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Michele Nappi, Stefano Ricciardi, Massimo Tistarelli

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Deceiving Faces: When Plastic Surgery Challenges Face Recognition

Michele Nappi, Stefano Ricciardi, Massimo Tistarelli

Abstract—An exponential growth of the number of plastic surgery treatments specific to face (from the minimally-invasive ones to the real surgical procedures) has characterized the last two decades and it seems likely that this phenomenon, that has social and cultural meanings and implications, could spread even further in the next years as the average cost of these treatments is lowering and the wish for "beautification" is becoming part of the global aesthetics sense. For these reasons, face recognition as an established research topic has a new major challenge: delivering methods capable of high recognition accuracy even in case probe and gallery differ by a surgical alteration of face shape. To this aim is of fundamental importance understanding the range and the extent of the modification produced by the various types of treatments or by a combination of them. We present a survey of the state of the art on this topic, starting by an analysis of the diffusion of the facial plastic surgey and describing the key aspects of each of the most statistically relevant treatments available, resumed by a synthetic table. The paper includes a brief description of all the approaches proposed in the field so far to the best of authors' knowledge and a comparison of the performance reported by the existing methods when applied to the most referenced plastic surgery face dataset to date. A critical discussion of the results achieved so far and an insight about the challenges that still have to be addressed concludes this work.

Keywords: Face recognition, plastic surgery, state of the art survey

1 INTRODUCTION

In the scientific literature on face recognition, an introduction is often found reporting the positive features of this biometric trait (universality, acceptability and collectability, resistance to circumvention and recognition accuracy) as well as its peculiar weakness to environmental variations such as lighting, pose and occlusion, and a wide range of intra-class variations related to expressions, aging and other voluntary (piercing, tattoos, make-up, etc.) and involuntary (scars, moles, skin deseases, facial thraumas, etc.) modifications of the face appearance. However, it is worth noting that in the battle to improve methods robustness to the aforementioned challenges, there is an implicit assumption of an "overall consistence of face shape" between the enrolled template and the probe image. In other terms, the type and the level of intra-class variations should not alter too deeply the overall physiognomy. In this sense, while a wide range of expression or lighting variations represent a typical addressed issue, it is obvious (when considering age variations) that nobody would expect a high recognition accuracy by comparing a child to a boy or a boy to an adult or even an adult to an old man, as during these stages of life facial features are subject to dramatic changes often undermining overall face's shape consistence.

Though this example might seem too extreme, when it comes to facial plastic surgery, the aforementioned assumption can possibly become not true anymore even within the same age group, depending on the extent and on the type of the procedure per-

- *M. Nappi is with the BipLab, University of Salerno, Fisciano SA, 84084, Italy. E-mail: mnappi@unisa.it*
- *S. Ricciardi is with the BipLab, University of Salerno, Fisciano SA, 84084, Italy. E-mail: sricciardi@unisa.it*
- *M. Tistarelli is with the Computer Vision Laboratory, University of Sassari, Alghero SS, 07041, Italy, tista@uniss.it*

formed. It is also important to highlight that, in its very nature, facial plastic surgery aims to improving facial appearance or restoring the original one, either according to a deliberate choice of the patient, motivated by aesthetic or psycological reasons, or due to functional needs, the former being largely the most diffused case.

The wish and sometimes the urge for a surgical improvement of face aspect is surely not new and it is related to a complex set of social-cultural factors strongly fostered by mass-media, but it is costantly increased in the last years as reported by the American Society of Plastic Surgeons (ASPS), representing 94% of all board-certified plastic surgeons in the U.S and among the largest plastic surgery specialty organizations in the world. According to this source [1], indeed, on a total of 14.6 million cosmetic plastic surgery procedures performed in the United States in 2012, more than 10 million pertained to face, of which more than 9 million were minimally-invasive procedures including botulinum toxin injections (6.1 millions), soft-tissue fillers (2 millions), chemical peel (1.1 millions), microdermabrasion (1 million) while the rest were actual surgical procedures including nose reshaping (0.25 millions), eyelid surgery (0.2 millions), facelift (0.13 millions) and a number of statistically less relevant procedures like chin augmentation, cheeckbones reshaping or ear reshaping. Another interesting statistic concerns the distribution of cosmetic procedures (both surgical and minimally invasive) among genders and ethnic groups. Indeed, while not surprisingly females account for almost 91% of total cosmetic procedures, males undergoing plastic surgery are reaching 10% with a constant increase year after year. With regard to ethnic group distribution, while Hispanics are almost stable, there is a 6-7% increase in Caucasians and African Americans and a 21% increase in Asian Americans. This wish for face "beautification" has inspired researchs like the ones by Eisenthal et al. [2] and Leyvand et al. [3], exploring aspects such as facial attractiveness and virtual face enhancement. However, as the figures reported above concern only the United States and considering that globalization applies to this field as well, it is easy to understand the potential relevance on a worldwide scale of this scenario to the topic of face recogntion in each of its applications. The impact of cosmetic surgery may vary from a light surface remodelling to a deep change in subject's main physiognomic traits, representing a serious challenge for recognition algorithms and, sometimes, for human recognition capability as well, as witnessed by cases of individuals undergoing multiple procedures and resulting in a completely rimodelled face geometry. Facial plastic surgery basically operates through reduction, augmentation or reshaping of face at a local or global level. From a more geometrical point of view the resulting visible effects can be subtractive, additive or both, while skin level (epidermis, dermis) changes can also lead to a modified surface appearance (color, texture). Consequently, face recognition after plastic surgery represents a topic that, besides being already relevant in terms of statistics, push many of the most diffused and recognized techiniques for facial features extraction and matching to their limits, as it forces to focus on the very essence of what makes a face that particular face to the aim of defining selected features possibly invariant to surgical procedures.

