exhibit significant amounts of both directional asymmetry and antisymmetry in skeletal and soft tissue structures is a well-accepted concept. However, despite this fact, facial symmetry is the first criterion when assessing facial attractiveness [45]. Fink et al. [14] have investigated symmetry and averageness of faces and concluded that symmetry was more important than averageness in facial attractiveness. Other studies have suggested that facial symmetry is actually perceived as less attractive than asymmetry, because perfect symmetry appears abnormal in an environment where asymmetry is normal [39]. This may be due to the fact that reducing asymmetry causes the face appear unemotional (human face is known to possess asymmetry in emotional expression).

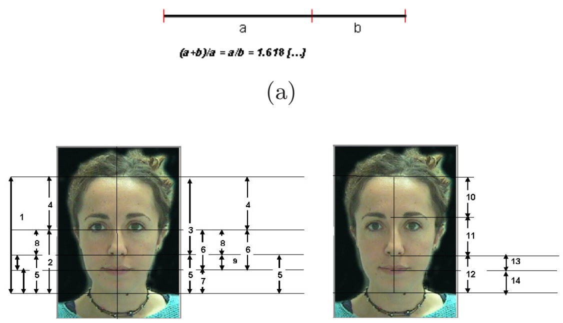
The skin and texture theory. The appearance of the skin seems to have an affect on the perception of attractiveness. Finka et al. in [15] demonstrated that women's facial skin texture affects male judgment of facial attractiveness and found that homogeneous skin (i.e., an even distribution of features relating to both skin color and skin surface topography) is most attractive. This theory also has direct implications for the composite faces theory. More specifically, the smooth complexion of the blurred and smoothed faces may underlie the attractiveness of averaged faces [21]. Skin texture, thickness, elasticity, and wrinkles or rhytids are also listed as critical factors contributing to one's overall facial appearance [45].

The (geometric) facial feature theory. When it comes to measuring attractiveness from facial cues, the most commonly used features are soft-tissue reference points (e.g., the point of transition between lower eyelid and cheek skin) and geometric features based on (skeletal) anatomic landmarks (e.g., a line drawn from the superior aspect of the external auditory canal to the inferior border of the infraorbital rim) [45]. A facial representation is obtained by calculating a set of geometric features (i.e., landmarks on the face) using the major facial points, including facial outline, eyebrows, eyes, nose, and mouth [45]. It has also been shown that it is possible to modify the attractiveness perception by changing the geometric features while keeping other factors constant [6]. Compared to other facial features, the chin, the upper lip, and the nose appear to have a great effect on the overall judgment of attractiveness [29].

The golden ratio theory. The Golden Ratio or Proportion is approximately the ratio of 1 to 0.618 or the ratio of 1.618 to 1 [4], [18] as shown in Fig. 2(a). According to the Golden Ratio theory, for female facial beauty in the case of a perfect, vertically aligned face, all the proportions must fit the Golden Ratio [31] (see Fig. 2(b)). In a recent cross-cultural beauty perception study, Mizumoto et al. [30] reported that there is no difference in golden proportions of the soft-tissue facial balance between Japanese and white women in terms of facial height components. Japanese women have well-balanced facial height proportions, except for a few measurements.

The facial thirds theory. This theory aims to assess the facial height. The theory states that a well-proportioned face may be divided into roughly equal thirds by drawing horizontal lines through the forehead hairline, the eyebrows, the base of the nose, and the edge of the chin (see Fig. 2(c)). Moreover, the distance between the lips and the chin should be double the distance between the base of the nose and the lips [12], [13], [19], [35].

The facial fifths theory. This theory evaluates the facial width by dividing the face into equal fifths. In an aesthetically pleasant face the width of one eye should equal one fifth of the total facial width, as well as the intercanthal distance or nasal base width.



(a) (b) (c)

Figure 2: (a) The Golden Proportion, and template images for (b) Golden Proportions and (c) Facial Thirds.

The juvenilised face theory. Ji and Kamachi investigated how the feminised or juvenilised faces were perceived in terms of attractiveness [20]. Feminised or juvenilised Japanese faces were created by morphing between average male and female adult faces or between average male (female) adult and boy (girl) faces. The results showed moderately juvenilised faces are perceived to be highly attractive. They found that most of the attractive juvenilised faces involved impressions corresponding to *elegance*, *mildness*, and *youthfulness*.

