Impact and Detection of Facial Beautification in Face Recognition: An Overview

Christian Rathgeb, Antitza Dantcheva, Christoph Busch

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2019.DOI

Impact and Detection of Facial Beautification in Face Recognition: An Overview

CHRISTIAN RATHGEB[1], ANTITZA DANTCHEVA[2], CHRISTOPH BUSCH[1]

[1]da/sec - Biometrics and Internet Security Research Group, Hochschule Darmstadt, Germany, {christian.rathgeb, christoph.busch}@h-da.de

[2]Inria, Sophia Antipolis, France, antitza.dantcheva@inria.fr

Corresponding author: Christian Rathgeb (e-mail: christian.rathgeb@h-da.de).

ABSTRACT Facial beautification induced by *plastic surgery*, *cosmetics* or *retouching* has the ability to substantially alter the appearance of face images. Such types of beautification can negatively affect the accuracy of face recognition systems. In this work, a conceptual categorisation of beautification is presented, relevant scenarios with respect to face recognition are discussed, and related publications are revisited. Additionally, technical considerations and trade-offs of the surveyed methods are summarized along with open issues and challenges in the field. This survey is targeted to provide a comprehensive point of reference for biometric researchers and practitioners working in the field of face recognition, who aim at tackling challenges caused by facial beautification.

INDEX TERMS Biometric recognition, face recognition, beautification, beautification detection, beautification impact mitigation, plastic surgery, facial cosmetics, makeup, facial retouching.

I. INTRODUCTION

Face recognition has been a highly active research field for the last several decades [1], [2], [3]. Towards deploying robust and reliable face recognition, a variety of covariates has been identified, which can negatively impact recognition accuracy, such as variations in pose, facial expression or image quality [3]. In addition, *facial beautification* [4] was determined to be able to significantly alter the perceived shape and texture of a human face and therefore to compromise the use of face recognition systems in security applications.

During enrolment, a classical face recognition system acquires a *reference face image* from an individual, proceeds to detect and pre-process it, and finally extracts a set of features which is stored as reference template. For a long period of time local handcrafted texture descriptors [5], *e.g.*, Local Binary Patterns (LBP) [6], [7], Histogram of Oriented Gradients (HOG) [8], [9] and Gabor filters [10], [11], were predominately applied for the purpose of feature extraction. These methods aggregate local descriptors into an overall face descriptor. A large variety of such face recognition systems has been proposed, for an overview the reader is referred to [1], [2], [3]. While face recognition remained a challenging problem for decades, more recently, developments in deep convolutional neural networks have shown impressive performance improvements [12], [13], [14], [15]. Deep face recognition systems are able to leverage very large databases of face images to learn rich and compact representations of faces.

At the time of authentication a *probe face image* is captured and processed in the same way and compared against a reference template of a claimed identity (verification) or up to all stored reference templates (identification). Current state-of-the-art face recognition technologies have already approached human-level recognition performance [16].

This survey revisits works focused on the *impact of facial beautification* on face recognition, as well as related *impact mitigation*. In addition, as part of the latter, approaches to reliable *detection of facial beautification* are surveyed. In particular, a setting of interest concerns the case, when reference and / or probe face image(s) have been affected by one of the following three facial beautification types.

- **Facial plastic surgery** constitutes a medically induced change, which aims at correcting facial characteristics or defects, with the goal of improving facial appearance. Related procedures predominantly result in *permanently* altered facial appearance. Notable examples include the correction of nose, lids, or facelift. Such interventions have gained increased interest with advancement of

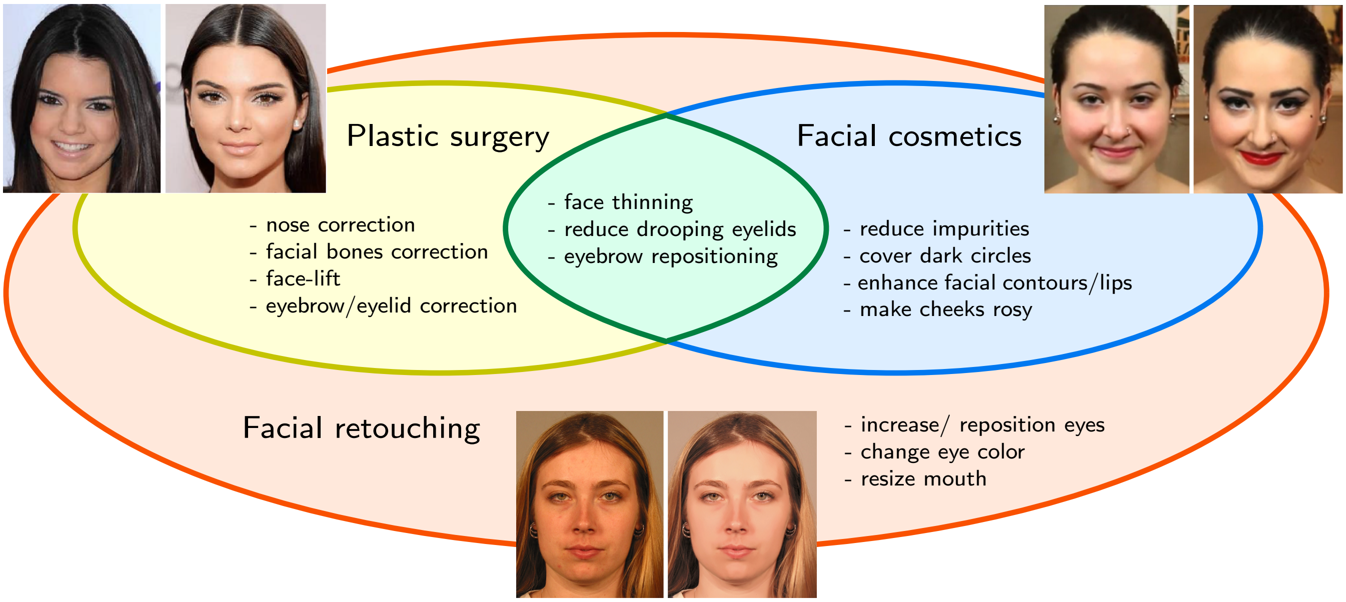


FIGURE 1: Interrelation between main types of beautification and listed examples of possible facial alterations. Example images before and after beautification show a nose correction and lip injections (plastic surgery), shaping of eyebrows, usage of eyeliner, eyeshadow, mascara, lipstick and face powder (facial cosmetics), and reduction of skin impurities, reduction of dark circles, slimming of face and change of ambient light (facial retouching).

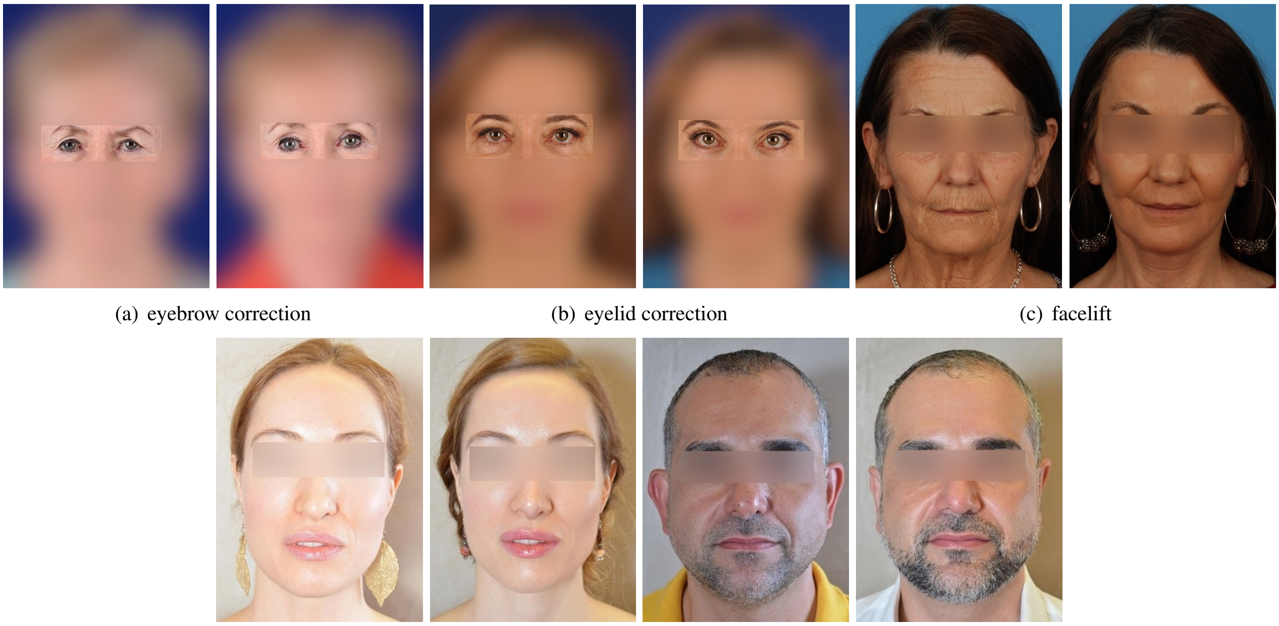
medical technology, affordable cost, as well as social acceptability. A scenario of interest in this context is when the reference image is acquired before and the probe image after plastic surgery. With respect to plastic surgery, associated impact on face recognition systems has been investigated, as well as the mitigation of the impact (see Section II).