In the attempt to answer to these open questions, this paper presents a comprehensive survey on the state of the art about this interesting and stimulating topic. Besides resuming the key aspects of all the approaches to face recognition specifically aimed to plastic surgery available to date, we report about the main research trends emerging through a comparison of the methodologies proposed so far which range from classical descriptors like Principal Component Analysys (PCA), Fisher Discriminant Analysis (FDA), Geometric Features (GF), Local Feature Analysis (LFA), Local Binary Patterns (LBP), Speeded Up Robust Features (SURF) and Neural Network based Gabor Transform (GNN), to less common approaches based on Evolutionary-Genetic algorithm (GA), Particle Swarm Optimization (PSO), Partitioned Iterated Function System (PIFS) and Structural Similarity Image Maps (SSIM).

As the specificity of each plastic surgery procedure has an impact to specific face regions that could be worth to consider for the research, we describe extensively each of the available procedures by means of a textual and graphical profile, also resumed in a comparative table. We also include a detailed description of the only face dataset specific to facial plastic surgery publicly available to date providing before-after shots. Finally we discuss the results provided in the field trying to analyze the potential and the limits of the main classes of methodologies (e.g. holistic vs region based, etc.) with the aim to draw a future path of research for improving existing techniques and developing new ones.

The reminder of the paper is organized as follows. Section 2 provides a detailed description of each of the most statistically relevant facial plastic surgery procedures performed, while Section 3 provides a summary of each of the works published so far specifically on the topic of face recognition after plastic surgery, to the best of author's knowledge and includes a comparison of the algorithms described according to a common set of objective data. Section 4 briefly recalls the features of the most cited publicly available face dataset with before/after surgery images. Section 5 presents an in depth discussion about the various aspects of the topic, trying to analyze the results achieved so far and the main open issues. Section 6 concludes the paper by summarizing our findings.

2 Understanding How Cosmetic Procedures Affect Face Appearance

To better understand the impact of facial plastic surgery to face recognition, for each of the most popular cosmetic procedures the level of change in facial traits is analyzed. Each subsection briefly describes a cosmetic procedure providing also a graphical representation of the face region affected and some pictures showing the effects on the face appearance, mostly coming from the ASPS website [1]. The following procedures are considered:

- *botulinum toxin injections*,
- *soft-tissue fillers*,
- *chemical peel*,
- *microdermabrasion*,
- *nose reshaping (rinhoplasty)*,
- *eyelid surgery* (*blepharoplasty)*,
- *facelift*,
- *brow lift*,
- *chin augmentation*,
- *cheeckbones reshaping*,
- *ear reshaping*.

2.1 Botulinum Toxin

Botulinum toxin is a purified substance that is derived from bacteria. Commonly known types of botulinum toxin type A injections include Botox and Dysport. Injections of botulinum toxin blocks muscular nerve signals, which then weakens the target muscle so it can't contract. The final result is a reduction of facial wrinkles.

Used to smooth:

- crow's feet;
- forehead furrows;
- frown lines.

Fig. 1. Two examples of botulinum toxin usage. Top: Frown lines before (left) and after (right). Bottom : Forehead furrows before (left) and after (right).

2.2 Dermal Fillers

Dermal fillers are used to diminish facial lines and restore volume and fullness in the face eventually lost during the aging process, due to the reduction of subcutaneous fat causing facial muscles to work closer to the skin surface and resulting in more apparent smile lines and crow's feet.

Used to:

- plump thin lips;
- enhance shallow contours;

- soften facial creases and wrinkles;
- improve the appearance of recessed scars.

Fig. 2. Examples of dermal fillers usage. Top: Frown lines before (left) and after (right). Bottom: Forehead furrows before and after

2.3 Chemical Peel

Chemical peel is one of the least invasive cosmetic surgery used to improve the appearance of face's skin. Sun exposure, acne, or just aging can leave skin texture uneven, wrinkled, spotted or scarred.