The frontal vs. lateral view theory. Valenzano et al. in [41] demonstrated that facial attractiveness in frontal and lateral views is highly correlated. Assessing facial attractiveness from lateral-view is gaining interest because certain anthropometric landmarks (glabella, nasion, rhinion, pogonion, etc.) can be located only in lateral view, and lateral view avoids the computational problems associated with the analysis of landmarks with bilateral symmetry [41].

Other factors. In addition to facial features, shape and form, people judge human faces using various other attributes such as pleasant expressions (e.g., a smile) and familiarity [21]. Supporting such claims is the multiple fitness model [7] that suggests that there is no single feature or dimension that determines attractiveness. Instead, various categories and combinations of features represent different aspects (or desirable qualities) of the perceived person. However, this theory still agrees that some facial qualities are perceived as universally (physically) attractive.

2.2 Bodily attractiveness

The most dominant bodily cue that affects the perception of female attractiveness (excluding the face) appear to be shape and weight. The shape cue is concerned with the ratio of the width of the waist to the width of the hips (the waist-to-hip ratio (WHR)) [40]. Thus, a lowWHR (i.e. a curvaceous body) is believed to correspond to the optimal fat distribution for high fertility, and therefore is perceived to be highly attractive. Tovee et al. in [40] focused on the perception of silhouettes of bodies in frontal view and proved that weight scaled for height (the body mass index (BMI)) is the primary determinant of sexual attractiveness rather than WHR. BMI was obtained by taking the path length around the perimeter of a figure and dividing it by the area within the perimeter (PAR). They also showed that visual cues, such as PAR, can provide an accurate and reliable index of an individual's BMI and could be used by an observer to differentiate between potential partners. Bilateral symmetry is another cue (in addition to BMI and WHR) that plays a significant role in female physical attractiveness. This is again due to the fact that asymmetry is usually caused by disease or parasites, and therefore has a negative impact on an individual's health.

2.3 Vocal attractiveness

Compared to facial and bodily attractiveness, the phenomenon of vocal attractiveness is relatively new. Overall, the notion of vocal attractiveness is defined by the prevailing view of *what sounds beautiful is good*. Voice in general appears to have a significant influence on listeners, it appears to affect the voice owner's success at mating and job applications [5]. For instance, lower pitch in male voices is considered to be a desirable attribute in a potential mate. Analogous to the well-established composite faces theory, averaging voices via auditory morphing appears to result in more attractive voices, irrespective of the speaker's or listener's gender [5]. Overall, however, vocal attractiveness appears to be based on multiple dimensions, including acoustic features such smoothness, distance to mean, and sexual dimorphism [5].

2.4 Female vs. Male Attractiveness

Majority of the studies on beauty perception focused on female faces and bodies. In the recent literature, there has been some attempt to also explore male facial beauty [33]. In his papers [33], Peseo describes the similarities and the slight differences of ratios and measurements for either gender to be considered attractive. He similarly bases his analysis on the Golden Proportions and Facial Thirds rules and adds several more ratios and criteria to them derived from other canons.

3. COMPUTATIONAL APPROACHES

Recent years have seen the introduction of various computational methods for either automatic attractiveness analysis and prediction or for attractiveness enhancement (via morphing) purposes. Machine analysis of beauty or attractiveness aims to investigate whether a machine can predict attractiveness ratings by learning a mapping from (facial) images to their attractiveness scores. The main challenge here is creating an automatic system that can predict the attractiveness level *as well as* human raters do. More specifically, evaluation is based on the ground truth obtained from tens of diverse human raters giving beauty grades to a collection of (facial) images. A representative framework illustrating these steps is shown in Figure 3.

3.1 Data and Annotations

Data acquisition and annotation to the aim of attractiveness analysis and modeling has mostly been done in an ad hoc manner. More specifically, each research group has used their own in-house database (e.g., [21]) or has opted for obtaining data from the web (e.g., [43], [44]), or using other databases acquired for face or facial expression recognition purposes (e.g., [17]).