- **Facial cosmetics** as opposed to plastic surgery are *non permanent*[1], but have the ability to substantially alter the facial appearance. Prominent examples for makeup alterations include altering of the perceived contrast of the eyes, size of the mouth, as well as skin quality and color. Cosmetics are widely used, tend to be simple to apply, cost efficient, socially acceptable and have hence become a daily necessity for many. The case when facial cosmetics are either applied only to the probe or the reference face image, or in a different manner in both images, is of particular interest in this survey. The impact of facial cosmetics on face recognition has been shown and diverse methods for makeup detection as well as cosmetics-robust facial recognition have been proposed (see Section III).
- **Facial retouching** often referred to as "photoshopping" concerns facial alterations in the *digital domain*. It involves beautification and hence modifications targeted to obtain similar results to those from plastic surgery and facial cosmetics. In addition, further modifications can be achieved such as repositioning or resizing of facial characteristics, *e.g.*, relocating eyes, hair line as well as enlarging of eyes or mouth. Photo face manipulation dates back to the advent of photography in the 19th century, and has ever since become a common practice. Recently, anti-photoshop legislations have been issued [17], stating that altered images of faces and bodies have to be labeled, as they can create a distorted view of reality. A relevant scenario includes when facial retouching is applied either to the reference or probe face image or to both in a different manner. Impact, as well as first approaches to automatically detect facial retouching have been recently introduced (see Section IV).

Figure 1 illustrates the three types of beautification, which aim at enhancing facial attractiveness, with examples of the associated alterations. Given the common aim, it is not surprising that alterations stemming from the different types of beautification are inter-related, *e.g.*, a thinner face can result from a facial bones correction, appropriate use of makeup, as well as from retouching. Due to almost unlimited possibilities of image editing, perceived results of facial retouching constitute a superset of results of plastic surgery and facial cosmetics.

Recently, facial beautification has received increased attention in the scientific community, as the survey proceeds to describe. Biometric research has placed emphasis on the impact of different types of beautification on face recognition, as well as its mitigation. The latter might be achieved through increased generalization capabilities of face recognition or a reliable beautification detection in conjunction with according processing, as elaborated here. This survey gives the first comprehensive overview and critical discussion of published

[1]Permanent makeup, *i.e.*, a cosmetic techniques which employs tattoos (permanent pigmentation of the dermis) as a means of producing designs that resemble makeup, is not handled in this survey paper.



(a) eyebrow correction (b) eyelid correction (c) facelift

(d) nose correction (e) facial bones correction

FIGURE 2: Examples of facial portrait images before (left) and after (right) different kinds of most popular facial plastic surgeries (web-collected images have been anonymized to protect the individuals' privacy).

literature in the field of face recognition related to all named types of beautification.

Apart from plastic surgery, makeup and facial retouching, further types of facial beautification exist, *e.g.*, facial tattoos or piercings, which are not covered in this work. Naturally, beautification affects facial analysis systems beyond face recognition, such as systems estimating aesthetics in an automated manner [18], which is also out of the scope of this survey.

The remainder of this survey is organized as follows: research on the recognition of surgically altered faces is surveyed in Section II; subsequently, works investigating the impact of facial cosmetics and facial retouching on face recognition are summarized in Section III and Section IV, respectively. Within these sections, background information is given for each type of beautification, in order to stress their relevance in the context of facial recognition. Subsequently, relevant findings with respect to the impact of each type of beautification, as well as high-level concepts and ideas regarding its mitigation are summarized, including proposed beautification detection approaches. Additionally, strengths and potential weaknesses of key concepts are discussed. For technical details of surveyed approaches the reader is referred to the according publications. Corresponding tables revisit algorithms, used databases and achieved performance results. If authors provided a single result in the publication text (*e.g.*, in the abstract or summary) for the recognition and/or detection performance, those values are taken directly. Otherwise, a representative result is chosen in good faith from the presented plots and tables, where performance metrics are directly adopted. Performance rates are mostly reported using standardized metrics for measuring biometric performance [19], *e.g.*, Equal Error Rate (ERR), Rank-1 Identification Rate (R-1), Genuine Match Rate (GMR) at a False Match Rate (FMR) or Correct Classification Rate (CCR). A direct comparison between published approaches is possible in case these are evaluated on the same database and results are reported using identical metrics. Otherwise, a comparison of published approaches in terms of reported detection performance would potentially be misleading and is purposely avoided in this survey. Thereafter, open issues and challenges are outlined in Section V. Finally, Section VI concludes the paper.

II. PLASTIC SURGERY

Medically induced face alterations might be profound and hence comprise a fundamental challenge for face recognition, as recently elaborated by Ross *et al.* [33]. The relevance of plastic surgery is further underlined by the prevalence worldwide, as reported by the International Society of Aesthetic Plastic Surgery (ISAPS) [34]. In particular, in the past five years over 20 million plastic surgeries were performed on head and face [34]. Procedures include removal of birth marks, moles, scars, facelift (rhytidectomy), the correction of nose (rhinoplasty), lips (filler injections), lids (blepharoplasty), eyebrows, facelift (rhytidectomy), cheeks (implants), chin (genioplasty), as well as ears (otoplasty). The five most prominent interventions are enlisted below.

1) **Eyebrow correction** aims at modifying asymmetrical eyebrow ptosis and deformations, in order to increase feminine and youthful appearance.

TABLE 1: Most relevant works on the impact of plastic surgery on face recognition.

Year	Authors	Database	Method(s)	Performance rates Unaltered	Performance rates Beautified	Beautification Detection	Remarks
2009	Singh *et al.* [20]	Plastic surgery database (504 subjects)	PCA, FDA, GF, LFA, LBP and GNN	–	34.1% GMR at 0.1% FMR (GNN)	–	Improvements reported for algorithm fusion
2010	Singh *et al.* [21]	Plastic surgery database (900 subjects)	PCA, FDA, GF, LFA, LBP and GNN	84.1% R-1 (GNN)	54.2% R-1 (GNN)		–
2011	De Marsico *et al.* [22]	[21]	Image sub-region matching with localized correlation index	–	70% R-1, 20% EER	–	–
2012	Aggarwal *et al.* [23]	[21]	Part-wise fusion of PCA-features with sparse representation	–	77.9% R-1	–	Training on MBGC [24]
2012	Jillela and Ross [25]	[21]	Score-level fusion of COTS systems, LBP and SIFT on ocular region	–	87.4% R-1	–	Report of low-quality images in [21]
2012	Kose *et al.* [26]	Simulated nose alterations on FRGCv1 (275 subjects)	Image block-based PCA, LDA and CLBP	81.27% R-1, 72.39% GMR at 0.1% FMR for 2D data (CLBP), 83.32% R-1, 72.49% GMR at 0.1% FMR for 3D data (LDA)	76.33% R-1, 66.26% GMR at 0.1% FMR for 2D data (CLBP), 75.12% R-1, 60.35% GMR at 0.1% FMR for 3D data (LDA)	–	Evaluations on 2D and 3D face data
2013	Bhatt *et al.* [27]	[21]	Multiobjective evolutionary granular algorithm	89.87% R-1	87.32% R-1	–	Unaltered taken from combined heterogeneous database
2013	Sun *et al.* [28]	[21]	SSIM index weighted multi-patch LBP fusion scheme	–	77.55% R-1	–	–
2014	Feng and Prabhakaran [29]	[21]	Gabor and texture features for facial parts recognition	96.8% R-1	85.35% R-1	–	–
2015	Kohli *et al.* [30]	[21]	Recognition: region-based compact binary face descriptors, 2×COTS <u>Detection</u>: compact binary face descriptors and multiple projective dictionary learning	0.72% EER (COTS)	3.63% EER (detection + COTS)	97.96% CCR	Integration of detection scheme to verification system
2015	Moeini *et al.* [31]	[21]	Fusion of texture features and 3D face reconstruction methods	–	95.3% R-1, 10.8% EER	–	–
2018	Suri *et al.* [32]	[21]	DenseNet with color, shape and texture space classifier	–	91.75% R-1 ∼90% GMR at 0.1% FMR	–	Database division in training and test set