Used to improve:

- acne or acne scars;
- age and liver spots;
- fine lines and wrinkles;
- freckles;
- irregular skin pigmentation;
- rough skin and scaly patches;
- scars;
- sun-damaged skin.

Fig. 3 Two examples of chemical peeling. Left: smoothing of fine lines, wrinkles and age spots. Right: acne and related scars reduction and overall skin smoothing.

2.4 Dermoabrasion/Microdermabrasion

Dermoabrasion/Microdermabrasion belong to the class of skin re-surfacing techniques like aforementioned chemical peeling. By these techniques, the outer layer of skin is removed to allow newer skin to grow and replace the older skin.

Microdermabrasion uses a minimally abrasive instrument to gently sand the skin, removing the thicker, uneven outer layer. This type of skin rejuvenation is used to treat light scarring, discoloration, sun damage, and stretch marks.

Traditional Dermabrasion performs skin resurfacing to a greater depth. This allows for treatment of a variety of skin problems. Dermabrasion can be used for scar revision, acne scarring, lip rhytids, as well as the treatment of rhinophyma.

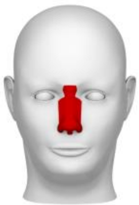
Used to improve:

- age spots and black heads;
- hyperpigmentation (patches of darkened skin);
- Skin appearance by exfoliating it;
- appearance of stretch marks;
- fine lines and wrinkles;
- aspect of enlarged pores;
- acneic skin and the scars left by acne.

Fig. 4. Dermabrasion vs. Microdermabrasion. Left: skin texture improved by microdermabrasion. Right: nose appearance and size improved by deep dermabrasion.

2.5 Rhinoplasty

Rhinoplasty is a surgical procedure aimed at enhancing facial harmony and the proportions of nose. It can also correct impaired breathing caused by structural defects in the nose.



Used to change:

- nose size in relation to facial balance;
- nose width at the bridge or in the size and position of the nostrils;
- nose profile with visible humps or depressions on the bridge;
- nasal tip that is enlarged or bulbous, drooping, upturned or hooked;
- nostrils that are large, wide, or upturned;
- nasal asymmetry.

Fig. 5. Two examples of rhinoplasty procedures on young subjects.

Only frontal and side contour of nose region are deeply affected.

2.6 Eyelid Surgery (Blepharoplasty)

Blepharoplasty, is a surgical procedure to improve the appearance of the eyelids. Surgery can be performed on either the upper and lower lids, or both. Whether a patient wants to improve her/his appearance or is experiencing functional problems with eyelids, eyelid surgery can be used to improve the aspect of the eyes region.

Used to treat:

- loose or sagging skin that creates folds or disturbs the natural contour of the upper eyelid;
- excess fatty deposits that appear as puffiness in the eyelids;
- bags under the eyes;
- drooping lower eyelids that reveal white below the iris;
- excess skin and fine wrinkles of the lower eyelid.

Fig. 6. Before and after (left to right) blepharoplasty on two subjects.

2.7 Facelift (Rhytidectomy)

Rhytidectomy, is a surgical procedure that improves visible signs of aging in the face and neck.

Used to treat:

- sagging in the middle of face
- deep creases below the lower eyelids;
- deep creases along the nose extending to the corner of the mouth;
- fat that has fallen or has disappeared;
- loss of skin tone in the lower face that creates jowls;

- loose skin and excess fatty deposits under the chin and jaw.

Fig. 7. Effects of facelift on two female subjects. Both the main face contours and local wrinkles/creases are affected by this treatment.

2.8 Brow Lift / Forehead ift

This surgical procedure aims at reducing the wrinkle lines that develop horizontally across the forehead, as well as those that occur on the bridge of the nose, between the eyes.

Used to:

- improve frown lines, the vertical creases that develop between the eyebrows
- raises sagging brows that are hooding the upper eyelids
- places the eyebrows in an alert position

Fig. 8. Brow lift affects either frown lines (high frequencies) or overall aspect of brow region (medium frequencies). Apparent eye dimension and shape might be affected as well.

2.9 Chin Surgery (Mentoplasty)

Mentoplasty, is a surgical procedure to reshape the chin either by enhancement with an implant or reduction surgery on the bone. Plastic surgeon may also recommend chin surgery to a patient having rhinoplasty in order to achieve facial proportion, as the size of the chin may magnify or minimize the perceived size of the nose.

Used to:

- modify chin 3D shape/contour by either augmenting or reducing it;
- improve overall face proportions, also as part of multiple facial surgical procedures.

Fig. 9. Chin surgery deeply affects overall face proportions (low frequencies) while preserving most of key facial features (medium/high frequencies).