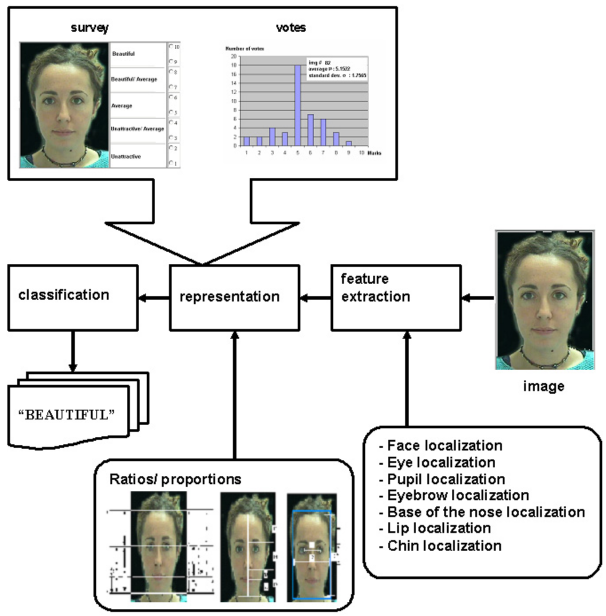


Figure 3: A representative framework for automatic analysis of female facial beauty [17].

Data. As representative examples of attractiveness data, hereby we list Kagian et al. [21] who use a database composed of 91 frontal facial images of young Caucasian American females (with a neutral expression), White et al. [43] who compiled images and associated attractiveness scores from the website `www.hotornot.com` (a website where users rate images of one another for attractiveness on a 1-10 scale), and Davis and Lazebnik [8] who created a heterogeneous dataset (images with varying viewpoint, facial expression, lighting, and image quality) of over three thousand images gathered from a website. The most noteworthy effort to date is the large-scale benchmark database for facial beauty analysis introduced by Chen and Zang [6]. The database contains 15,393 female and 8,019 male photographs (in frontal view with neutral expression, 441*358 pixels in size) of Chinese people, 875 of them labeled as beautiful (587 female and 288 male). Similarly to other relatively new research fields (e.g., affective computing [16]), the field of attractiveness analysis and modeling is in need of creating the so-called *data acquisition protocol* that consists of context (application domain), subjects (age, gender and cultural background), modalities, and type of data to be recorded. To date, recorded and used data fall into the posed (with a neutral expression) and visual (static images) data category. Acquiring attractiveness data in a dynamic and multimodal setting (i.e., induced via clips or occurring during an interaction, recorded in an audio-visual manner) will certainly advance our understanding of various factors that affect the perception and interpretation of human attractiveness.

Annotation. Unlike other relevant research fields (e.g., affective computing [16]), currently, there exist no publicly available annotation tool that can be used for annotating attractiveness data. To date, visual attractiveness data annotation has been done by asking a (diverse) set of human raters to view the facial/bodily images and pick a level along the (discretized) scale provided (e.g., [17]). Researchers seem to use different attractiveness levels: either a seven-point Likert scale (1 = very unattractive, 7 = very attractive) [21], or a ten-point Likert scale (e.g., 1:least attractive – minimum; 10: most attractive – maximum [17]), or integers in an arbitrary range, (e.g., -1: definitely not interested in meeting the person for a date; 0: not interested in meeting the person; 1: interested in meeting the person; 2: definitely interested in meeting the person [44]). Ratings are usually collected via the specific website's interface (e.g., `www.hotornot.com` [43]) or with a specifically designed *html* interface (e.g., [17],[21]). The final attractiveness rating is usually calculated as the mean rating across all raters. However, using only the mean rating as ground truth might not be sufficiently descriptive, e.g. two images with similar mean ratings might have different variance values. Taking into account such aspects of the ratings has been reported to be extremely important when training and evaluating automatic attractiveness predictors [17].