2) **Eyelid correction** aims at removing fat deposits, excess tissue, or muscle from the eyelids to improve the appearance of the eyes.
3) **Facelift** is targeted to remove wrinkles and excess facial skin, to tighten sagging tissues, and redrape skin on the patient's face and neck, imparting a youthful appearance.
4) **Nose correction** constitutes the most common surgery procedure, forming the appearance of the nose by adding or removing bone or cartilage, grafting tissue from another part of the body, or implanting synthetic material to alter the shape of the nose.
5) **Facial bones correction** is aimed at augmenting the facial skeletal in the genial, mandibular angle, and malar areas, in order to rectify facial contour deformities.

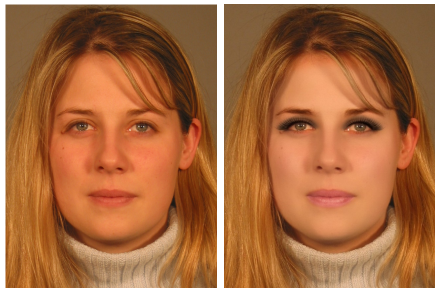
Examples of images before and after said surgeries are depicted in Figure 2. For more details on different types of plastic surgeries, the reader is referred to the ISAPS Global Statics [34]. Interestingly, eyelid corrections and facelifts jointly comprise two thirds of all plastic surgeries on faces, followed by nose corrections which represent almost one quarter. Finally, eyebrow corrections and facial bones corrections jointly constitute only around five percent.

Table 1 provides an overview of most pertinent works investigating the impact of plastic surgery on face recognition along with used databases, applied methods and obtained results. Pioneering work in this field was done by Singh *et al.* [20], who provided the first publicly available plastic surgery database[2], intended for face recognition research, which was later extended [21]. This database, which includes images collected from the web, was utilized by researchers, who evaluated various face recognition methods on it ever since. Notably, over the past years, face recognition performance has significantly improved. Specifically, while early performance rates comprised 34.1% GMR at 0.1% FMR (associated to 2-D Log Polar Gabor Transform (GNN) [20]), recent deep learning approaches have significantly increased performance rates to 91.75% R-1 and ∼90% GMR at 0.1% FMR (associated to a method introduced by Suri *et al.* [32]). Further, it can be observed that many approaches, which were designed to be resilient to plastic surgery, process face images in a patch-wise manner, also referred to as "part-wise", "image block-wise" or "sub-region-wise", *e.g.*, [22], [23], [26], [28]. The rationale of these schemes was to deem the feature extraction to face patches, which are not affected by plastic surgery, *e.g.*, leaving out the nose region during feature extraction was naturally expected to result in a face recognition system, which is robust to nose correction. Generally speaking, while these image patch-based approaches have been shown to lessen the performance degradation caused by plastic surgery, they were not able to fully mitigate the effects of plastic surgery. Additionally, multi-algorithm fusions have been proposed to achieve a higher robustness to facial alterations caused by plastic surgery, *e.g.*, as showcased by Jillela and Ross [25] and Moeini *et al.* [31]. The advantage of a multi-algorithm fusion is that it increases the amount of extracted facial information, if fused feature extractors complement each other. Consequentially, the resulting multi-biometric face recognition system is expected to achieve generally enhanced robustness.

Focusing on the detection of plastic surgery, Kohli *et al.* [30] proposed a region-based multiple projective dictionary learning approach. In an image pair-based training, binary face descriptors were extracted locally or globally depending on types of plastic surgery. These texture features were used to learn to distinguish image pairs, where one face has been surgically altered, as well as image pairs containing unaltered

[2]Plastic Surgery Face Database available at http://www.iab-rubric.org/resources.html

(a) makeup (taken from YMU)



(b) digital makeup using ModiFace [35]

(c) GAN-based makeup transfer by Chang *et al.* [36]

FIGURE 3: Examples of application of makeup: a facial portrait image before (left) and after (right) applying (a) makeup and (b) digital makeup; (c) GAN-based makeup style transfer in which a makeup style is transfered from a reference (left) to a source image (middle) resulting in an output face image with digital makeup (right).

faces. If plastic surgery was detected, the underlying face recognition applied a specific type of feature extraction to the face image. In case the detection methods work accurately, the performance of the original face recognition system remains unaltered, if no plastic surgery is detected.

III. FACIAL COSMETICS

Makeup poses a challenge to automated face recognition due to its potential to substantially alter the facial appearance in a simple and cost efficient manner. For instance, such alterations can alter the perceived facial shape by accentuating contouring techniques, enhance or reduce the perceived size of the mouth, alter the appearance and contrast of the mouth by adding color or conceal dark circles underneath the eyes. In addition to the aforementioned effects, cosmetics can also be used to successfully camouflage as well as affect wrinkles, birth moles, scars or tattoos. The use of cosmetic products yields important functional and emotional benefits. A vast cosmetics market, in 2017 in Europe valued at €77.6 billion [37], in 2016 in the US at $63 billion [38], is typically targeted towards women, attempts to improve facial aesthetics while projecting good health.

Makeup can be applied mainly in three regions of the face, as described in [39]:

1) **Skin makeup**, *e.g.*, face powder, appearance rouge or contour powder, is utilized to alter skin color and texture, suppress wrinkles, and cover blemishes and aging spots;
2) **Lip makeup**, *e.g.*, lipstick or lip gloss, is commonly used to accentuate the lips (by altering contrast and the perceived shape) and to restore moisture.
3) **Eye makeup**, *e.g.*, mascara, eye shadow, or eyebrow pencils, is widely used to increase the contrast in the periocular region, change the shape of the eyes, and accentuate the eye-brows.

Furthermore, the application of makeup can be categorized with respect to intensity [39] as *light makeup* (makeup cannot be easily perceived, since the applied colors correspond to natural skin, lip and eye colors) and *heavy makeup* (makeup is clearly perceptible, *e.g.*, dark lips or strongly accentuated eyes).

Makeup can also be applied in the digital domain[3] [56], [57] by a set of existing software applications, *i.e.*, [58], [35], which allow for a synthetical face-modification, simulating the application of makeup. This is referred to as "digital makeup" or "synthetic makeup".

More recently, Generative Adversarial Networks (GANs) have enabled an automated transfer of full makeup styles, *e.g.*, [36], [59]. Such transfer is motivated by the demand of users attempting to copy makeup styles of other individuals such as celebrities. In addition, GANs were conditioned on beauty scores [60], in order to generate realistic facial images using Progressive Growing of GANs (PGGAN) [61]. Similarly, Liu *et al.* [62] proposed a two-stage deep network for beautification, where a multi-label CNN evaluated the quality of faces, followed by a Bayesian GANs framework, automatically generating photo-realistic beautified faces.

[3] Precisely, digital makeup is categorized as retouching. Nevertheless, for the sake of completeness, works investigating the effects of digital makeup on face recognition are discussed in this section.

TABLE 2: Most relevant works on the impact of facial cosmetics on face recognition.