3.2 Preprocessing and Representation

Experiments have shown that (geometric) features based on measured proportions, distances (as illustrated in Fig. 2(b)) and angles of faces are most effective in capturing the notion of facial attractiveness [9], [21]. Therefore, a number of automatic attractiveness analyzers and predictors have opted for using the geometric representation (e.g., [17], [21]). The preprocessing step then comprises normalizing the image intensity distribution, detecting the facial region, and localizing the facial feature points such as eyes, eyebrows, nose and lips (e.g., [17], [21]). There also exist automatic analyzers that opt for an affine rectification that maps automatically detected landmarks (eyes, nose, and corners of the mouth) onto canonical locations (e.g., [8]).

Another common approach is to represent a (whole) face as points in a face space where the geometric variation is reduced in complexity and each face is represented by a tractable vector. Some well-known methods used in creating a face space include the eigenface projection (principal component analysis) (e.g., [41]), Gabor decompositions (e.g., [44]) or manifolds (e.g., [8]).

For classifying faces into attractive or unattractive, Eisenthal et al. [9] reported that geometric features (based on pairwise distances between fiducial points) were superior to textural features (eigenface projections). Moreover, from a human perspective, results obtained from geometric feature representation are more amenable to interpretation compared to the eigenface representation. However, as has been reported in [1], the recognition stage may be negatively affected if (fiducial) facial points are located inaccurately. Kagian et al. suggested that using a richer representation might contribute to the overall success of an automatic beauty predictor [22]. Accordingly, Sutic et al. [38] have chosen to combine the eigenface and the ratio-based features for face representation, and a number of researchers have started including other visual cues such as (mean) hair color, skin color and skin texture for automatic attractiveness prediction (e.g., [21]).

Overall, the preprocessing stage may become challenging if images contain resampling artifacts, uncontrolled lighting and pose, and external objects such as eyeglasses or hands, etc.

3.3 Analysis and Prediction

Overall, research on quantifying and computing beauty and attractiveness has predominantly focused on analyzing the face. Aarabi et al. [1] introduced an automatic beauty analyzer that extracts 8 geometric ratios of distances between a number of facial feature points (eyes, brows, and mouth) and uses k-nearest neighbors (k-NN) to classify facial images into one of the four beauty categories. When tested on a validation set of 40 images, the system achieved 91% correct classification. The beauty predictor of White et al. [43] uses textural features to predict the mean attractiveness scores assigned to 4000 face images (downloaded from `www.hotornot.com`) using ridge regression (with a Gaussian RBF kernel). The best prediction results (a correlation coefficient of 0.37) were obtained using kernel Principal Component Analysis (PCA) on the face pixels. Gunes and Piccardi [17] presented an automatic system that analyzes frontal facial images in terms of golden proportions and facial thirds in order to recognize their beauty by means of supervised learning. Each face was represented in terms of distances between facial features and a decision tree was then trained using the obtained ground truth and the extracted ratios. The standardized classifier error (by using variance in human ratings) was found to be on average less than the standard deviation within the class. Eisenthal et al. [9] focused on classifying face images as either attractive or unattractive using Support Vector Machines (SVMs), k-NN, and standard linear regression. When tested on two databases (each containing 92 images of young women from the USA and Israel posing neutral facial expressions), best results were obtained using geometric features based on pairwise distances between fiducial points (a correlation coefficient of 0.6) using linear regression and SVMs (eigenface projections provided a correlation coefficient of 0.45). The attractiveness predictor of Kagian et al. [21] uses 90 principal components of 6972 distance vectors (between 84 fiducial point locations) and standard linear regression to predict mean attractiveness scores of female facial images. Kagian et al. tested their system using the female Israeli database of Eisenthal et al. [9] and achieved a correlation of 0.82 with mean attractiveness scores provided by human raters (along a range 1–7). Davis and Lazebnik [8] focused on representing the face via a shape model and using manifold kernel regression technique to explore the relationship between facial shape and attractiveness (on a heterogeneous dataset of over three thousand images gathered from the Web). Whitehill and Movellan [44] presented an automatic approach to learning the personal facial attractiveness preferences of individual users from example images. The system uses a variety of low level representations such as PCA, Gabor filter banks, and Gaussian RBFs as well as image representations based on higher-level features (i.e., automated analysis of facial expressions, and SVMs for regression. When evaluated on a dataset of images collected from an online dating site, the system achieves correlations of up to 0.45 on the attractiveness predictions for individual users. The system was evaluated using 8 users. For each person, performance was computed as the average (over all folds) Pearson correlation of predicted attractiveness with the human-labeled ratings. When the system was fed with facial action unit (AU) features, the prediction accuracy improved only marginally. Therefore, how facial expressions contribute to the perception and prediction of facial attractiveness needs to be investigated further. Chen and Zang introduced a benchmark database for (female and male) facial beauty analysis in [6]. The extracted geometric features were normalized and projected to tangent space (a linear space where the Euclidean distance can be used to measure differences between shapes). After preprocessing, the statistics of the geometric features were calculated. PCA was used for summarizing the main modes of variation and dimensionality reduction. Their results indicated that first PC includes the variation of face width, the second PC includes the variations of eyebrow length and face shape, and the third PC includes the variation of configuration of facial organs, etc. The shapes were then modeled as a multivariate Gaussian distribution. Kullback-Leibler (KL) divergence was used for measuring the difference between distributions of attractive faces and the whole population. Their results showed that averageness hypothesis and symmetry hypothesis reveal much less beauty related information than multivariate Gaussian model. Sutic et al. [38] chose to combine eigenface and ratio-based feature representation and compared k-NN, neural network and AdaBoost algorithms for a two-class (more vs. less attractive) and a four-class (with quartile class boundaries: 3.0, 7.9, and 9.0 of maximum 10) attractiveness classification problem on a dataset of 2250 female images (extracted from the website `www.hotornot.com`). For the two-class problem, 61% classification accuracy was obtained using k-NN and geometric features, and 67% classification accuracy was obtained using k-NN and the distances in the eigenface space. Using ratio features and AdaBoost provided a classification accuracy of 55%. The results also indicated that facial symmetry is an important feature for machine analysis of facial beauty as well as using a wide set of features.