Year	Authors	Database	Method(s)	Performance rates Unaltered	Beautified	Beautification Detection	Remarks
2012	Dantcheva *et al.* [39]	YMU (99 subjects), VMU (51 subjects)	GF, LBP, LGBP, COTS	3.78% EER on YMU (LGBP)	15.89% EER on YMU (LGBP), 5.44%, 2.90,% and 5.42% EER on subsets of VMU (LGBP)	–	–
2012	Feng *et al.* [40]	In-house (600 female subjects)	Fusion of texture analysis-based skin makeup detection based and contour analysis-based eye/lip makeup detection	–	–	95.25% CCR	–
2013	Eckert *et al.* [41]	FCD (50 subjects)	LBP	∼85% IR	∼95% IR	–	Increase of accuracy for intermediate makeup
2013	Chen *et al.* [42]	YMU, MIW (125 subjects)	Recognition: MSLBP, Detection: fusion of color, shape and texture descriptors with SVM/AdaBoost	92.72% at 1% FMR on YMU (MSLBP)	54.10% at 1% FMR on YMU (MSLBP)	91.2% CCR	Application of MSQI technique if one image is detected to have makeup
2014	Chen *et al.* [43]	MIGA (62 subjects)	Sex prediction: COTS, AdaBoost, OpenBR Age prediction: OpenBR	78.33% CCR (AdaBoost) for male, 71.88% CCR (OpenBR) for female, 5.84 years mean average difference	30% CCR (AdaBoost) for male, 46.87% CCR (OpenBR) for female, 7.67 years mean average difference	–	Sex and age prediction
2014	Guo *et al.* [44]	In-house (501 subjects)	Recognition: PCA, HoG and LBP with correlation-based matching Detection: fusion of skin color tone, skin smoothness, texture and highlight	–	∼80% RR (PCA and HoG)	96.0% CCR (color and smoothness features)	Recognition rate (RR) not defined
2015	Kose *et al.* [45]	FCD, YMU, MIW	Feature level fusion of LGBP and HoG features with SVM	–	–	89.26% CCR on FCD, 98.5% CCR on YMU, 99.35% CCR on MIW	–
2015	Moeini *et al.* [31], [46]	YMU, VMU	Fusion of texture features and 3D face reconstruction methods	–	97.7% R-1, 6.4% EER on YMU, 99.3% R-1, 5.3% EER on VMU	–	–
2015	Liu *et al.* [47]	YMU, MIW	Selected gradient orientation of entropy information with SVM	–	–	91.72% CCR on YMU, 98.05% CCR on MIW	–
2015	Rujirakul and So-In [48]	YMU, VMU	Parallel Pearson correlation condition	–	–	∼90% RR on YMU, 100% RR on VMU	Recognition rate (RR) not defined
2016	Chen *et al.* [49]	YMU	Ensemble of patch-based LGGP, HGORM and DS-LBP features with weight learning, patch sampling, random subspace construction and SRC or CRC comparison	0.62% EER	69.24% GMR at 0.1% FMR, 7.59% EER	–	Further improvement when fused with COTS systems
2016	Wang and Kumar [50]	DMFaces (410 subjects)	Block-based LBP, 2×COTS	–	8.1% EER (COTS)	–	–
2016	Wang and Fu [51]	SMU (255 subjects), YMU, MIW, VMU	Detection: Locality-constrained low-rank dictionary learning with PCA and multivariate ridge regression model Removal: Locality-constrained coupled dictionary learning	–	87.73% RR on SMU (detection + removal)	∼85% CCR on SMU, 91.59% CCR on YMU, 91.41% CCR on MIW, 93.75% CCR on VMU	Recognition rate (RR) not defined
2018	Li *et al.* [52]	[44], [53], [54]	Bi-level adversarial network	–	65.9% GMR at 0.1% FMR on [44], 38.9% GMR at 0.1% FMR on [53], 52.6% GMR at 0.1% FMR on [54]	–	–
2018	Banerjee and Das [55]	YMU, VMU	End-to-end siamese convolutional neural network	–	87.65% GMR at 0.1% FMR, 4.28% EER on YMU	–	Makeup style transfer as pre-processing

Example images before and after applying the aforementioned types of makeup are depicted in Figure 3. Relevant works investigating the impact of makeup on face recognition and proposing makeup detection methods are listed in Table 2. Dantcheva *et al.* [39] firstly systematically studied the effects of makeup on different face recognition systems. They collected a dataset containing facial image pairs from YouTube makeup tutorials. In addition, a virtual makeup database was created based on the FRGC database [24]. Both databases were made publicly available[4]. Another makeup database has been made publicly available[5] in [50]. It was shown that the performance of face recognition systems was significantly negatively affected, in the case that either the reference or probe image had been altered by makeup. Similar studies, confirming the above findings were conducted by Wang and Kumar [50] and Eckert *et al.* [41]. Interestingly, the latter study showcased that identification accuracy can increase, given that the faces in probe and reference images have been altered by a similar makeup style. This effect was explained by the ability of makeup to enhance facial characteristics.

Motivated by the observed general decrease in biometric performance, caused by the application of makeup, a number of face feature extraction and comparison techniques were proposed, in order to design face recognition systems, which are robust to alterations resulting from the application of makeup, *e.g.*, [45], [49]. Proposed approaches fused information obtained from multiple types of features. Additionally, a patch-wise processing framework was proposed to be relatively resilient to makeup. Further, Barr *et al.* [63] evaluated an active clustering method with ensembles on a makeup database.

Towards achieving makeup-resilient face recognition, a set of methods to detect makeup have been introduced, *e.g.*, in [42], [44], [40], [51], [47]. Such makeup detection schemes generally analyze facial color, shape and texture. In particular, skin features such as color and smoothness were effectively extracted by applying suitable texture descriptors, *e.g.*, LBP and HOG, together with machine learning-based classifiers. Once a processed face image, which has been altered by the application of facial makeup is detected, the face recognition system can react accordingly, *e.g.*, by employing feature extraction with different parameters. That is, higher flexibility of the overall system is achieved.

Overall, encouraging results were reported for the task of *makeup detection* even on unconstrained databases. Specifically, correct classification rates clearly above 90% were achieved by different research groups on diverse makeup databases, including the unconstrained Makeup in the Wild (MIW) dataset. Given that makeup has been detected in a facial image, feature extraction and comparison techniques could be adapted accordingly, as suggested by Chen *et al.* [42]. Wang and Fu [51] proposed a makeup decomposition method in order to digitally remove facial makeup. Such a

[4] Databases available at http://www.antitza.com/makeup-datasets.html

[5] The Hong Kong Polytechnic University Disguise and Makeup Faces Database available at http://www.comp.polyu.edu.hk/~csajaykr/DMFaces.htm

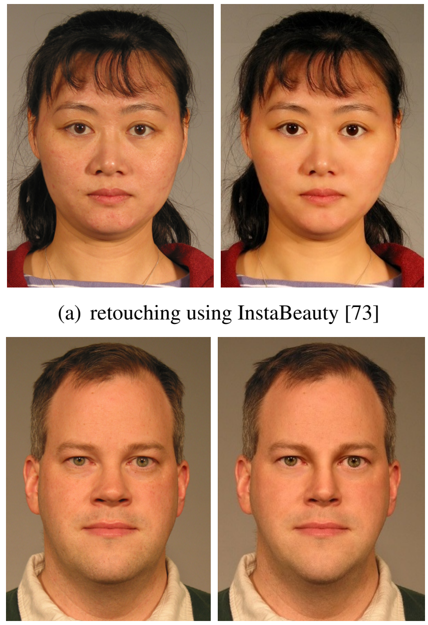
scheme can be used as additional pre-processing step in a face recognition system in case makeup was detected. In contrast, Banerjee and Das [55] suggested to replicate the facial makeup of the reference image to the probe image. More recently, Derman *et al.* [64] proceeded to integrate a makeup detection method into a multi-modal biometric system.

In addition and related to the above, the impact of facial cosmetics on soft-biometric extraction systems was investigated by Chen *et al.* [43]. Associated results suggested that alterations caused by facial cosmetics significantly decreased the accuracy of various sex-prediction and age-estimation algorithms. In accordance to that, reliable makeup detection represents an essential pre-processing step for robust facial soft biometric estimators as suggested by Feng *et al.* [40].