3.4 Morphing and Enhancement

More recently, a number of systems that are able to automatically enhance or beautify an input facial image have also been introduced. The system of Arakawa et al. [3] is based on the assumption that homogeneous skin is generally more attractive. Therefore, this method exploits a set of image filters able to reduce face imperfections, like wrinkles and moles. The enhanced images were qualitatively evaluated. The system of Liu et al. [25], automatically beautifies face portraits, replacing the original background with a virtual one and by altering the skin color of the subjects by means of color temperature estimation. The system of Liu et al. [26] was designed to improve the image quality for video conferencing by estimating an appealing color model using a set of professionally photographed facial images that depict celebrities. Then, during a video conference, for each frame, the color of the face region is changed, in order to move it toward the estimated appealing color model. The system of Leyvand et al. [24] is based on the beauty prediction method proposed by Eisenthal et al. [9] and increases the attractiveness rating of female facial images by using a Support Vector Regressor (trained to associate attractiveness ratings to facial images). An input image is represented using a set of landmarks from which a point in a high dimensional face space is computed using a set of distances between them. Given an input image, its position in the face space is moved by using the potential field defined by the regressor to increase the associated rating. Then, the corresponding 2D warp is applied to enhance the input image. The system of Melacci et al. in [28] (i.e., the VENUS system) is able to automatically enhance male and female frontal facial images exploiting a database of celebrities as reference patterns for attractiveness. Each face was represented by 49 landmark points that were manually placed on the learning set, but automatically found on input images using active shape models (ASMs). The faces were compared by remapping the landmarks by means of interpolating splines to extract shape-based representations. Given the input image, its landmarks were compared against the known beauty templates and moved towards the k-nearest ones by 2D image warping. The system performance was evaluated by 20 volunteers, and 73.9% of the beautified faces were perceived to be more attractive than the original pictures.

4. CONCLUSION AND OUTLOOK

Although the perception of beauty has been studied for years, researchers have not yet reached consensus on which factors are dominant in the perception and assessment of human attractiveness. The overview provided in this paper indicates that there is a recent interest in automatic analysis, prediction and enhancement of human physical attractiveness. This is possibly due to the recent emphasis on idealized physical looks and tremendous demand for aesthetic surgery, as well as other application areas such as computer assisted search of partners in online dating services [44], animation, advertising, computer games, video conferencing, etc.