IV. FACIAL RETOUCHING

Beautification based on facial retouching might substantially change the appearances of individuals' faces. Alterations similar to those achieved by plastic surgery or makeup can be obtained by digitally retouching facial images. Beyond that, further changes can be made to face images in the digital domain, such as slimming cheeks, enlarging eyes, smoothing skin, brightening teeth, as well as removing blemishes. Besides professional image editing software such as Photoshop, there exist numerous mobile applications, *i.e.*, apps, which provide dozens of filters and special beautification effects that can be applied even by unskilled users. In addition, such apps might be employed to reduce fish-eye effect or unwanted front-facing camera lens distortions [69]. Hence, facial retouching plays an important role in different scenarios, where face recognition technologies are deployed:

1) **Social media:** If face recognition *e.g.*, as part of a forensic investigation is applied to images, which have been obtained from social media such as Facebook or Instagram, the application of retouching is highly probable. Nowadays, an increasing amount of facial images are being captured using smart phones, *e.g.*, by making "selfies" [70]. To ensure the best outcome, users often edit these images before sharing them, *e.g.*, via social media. In particular, so-called "beautification apps" represent common tools that can be applied to improve facial appearance. Modifications resulting from such apps may represent a new challenge for face recognition technologies. Similar use-cases might become utmost relevant for face biometrics in the future, considering the increasing use of social media and the amount of available beautification apps.
2) **Document issuance:** Different kinds of image manipulation including beautification might be performed prior to the issuance of an electronic travel document. In many countries, face images used for the ePassport issuance are provided by the applicant. Based on this security gap in the process, the vulnerability of face recognition systems to so-called morphing attacks has been recently exposed [71], [72]. Similarly, facial retouching could be applied, which could significantly degrade the performance of a face recognition system, *e.g.*, at automated border controls.



(a) retouching using InstaBeauty [73]

(b) retouching using FotoRus [74]

FIGURE 4: Examples of images before (left) and after (right) facial retouching of a female and a male face image using different mobile beautification apps.

Figure 4 shows examples of applying facial retouching. Table 3 lists most relevant works investigating the impact of facial retouching on face recognition along with used databases, applied methods and reported results. Evidently, research regarding this topic is still in statu nascendi. Ferrara *et al.* [65], [75] were the first to measure the impact of digital beautification on face recognition systems. Besides other image manipulations, *e.g.*, geometrical distortions and morphing, they reported a significant performance degradation for diverse face recognition systems after the application of heavy facial retouching. These findings have been confirmed in further works, *e.g.*, [66], [67].

Additionally, facial retouching detection schemes as well as a publicly available[6] database have been proposed [66], [67]. Different deep learning techniques have been suggested to distinguish between unaltered and retouched facial images, which to some extent appear rather unnatural. For training purposes a sufficient amount of retouched facial images was generated automatically. The proposed system [66] has been shown to outperform a re-implementation of an image forensics-based approach [76] in terms of detection accuracy. Interestingly, the named approach proposed by Bharati *et al.* [66] was also reported to exhibit almost perfect detection performance for the task of makeup detection, even on databases where no retouching has been applied, *e.g.*, YMU.

[6]ND-IIITD Retouched Face Database available at https://cvrl.nd.edu/projects/data/

TABLE 3: Most relevant works on the impact of facial retouching on face recognition.

Year	Authors	Database	Method(s)	Performance rates Unaltered	Performance rates Beautified	Beautification Detection	Remarks
2013	Ferrara *et al.* [65]	AR face with LiftMagic (118 subjects)	2× COTS, SIFT	∼0% EER (COTS)	∼ 2%, ∼5%, ∼17% EER for low/medium/high intensity (COTS)	–	3 intensities of beautification, small amount of comparisons
2016	Bharati *et al.* [66]	ND-IIITD Retouched Faces (325 subjects), Celebrity (165 subjects)	Recognition: COTS, OpenBR Detection: face patch-based deep supervised RBM with SVM	100% R-1 (COTS)	97.67% R-1 (average, COTS)	87.1% CCR on ND-IIITD Retouched Faces, 96.2% CCR on Celebrity	7 types of beautification
2017	Bharati *et al.* [67]	Multi-Demographic Retouched Faces (600 subjects)	Sub-class supervised sparse Autoencoder	–	–	94.3% CCR (on average)	–
2019	Jain *et al.* [68]	ND-IIITD Retouched Faces	CNN with SVM	–	–	99.65% CCR	–

This suggests that this scheme detected exaggerated facial appearances, which might as well result from facial cosmetics. In contrast, this system might fail to detect retouched face images which retain a natural look. Further, Bharati *et al.* [67] investigated images, belonging to two genders, male and female, and three ethnicities, Indian, Chinese, and Caucasian, retouched using two different software packages. The paper presented the limitations of state-of-the-art algorithms, *i.e.*, algorithms based on general purpose texture descriptors and the scheme of [66], in cross-ethnicity evaluations. It was shown that the performance of these algorithms was negatively affected, when trained on different ethnicities. A deep learning approach for the purpose of detecting any kind of facial retouching (including GAN-based alterations) was further proposed [68]. With respect to beautification detection, impressive performance rates (>99% CCR) were reported when training and testing were conducted on disjoint subsets of the database introduced in [66]. Moreover, the authors emphasized that image compression artefacts can cause a decrease in the detection accuracy, if they are only present in retouched images. Generally, detection accuracy is expected to degrade, if severe image compression is applied as post-processing as recently reported in the work of Wang *et al.* [77]. The development of deep learning-based re-touching detection schemes is facilitated by the possibility to automatically generate a sufficient amount of training data. However, as opposed traditional image forensic-based manipulation detection schemes [76], [78], further studies are required to investigate which types of features are learned by the aforementioned approaches.

Deviating from the aforementioned scenarios, the need for a reliable detection of digitally beautified face images was further motivated by the introduction of the so-called "photoshop law" [17]. In particular, human behaviour was often contrived by advertising and based on a digitally manipulated image of reality. As a result, people's preferences were often ill-formed and their choices, seemingly rational, produced ill-advised effects. In response, in 2014 the state of Israel enacted a law that was supposed to alleviate growing eating disorders hazards caused by digitally retouched imagery used in advertisements. While since 2017 a similar law applies in France, in several other countries, *e.g.*, Belgium, Spain, Italy or Germany, suitable regulations and laws are discussed regularly [17]. Since then, digitally retouched photos have to be labeled with "edited photograph". However, smoothing skin, removing blemishes, airbrushing, changing hair colour, and other "minor" image edits are being excluded [79]. That is, to a certain extent, automated detection systems could be used as a tool to enforce said type of legislation.

V. ISSUES AND CHALLENGES

A number of issues and challenges remain open in biometric research related to facial beautification:

Database generation The publication of face image databases used in biometric research is strongly recommended and vital to facilitate reproducible research [80]. Nonetheless, researchers have to consider many trapdoors when collecting databases for research regarding facial beautification. In order to measure the effects of plastic surgery on face recognition systems in the presence and absence of plastic surgery, additional (subsets of) publicly available face databases were used, *e.g.*, AR-Face in [21]. This modus operandi became firmly established since mostly only image pairs showing faces before and after plastic surgery are available on the web and, hence, also in the widely-used database of Singh *et al.* [21]. Regarding this matter the work in Kose *et al.* [26] represents an exception, since plastic surgeries were simulated and hence, a direct comparison before and after said simulation can be performed. Without simulations a direct comparison would only be possible, if more than one image would be available before and after plastic surgeries. If an additional face image database is used, it should exhibit properties similar to the used plastic surgery face image data. Otherwise, comparisons might not be fair and, thus, obtained results might be misleading.

Jillela and Ross [25] reported a varying image quality in the database of Singh *et al.* [21], in particular with respect to inter-ocular distances and pose. For example images of named database, the reader is referred to [25] and [22]. While those variations certainly occur in real-world scenarios, they hamper an isolation of the actual influence of plastic surgery. Moreover, if an additional face database contains more constrained images, obtained results on both databases become incomparable.

With respect to digitally applied beautification, it is important that applied alterations result in realistic facial appearance. For instance, in Bharati *et al.* [66] partly exaggerated beautifications were performed resulting in doll-like looking faces. In general, databases containing beautified face images need to reflect real-world scenarios in order to obtain practical relevant results.

Results reporting The metrics used for measuring biometric performance are well-defined and standardized [19]. Related metrics are required, in order to achieve comparable results. In biometric research on facial beautification, some works used performance metrics which are not clearly defined, *e.g.*, [44], [48]. Further, some works used performance metrics, which are of less relevance in operational deployments of face recognition. In particular, research works on plastic surgery were mostly compared by reporting the obtained R-1. However, reporting R-1 is less pertinent, given that in reality fixed decision thresholds are applied. Note that a first ranked similarity score can be below a system's decision threshold.

Tables 1–3 suggest the difficulty in comparing across methods for two primary reasons: (a) the datasets used for evaluation exhibit wide variations in number of subjects and quality, (b) the performance metrics and protocols used are not the same.

Deep Neural Networks (DNNs) With the advent of DNNs, the performance of face recognition systems has skyrocketed. It has been shown that DNNs can be trained with large amounts of data to learn a face representation that is robust to the variations present in the training data. Due to the high generalization capabilities of DNNs specifically and recognition systems in general, the performance of face recognition systems in unconstrained environments, *e.g.*, regarding illumination, pose, image quality or cameras, improved significantly. This suggests that current algorithms have gained more robustness with respect to the different types of beautification. Benchmarks of state-of-the-art (commercial and open-source) face recognition systems are required to further investigate this hypothesis. However, recently researchers found that the improved generalizability of deep face recognition systems increases their vulnerability against attacks, *e.g.*, spoofing attacks (also referred to as presentation attacks) [81] or face morphing attacks [71], [72].

Security aspects Facial beautification can have security implications on face recognition systems. For instance, plastic surgery can be performed to conceal the identity of a subject [33]. In the same manner, makeup can be applied with the aim of identity concealment [82] or even to prevent face detection [83]. More importantly, when applied by professional makeup artists facial makeup can be used for impersonation, *i.e.*, to launch presentation attacks to face recognition systems, as it has been evidenced by Chen *et al.* [82]. It is to be noted that beautification induced by makeup can be circumvented by 3D face analysis [46], as well as to a great extent by investigating spectra beyond the visible one. Certainly, there is a need for reliable presentation attack detection in face recognition systems [84], [85]. Robustness against presentation attacks based on plastic surgery or makeup represents an open research challenge, in particular because presentation attack detection methods must not negatively impact the recognition performance of the underlying face recognition system.

Interrelation with other research fields There exist many works in different fields of research, which are strongly related to facial beautification. However, more or less obvious interrelations are frequently neglected by researchers. For instance, research studies on facial ageing [86], [87] are related to facial beautification techniques which attempt to achieve a more youthful facial appearance, *e.g.*, facelift or certain types of skin makeup. Findings of how to compensate for facial ageing effects might be directly applied to design face recognition systems which are resilient to facial beautification. Techniques from the field of image forensics [88], in particular tampering detection methods, might be employed to detect digitally beautified face images. Also, presentation attack detection methods for face recognition systems [84], [85], especially those designed for skin detection, could be applied for detecting facial beautification. Further, techniques, which have been proposed for the integration of detection modules to face recognition systems might also be of interest for researchers developing beautification detection methods. In summary, information exchange between named areas of research is necessary, in order to effectively advance face recognition technologies.

Facial beautification is expected to remain a challenge in face recognition and beyond. For example, distinct types of plastic surgery have been shown to also negatively affect periocular recognition [89] and ear recognition [90]. Similarly, the presence of makeup has been shown to hamper reliable sex prediction from iris images [91], while cosmetic lenses can be used to perform presentation attacks on iris recognition systems [92], [93].

Other types of beautification Apart from plastic surgery, makeup and facial retouching, there are further types of facial beautification that might impact face recognition systems. For example, facial tattoos are expected to negatively affect the recognition performance of face recognition systems. Similarly, performance drops might as well be caused by facial accessories like piercings or cosmetic lenses. With respect to face recognition, the impact of such types of beautification remains to be investigated.

Integration of detection systems While several methods for beautification detection have been proposed, an effective integration of introduced detection modules into the processing chain of a face recognition system remains an open challenge. Performance evaluations of face recognition systems applying beautification detection at the time of authentication are commonly neglected; [30], [42], [64] being exceptions.

Impact of beautification on human face recognition the impact of makeup on human ability to recognize faces has been studied by Ueda and Koyama [94]. The authors concluded that light makeup slightly increases human recognizability, whereas heavy makeup significantly decreases it. Similar studies would need to be conducted for other types of beautification in order to measure their impact on humans' ability to recognize faces.

VI. SUMMARY

Beauty lies in the eye of the beholder – yet, beautification resulting from plastic surgery, facial cosmetics or facial retouching, targeted towards beauty canons, has become omnipresent in our modern day society. Alterations caused by these types of beautification represent a great challenge for biometric systems, in particular for face recognition technologies, which are nowadays deployed in various application scenarios ranging from access control for mobile devices to automated border control. Numerous works have been published in either field, which are surveyed in this work. Finally, important interrelations are pointed out along with open issues and challenges.

ACKNOWLEDGEMENTS

This work was partially supported by the German Federal Ministry of Education and Research (BMBF) and by the Hessen State Ministry for Higher Education, Research and the Arts (HMWK) within the Center for Research in Security and Privacy (CRISP), as well as by the French Government (National Research Agency, ANR) under grant agreement ANR-17-CE39-0002.

REFERENCES

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition," ACM Computing Surveys, vol. 35, no. 4, pp. 399–458, dec 2003.

[2] A. F. Abate, M. Nappi, D. Riccio, and G. Sabatino, "2D and 3D face recognition: A survey," Pattern Recognition Letters, vol. 28, no. 14, pp. 1885 – 1906, 2007.

[3] S. Z. Li and A. K. Jain, Eds., Handbook of Face Recognition. Springer London, 2011.

[4] D. B. Yarosh, "Perception and deception: Human beauty and the brain," Behavioral Sciences, vol. 9, no. 4, p. 34, 2019.

[5] L. Liu, J. Chen, P. Fieguth, G. Zhao, R. Chellappa, and M. Pietikäinen, "From BoW to CNN: Two Decades of Texture Representation for Texture Classification," International Journal of Computer Vision, vol. 127, no. 1, pp. 74–109, Jan 2019.

[6] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face recognition with local binary patterns," in European Conf. on Computer Vision (ECCV), T. Pajdla and J. Matas, Eds., 2004, pp. 469–481.

[7] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp. 2037–2041, 2006.

[8] A. Albiol, D. Monzo, A. Martin, J. Sastre, and A. Albiol, "Face recognition using HOG-EBGM," Pattern Recognition Letters, vol. 29, no. 10, pp. 1537 – 1543, 2008.

[9] O. Deniz, G. Bueno, J. Salido, and F. D. la Torre, "Face recognition using histograms of oriented gradients," Pattern Recognition Letters, vol. 32, no. 12, pp. 1598 – 1603, 2011.

[10] Wenchao Zhang, Shiguang Shan, Wen Gao, Xilin Chen, and Hongming Zhang, "Local Gabor binary pattern histogram sequence (LGBPHS): a novel non-statistical model for face representation and recognition," in Int'l Conf. on Computer Vision (ICCV), 2005.

[11] M. Yang and L. Zhang, "Gabor feature based sparse representation for face recognition with gabor occlusion dictionary," in Int'l Conf. on Computer Vision (ICCV), 2010.

[12] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," in British Machine Vision Conf. (BMVC). British Machine Vision Association, 2015.

[13] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in Proceedings of the 2015 Conf. on Computer Vision and Pattern Recognition (CVPR). IEEE, 2015.

[14] M. Kawulok, M. E. Celebi, and B. Smolka, Advances in Face Detection and Facial Image Analysis, 1st ed. Springer, 2016.

[15] R. Ranjan, S. Sankaranarayanan, A. Bansal, N. Bodla, J. Chen, V. M. Patel, C. D. Castillo, and R. Chellappa, "Deep learning for understanding faces: Machines may be just as good, or better, than humans," IEEE Signal Processing Magazine, vol. 35, no. 1, pp. 66–83, 2018.

[16] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," in Conf. on Computer Vision and Pattern Recognition (CVPR'14), 2014, pp. 1701–1708.

[17] J. Szewczyk, "Photoshop law: Legislating beauty in the media and fashion industry," SSRN Electronic Journal, 01 2014.

[18] A. Dantcheva and J.-L. Dugelay, "Assessment of female facial beauty based on anthropometric, non-permanent and acquisition characteristics," Multimedia Tools and Applications, vol. 74, no. 24, pp. 11 331–11 355, 2015.

[19] ISO/IEC JTC1 SC37 Biometrics, ISO/IEC 19795-1:2006. Information Technology – Biometric Performance Testing and Reporting – Part 1: Principles and Framework, Int'l Organization for Standardization and Int'l Electrotechnical Committee, 2006.