Overall, despite having common grounds with other multidisciplinary research fields such as social signal processing, automatic human attractiveness prediction and enhancement is in its infancy. Firstly, not all theories of attractiveness have been explored for computation, prediction and enhancement of human beauty. Secondly, researchers have not investigated the particular reason(s) for the observer ratings obtained. Utilizing the rationale for the observer ratings could be extremely useful in obtaining a deeper insight into the data at hand and designing better automatic attractiveness predictors and enhancers. Additionally, the comparison of results attained by different surveyed systems is difficult to conduct as systems use different training/testing datasets (which differ in the way data was elicited and annotated), they differ in the underlying representation model as well as in the utilized classification (recognition vs. regression) and enhancement method, and evaluation criterion. As a consequence, many issues remain unclear: i) how to create benchmark databases (e.g., 2-D vs. 3-D facial / bodily images, vocal and audio-visual data, higher level features like texture / color, hair style, etc.); ii) how to analyze the physical cues (single-cue vs. multiple-cue and multi-modal analysis); and iii) how including behavioral cues (e.g., smile, laughter) will affect the automatic analysis and enhancement procedures. Solutions to these issues can be potentially sought in other relevant research fields such as affective computing and social signal processing (see [16], [42]).

5. REFERENCES

[1] P. Aarabi et al. The automatic measurement of facial beauty. In *Proc. of IEEE SMC*, 2001.

[2] T. Alley & M. Cunningham. Averaged faces are attractive, but very attractive faces are not average. *Psychol. Sci.*, 2:123Ű-125, 1991.

[3] K. Arakawa & K. Nomoto. A system for beautifying face images using interactive evolutionary computing. In *Proc. of Int. Symposium on Intelligent Signal Processing and Communication Systems*, pages 9–12, 2005.

[4] M. Borissavlievitch. *The Golden Number and the Scientific Aesthetics of Architecture*. A. Tiranti, London, 1958.

[5] L. Bruckert et al. Vocal attractiveness increases by averaging. *Current Biology*, 20:116–120, 2010.

[6] F. Chen & D. Zhang. A benchmark for geometric facial beauty study. In *LNCS 6165*, pages 21–32, 2010.

[7] M. Cunningham et al. Their ideas of beauty are, on the whole, the same as ours. *Journal of Personality and Social Psychology*, 68:261–279, 1995.

[8] B. Davis & S. Lazebnik. Analysis of human attractiveness using manifold kernel regression. In *Proc. of Int. Conf. on Image Processing*, pages 109–112, 2008.

[9] Y. Eisenthal et al. Facial attractiveness: beauty and the machine. *Neural Comput.*, 18:119-Ű142, 2006.

[10] L. Farkas. Linear proportions in above-and below-average womenŠs faces. In C. C. Thomas, editor, *Anthropometric facial proportions in medicine*, pages 119Ű-129. Springfield, 1987.

[11] L. Farkas. *Anthropometry of the Head and Face*. Raven Press, New York, 1994.

[12] L. Farkas et al. Vertical and horizontal proportions of the face in young adult north american caucasians. *Plastic and Reconstructive Surgery*, 75:328–338, 1985.

[13] L. Farkas & J. Kolar. Anthropometrics and art in the aesthetics of women's faces. *Clinics in Plastic Surgery*, 14:599–616, 1987.

[14] B. Fink et al. Human (homo sapiens) facial attractiveness in relation to skin texture and color. *J. Comp. Psychol.*, 115:92–99, 2001.

[15] B. Finka et al. Visible skin color distribution plays a role in the perception of age, attractiveness, and health in female faces. *Evolution and Human Behavior*, 27:433–Ű442, 2006.

[16] H. Gunes & M. Pantic. Automatic, dimensional and continuous emotion recognition. *Int'l Journal of Synthetic Emotions*, 1(1):68–99, 2010.

[17] H. Gunes & M. Piccardi. Assessing facial beauty through proportion analysis by image processing and supervised learning. *Int. Journal of Man-Machine Studies*, 64:1184–1199, 2006.

[18] H. E. Huntley. *The Divine Proportion: A Study in Mathematical Beauty*. Dover Publications, NY, 1970.

[19] Y. Jefferson. Facial aesthetics-presentation of an ideal face. *Journal of General Orthodontics*, 4:18–23, 1993.

[20] H. I. Ji et al. Analyses of facial attractiveness on feminised and juvenilised faces. *Perception*, 33:135–145, 2004.

[21] A. Kagian et al. A humanlike predictor of facial attractiveness. *Adv. Neural Info. Proc. Syst.*, 19:674–683, 2008.

[22] A. Kagian et al. A machine learning predictor of facial attractiveness revealing human-like psychophysical biases. *Vision Research*, 48:235–243, 2008.

[23] J. Langlois & L. Roggman. Attractive faces are only average. *Psychol. Sci.*, 1:115–121, 1990.

[24] T. Leyvand et al. Digital face beautification. In *Proc. of ACM SIGGRAPH*, page 169, 2006.

[25] H. Liu et al. Portrait beautification: a fast and robust approach. *Image Vis. Comput.*, 25:1404–1413, 2007.

[26] Z. Liu et al. Learning-based perceptual image quality improvement for video conferencing. In *Proc. of IEEE ICME*, pages 1035–1038, 2007.

[27] G. Mark & A. Voss. Attractivity in virtual environments: getting personal with your agent. In *Proc. of AAAI fall symposium on socially intelligent agents*, 1997.

[28] S. Melacci et al. A template-based approach to automatic face enhancement. *Pattern Anal. Applic.*, 13:289–300, 2010.

[29] G. Michiels & A. Sather. Determinants of facial attractiveness in a sample of white women. *Int. J. Adult Orthod. Orthognath. Surg.*, 9:95–103, 1994.

[30] Y. Mizumoto et al. American journal of orthodontics and dentofacial orthopedics. *Image and Vision Computing*, 136:168–174, 2009.

[31] C. Parris & J. Robinson. The bold and the beautiful according to plastic surgeons. Technical report, Dallas, Texas, 1999.

[32] I. S. Penton-Voak et al. Computer graphic studies of the role of facial similarity in judgements of attractiveness. *Current psychology: developmental, learning, personality, social*, 8:104–117, 1999.

[33] G. Peseo. The beauty of homo sapiens: standard canons, ethnical, geometrical and morphological facial biotypes (part one). *Virtual Journal of Orthodonics*, 4, 2002.

[34] G. Rhodes & T. Tremewan. Averageness exaggeration and facial attractiveness. *Psychological science*, 7:105–115, 1996.

[35] M. Ricketts. Divine proportions in facial aesthetics. *Clinics in Plastic Surgery*, 9:401–422, 1982.

[36] A. J. Rubenstein et al. Infant preferences for attractive faces: a cognitive explanation. *Developmental psychology*, 35:848–855, 1999.

[37] S. Branham Creating physical personalities for agents with faces: Modeling trait impressions of the face. In *Proc. of Workshop on Attitudes, Personality and Emotions in User-Adapted Interaction*, 2001.

[38] D. Sutic et al. Automatic evaluation of facial attractiveness. In *Proc. of MIPRO*, 2010.

[39] J. Swaddle & I. Cuthill. Asymmetry and human facial attractiveness: symmetry may not always be beautiful. *Psychol. Sci.*, 261:111–Ű116, 1995.

[40] M. J. Tovee et al. Visual cues to female physical attractiveness. *Proc. R. Soc. Lond. B*, 1999:211–218, 2011.

[41] D. R. Valenzano et al. Shape analysis of female facial attractiveness. *Vision Research*, 46:1282–Ű1291, 2006.

[42] A. Vinciarelli et al. Social signal processing: Survey of an emerging domain. *Image Vision Comput.*, 27:1743–1759, 2009.

[43] R. White et al. Automatic prediction of human attractiveness. *UC Berkeley CS280A Project*, 2004.

[44] J. Whitehill & J. R. Movellan. Personalized facial attractiveness prediction. In *Proc. of IEEE FGR*, pages 1–7, 2008.

[45] M. S. Zimbler & J. Ham. Aesthetic facial analysis. In *Cummings Head and Neck Surgery*. St. Louis, Mosby.