[20] R. Singh, M. Vatsa, and A. Noore, "Effect of plastic surgery on face recognition: A preliminary study," in 2009 IEEE Computer Society Conf. on Computer Vision and Pattern Recognition Workshops, 2009, pp. 72–77.

[21] R. Singh, M. Vatsa, H. S. Bhatt, S. Bharadwaj, A. Noore, and S. S. Nooreyezdan, "Plastic surgery: A new dimension to face recognition," IEEE Trans. on Information Forensics and Security, vol. 5, no. 3, pp. 441–448, 2010.

[22] M. De Marsico, M. Nappi, D. Riccio, and H. Wechsler, "Robust face recognition after plastic surgery using local region analysis," in Proceedings of the 8th Int'l Conf. on Image Analysis and Recognition - Volume Part II, ser. ICIAR'11, 2011, pp. 191–200.

[23] G. Aggarwal, S. Biswas, P. J. Flynn, and K. W. Bowyer, "A sparse representation approach to face matching across plastic surgery," in 2012 IEEE Workshop on the Applications of Computer Vision (WACV), 2012, pp. 113–119.

[24] P. J. Phillips, P. J. Flynn, J. R. Beveridge, W. T. Scruggs, A. J. O'Toole, D. Bolme, K. W. Bowyer, B. A. Draper, G. H. Givens, Y. M. Lui, H. Sahibzada, J. A. Scallan, and S. Weimer, "Overview of the multiple biometrics grand challenge," in Advances in Biometrics, M. Tistarelli and M. S. Nixon, Eds., 2009, pp. 705–714.

[25] R. Jillela and A. Ross, "Mitigating effects of plastic surgery: Fusing face and ocular biometrics," in 2012 IEEE Int'l Conf. on Biometrics: Theory, Applications and Systems (BTAS), 2012, pp. 402–411.

[26] N. Kose, N. Erdogmus, and J. Dugelay, "Block based face recognition approach robust to nose alterations," in 2012 IEEE Int'l Conf. on Biometrics: Theory, Applications and Systems (BTAS), 2012, pp. 121–126.

[27] H. S. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, "Recognizing surgically altered face images using multiobjective evolutionary algorithm," IEEE Trans. on Information Forensics and Security, vol. 8, no. 1, pp. 89–100, 2013.

[28] Y. Sun, M. Tistarelli, and D. Maltoni, "Structural similarity based image quality map for face recognition across plastic surgery," in 2013 IEEE Int'l Conf. on Biometrics: Theory, Applications and Systems (BTAS), 2013, pp. 1–8.

[29] R. Feng and B. Prabhakaran, "A novel method for post-surgery face recognition using sum of facial parts recognition," in IEEE Winter Conf. on Applications of Computer Vision, 2014, pp. 1082–1089.

[30] N. Kohli, D. Yadav, and A. Noore, "Multiple projective dictionary learning to detect plastic surgery for face verification," IEEE Access, vol. 3, pp. 2572–2580, 2015.

[31] A. Moeini, K. Faez, and H. Moeini, "Face recognition across makeup and plastic surgery from real-world images," Journal of Electronic Imaging, vol. 24, no. 5, pp. 1 – 12 – 12, 2015.

[32] S. Suri, A. Sankaran, M. Vatsa, and R. Singh, "On matching faces with alterations due to plastic surgery and disguise," in 2018 IEEE Int'l Conf. on Biometrics: Theory, Applications and Systems (BTAS), 2018, pp. 1–8.

[33] A. Ross, S. Banerjee, C. Chen, A. Chowdhury, V. Mirjalili, R. Sharma, T. Swearingen, and S. Yadav, "Some research problems in biometrics: The future beckons," in Int'l Conf. on Biometrics (ICB), 2019.

[34] "ISAPS Global Statistics," https://www.isaps.org/medical-professionals/isaps-global-statistics/, December 2018.
[35] ModiFace. Virtual MakeUp. http://modiface.com/. ModiFace. Accessed Jun. 2019.
[36] H. Chang, J. Lu, F. Yu, and A. Finkelstein, "PairedCycleGAN: Asymmetric style transfer for applying and removing makeup," in Int'l Conf. Computer Vision and Pattern Recognition (CVPR), Jun. 2018.
[37] Cosmetics Europe. (2018, May) Socio-Economic Contribution of the European Cosmetics Industry. https://www.cosmeticseurope.eu/. Cosmetics Europe. Accessed Jun. 2019.
[38] L. Whipp. (2016, Apr.) Changing face of cosmetics alters $63bn US beauty market. https://www.ft.com/. Financial Times. Accessed Jun. 2019.
[39] A. Dantcheva, C. Chen, and A. Ross, "Can facial cosmetics affect the matching accuracy of face recognition systems?" in 2012 IEEE Int'l Conf. on Biometrics: Theory, Applications and Systems (BTAS), 2012, pp. 391–398.
[40] R. Feng and B. Prabhakaran, "Quantifying the makeup effect in female faces and its applications for age estimation," in 2012 IEEE Int'l Symposium on Multimedia, 2012, pp. 108–115.
[41] M. Eckert, N. Kose, and J. Dugelay, "Facial cosmetics database and impact analysis on automatic face recognition," in 2013 IEEE Int'l Workshop on Multimedia Signal Processing (MMSP), 2013, pp. 434–439.
[42] C. Chen, A. Dantcheva, and A. Ross, "Automatic facial makeup detection with application in face recognition," in 2013 Int'l Conf. on Biometrics (ICB), 2013, pp. 1–8.
[43] ——, "Impact of facial cosmetics on automatic gender and age estimation algorithms," in 2014 Int'l Conf. on Computer Vision Theory and Applications (VISAPP), vol. 2, 2014, pp. 182–190.
[44] G. Guo, L. Wen, and S. Yan, "Face authentication with makeup changes," IEEE Trans. on Circuits and Systems for Video Technology, vol. 24, no. 5, pp. 814–825, 2014.
[45] N. Kose, L. Apvrille, and J. Dugelay, "Facial makeup detection technique based on texture and shape analysis," in 2015 IEEE Int'l Conf. and Workshops on Automatic Face and Gesture Recognition (FG), vol. 1, 2015, pp. 1–7.
[46] A. Moeini, H. Moeini, F. Ayatollahi, and K. Faez, "Makeup-invariant face recognition by 3d face: Modeling and dual-tree complex wavelet transform from women's 2d real-world images," in 22nd Int'l Conf. on Pattern Recognition (ICPR). IEEE, 2014, pp. 1710–1715.
[47] K.-H. Liu, T.-J. Liu, H.-H. Liu, and S.-C. Pei, "Facial makeup detection via selected gradient orientation of entropy information," in IEEE Int'l Conf. on Image Processing (ICIP). IEEE, 2015, pp. 4067–4071.
[48] K. Rujirakul and C. So-In, "P-pcc: parallel pearson correlation condition for robust cosmetic makeup face recognitions," in Information Science and Applications. Springer, 2015, pp. 259–266.
[49] C. Chen, A. Dantcheva, and A. Ross, "An ensemble of patch-based subspaces for makeup-robust face recognition," Information Fusion, vol. 32, pp. 80 – 92, 2016, sI Information Fusion in Biometrics.
[50] T. Y. Wang and A. Kumar, "Recognizing human faces under disguise and makeup," in IEEE Int'l Conf. on Identity, Security and Behavior Analysis (ISBA), 2016, pp. 1–7.
[51] S. Wang and Y. Fu, "Face behind makeup," in AAAI Conf. on Artificial Intelligence, 2016.
[52] Y. Li, L. Song, X. Wu, R. He, and T. Tan, "Anti-makeup: Learning a bi-level adversarial network for makeup-invariant face verification," in AAAI Conf. on Artificial Intelligence, 2018.
[53] Y. Sun, L. Ren, Z. Wei, B. Liu, Y. Zhai, and S. Liu, "A weakly supervised method for makeup-invariant face verification," Pattern Recognition, vol. 66, pp. 153 – 159, 2017.
[54] J. Hu, Y. Ge, J. Lu, and X. Feng, "Makeup-robust face verification," in IEEE Int'l Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2013, pp. 2342–2346.
[55] S. Banerjee and S. Das, "Makeupmirror: mirroring make-ups and verifying faces post make-up," IET Biometrics, vol. 7, no. 6, pp. 598–605, 2018.
[56] J. Li, C. Xiong, L. Liu, X. Shu, and S. Yan, "Deep face beautification," in ACM Int'l Conf. on Multimedia. ACM, 2015, pp. 793–794.
[57] B. Zhang, X. Xiao, and G. Lu, "Facial beauty analysis based on features prediction and beautification models," Pattern Analysis and Applications, vol. 21, no. 2, pp. 529–542, 2018.
[58] Portrait Pro. Portrait pro - easy photo editing software. http://www.portraitprofessional.com/. Anthropics Technology Ltd. Accessed Jun. 2019.
[59] T. Li, R. Qian, C. Dong, S. Liu, Q. Yan, W. Zhu, and L. Lin, "BeautyGAN: Instance-level Facial Makeup Transfer with Deep Generative Adversarial Network," in 26th ACM Int'l Conf. on Multimedia, ser. MM '18, 2018, pp. 645–653.
[60] N. Diamant, D. Zadok, C. Baskin, E. Schwartz, and A. M. Bronstein, "Beholder-GAN: Generation and Beautification of Facial Images with Conditioning on Their Beauty Level," arXiv preprint arXiv:1902.02593, 2019.
[61] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive Growing of GANs for Improved Quality, Stability, and Variation," CoRR, vol. abs/1710.10196, 2017. [Online]. Available: http://arxiv.org/abs/1710.10196
[62] J. Liu, S. Li, W. Song, L. Liu, H. Qin, and A. Hao, "Automatic Beautification for Group-Photo Facial Expressions Using Novel Bayesian GANs," in Int'l Conf. on Artificial Neural Networks. Springer, 2018, pp. 760–770.
[63] J. R. Barr, K. W. Bowyer, and P. J. Flynn, "Framework for active clustering with ensembles," IEEE Trans. on Information Forensics and Security, vol. 9, no. 11, pp. 1986–2001, 2014.
[64] E. Derman, C. Galdi, and J.-L. Dugelay, "Integrating facial makeup detection into multimodal biometric user verification system," in Int'l Workshop on Biometrics and Forensics (IWBF). IEEE, 2017, pp. 1–6.
[65] M. Ferrara, A. Franco, D. Maltoni, and Y. Sun, "On the impact of alterations on face photo recognition accuracy," in Image Analysis and Processing (ICIAP). Springer, 2013, pp. 743–751.
[66] A. Bharati, R. Singh, M. Vatsa, and K. W. Bowyer, "Detecting facial retouching using supervised deep learning," IEEE Trans. on Information Forensics and Security, vol. 11, no. 9, pp. 1903–1913, 2016.
[67] A. Bharati, M. Vatsa, R. Singh, K. W. Bowyer, and X. Tong, "Demography-based facial retouching detection using subclass supervised sparse autoencoder," in 2017 IEEE Int'l Joint Conf. on Biometrics (IJCB), 2017, pp. 474–482.
[68] A. Jain, R. Singh, and M. Vatsa, "On Detecting GANs and Retouching based Synthetic Alterations," in 2018 IEEE 9th Int'l Conf. on Biometrics Theory, Applications and Systems (BTAS), 2018, pp. 1–7.
[69] B. Ward, M. Ward, O. Fried, and B. Paskhover, "Nasal distortion in short-distance photographs: The selfie effect," JAMA Facial Plastic Surgery, vol. 20, 2018.
[70] S. Diefenbach and L. Christoforakos, "The selfie paradox: Nobody seems to like them yet everyone has reasons to take them. an exploration of psychological functions of selfies in self-presentation," Frontiers in Psychology, vol. 8, p. 7, 2017.
[71] M. Ferrara, A. Franco, and D. Maltoni, "The magic passport," in Int'l Joint Conf. on Biometrics (IJCB), 2014.
[72] U. Scherhag, C. Rathgeb, J. Merkle, R. Breithaupt, and C. Busch, "Face recognition systems under morphing attacks: A survey," IEEE Access, 2019.
[73] Fotoable Inc. InstaBeauty - Makeup Selfie Cam. https://play.google.com/store/apps/details?id=com.fotoable.fotobeauty. Fotoable, Inc. Accessed Dec. 2018.
[74] Fotoable, Inc. FotoRus - Camera & Photo Editor. https://play.google.com/store/apps/details?id=com.wantu.activity. Fotoable, Inc. Accessed Dec. 2018.
[75] M. Ferrara, A. Franco, and D. Maltoni, "On the effects of image alterations on face recognition accuracy," in Face Recognition Across the Imaging Spectrum. Springer, 2016, pp. 195–222.
[76] E. Kee and H. Farid, "A perceptual metric for photo retouching," Proceedings of the National Academy of Sciences, vol. 108, no. 50, pp. 19 907–19 912, 2011.
[77] S. Wang, O. Wang, A. Owens, R. Zhang, and A. A. Efros, "Detecting photoshopped faces by scripting photoshop," CoRR, vol. abs/1906.05856, 2019. [Online]. Available: http://arxiv.org/abs/1906.05856
[78] E. Kee, J. F. O'Brien, and H. Farid, "Exposing photo manipulation from shading and shadows," ACM Trans. on Graphics, vol. 33, no. 5, pp. 165:1–165:21, 2014, presented at SIGGRAPH 2014.
[79] N. Eggert. BBC News: Is she Photoshopped? In France, they now have to tell you. https://www.bbc.com/news/world-europe-41443027. 30th September, 2017.
[80] P. Vandewalle, J. Kovacevic, and M. Vetterli, "Reproducible research in signal processing," IEEE Signal Processing Magazine, vol. 26, no. 3, pp. 37–47, 2009.
[81] A. Mohammadi, S. Bhattacharjee, and S. Marcel, "Deeply vulnerable: a study of the robustness of face recognition to presentation attacks," IET Biometrics, vol. 7, no. 1, pp. 15–26, 2018.
[82] C. Chen, A. Dantcheva, T. Swearingen, and A. Ross, "Spoofing faces using makeup: An investigative study," in 2017 IEEE Int'l Conf. on Identity, Security and Behavior Analysis (ISBA), 2017, pp. 1–8.

[83] A. Harvey. (2010, Apr.) Camouflage from face detection. https://cvdazzle.com/. CV Dazzle. Accessed Jun. 2019.
[84] J. Galbally, S. Marcel, and J. Fierrez, "Biometric antispoofing methods: A survey in face recognition," IEEE Access, vol. 2, pp. 1530–1552, 2014.
[85] R. Ramachandra and C. Busch, "Presentation attack detection methods for face recognition systems: A comprehensive survey," ACM Computing Surveys, vol. 50, no. 1, pp. 8:1–8:37, 2017.
[86] A. Lanitis, "A survey of the effects of aging on biometric identity verification," Int'l Journal of Biometrics, vol. 2, 01 2010.
[87] L. Best-Rowden and A. K. Jain, "Longitudinal study of automatic face recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 40, no. 1, pp. 148–162, 2018.
[88] A. Piva, "An overview on image forensics," ISRN Signal Processing, vol. 2013, 01 2013.
[89] K. B. Raja, R. Raghavendra, and C. Busch, "Biometric recognition of surgically altered periocular region: A comprehensive study," in Int'l Conf. on Biometrics (ICB), 2016.
[90] R. Ramachandra, K. B. Raja, S. Venkatesh, and C. Busch, "Improved ear verification after surgery - an approach based on collaborative representation of locally competitive features," Pattern Recognition, vol. 83, pp. 416 – 429, 2018.
[91] A. Kuehlkamp, B. Becker, and K. Bowyer, "Gender-from-iris or gender-from-mascara?" in IEEE Winter Conf. on Applications of Computer Vision (WACV), 2017, pp. 1151–1159.
[92] O. Sharifi and M. Eskandari, "Cosmetic detection framework for face and iris biometrics," Symmetry, vol. 10, no. 4, p. 122, 2018.
[93] A. Czajka and K. W. Bowyer, "Presentation attack detection for iris recognition: An assessment of the state of the art," ACM Computing Surveys, vol. 1, no. 1, pp. 1–35, 2018.
[94] S. Ueda and T. Koyama, "Influence of make-up on facial recognition," Perception, vol. 39, no. 2, pp. 260–264, 2010.