2.10 Cheekbones Reshaping

This is a surgical procedure intended to improve the overall face appearance by either a reduction or an augmentation or cheeks shape. Cheek-bones reduction is very requested by Asian people and it represents a key procedure to make Asian face looks smaller. In zygomatic reduction, both ends are cut and the intervening bone segment (zygomatic bone) is moved inward, backward and downward. As a result, cheek prominence is depressed and the patient can get small, shallow face.

Used to:

- modify chin 3D shape/contour by either augmenting or reducing it;
- modify dramatically overall face proportions, also as part of multiple facial surgical procedures
-

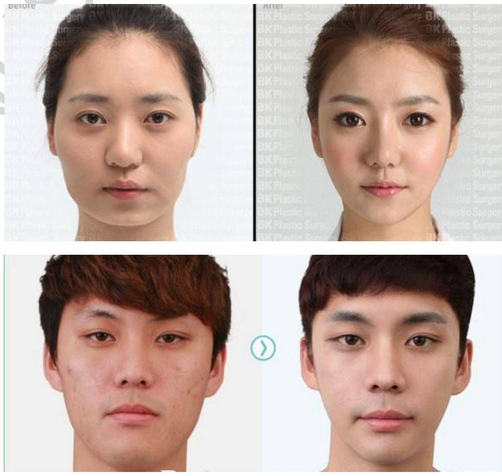


Fig. 10. Brow lift affects either frown lines (high frequencies) or overall aspect of brow region (medium frequencies). Apparent eye dimension and shape might be affected as well.

2.11 Ear Surgery (Otoplasty)

Otoplasty can modify the shape, position or proportion of the ear and it is mainly used to creating a more natural ear shape, bringing balance and proportion to the overall face. Ear surgery can also correct defects in the ear structure that is present at birth that becomes apparent with development or it can treat misshapen ears caused by injury.

Used to:

- modify chin 3D shape/contour by either augmenting or reducing it;
- modify dramatically overall face proportions, also as part of multiple facial surgical procedures.

Fig. 11. Otoplasty affects only the external-ear region (low frequencies) so, depending on whether a particular face recognition method considers this region or not, this procedure could have limited or no effect to tha aims of recognition.

TABLE 1
Summary of main facial plastic surgeries. For each of the twelve surgical procedures listed in the first column, the table reports the facial region interested, the main spatial frequencies involved, the extension of the region affected, the extent of the impact typically expected and the percentage of diffusion of each procedure (with regard to the total number of facial plastic surgeries performed in one year).

Surgical procedure	**Facial region**	**Spatial frequencies**	**Extension of face surface**	**Potential impact**	**Relative diffusion**
Botulinum toxine	Forehead	High	Medium	Low to Medium	52%
Dermal fillers	Periocular / smile lines	High	Limited	Medium	19%
Chemical peel	Whole face	High	Wide	Low	9%
Dermoabrasion (*Resurfacing*)	Whole face	High/Medium	Wide	Low to Medium	0,6%
Microdermoabrasion	Whole face	High	Wide	(very) Low	8%
Nose reshaping (*Rhinoplasty*)	Nose	Low	Limited	Medium	1,8%
Eyelid surgery (*Blepharoplasty*)	Periocular region	Medium	Limited	Low to Medium	1,8%
Facelift (*Rhytidectomy*)	Whole face	Low to High	Wide	High	1.1%
Brow lift (*Forehead lift*)	Forehead	Medium/High	Limited	Medium	0.4%
Chin surgery (*Mentoplasty*)	Lower face region	Low	Medium	High	0.15%
Cheekbones reshaping	Zygomatic region	Low	Medium	High	0.1%
Ear surgery (*Otoplasty*)	Ears	Low	Limted	Low	0.2%

In Table 1, the main features of the aforementioned cosmetic plastic surgery procedures are summarized, together with the impact on the face appearance.

3 State of the Art in Face Recognition after Plastic Surgery

In this section, the main works specifically related to the topic of face recognition in plastic surgery have been divided into two general categories.

The first category includes studies comparing some of the best-established, mostly holistic, face recognition methods, with the purpose of assessing the level of performance achievable when matching face images captured before and after plastic surgery.

The second and larger category includes a wide range of approaches featuring a local/region-based strategy to reduce recognition error and to improve reliability.

Finally, it is worth considering a third category of methods addressing recognition in presence of heterogeneous face representations (e.g.: visible, IR/NIR, depth images, 2D facial sketches/drawings, etc.) or even in case of counterfeit faces since these kind of "variations" could be possibly assimilated to facial fatures alterations involved in plastic surgery procedures.

For each category, the most relevant papers are presented in chronological order, from the first to the last published.

3.1 Holistic Methods

The seminal work developed by Singh, Vatsa and Noore [4], formally introduces plastic surgery as a challange for face recognition algorithms. The authors present an experimental study to quantitatively evaluate the performance of face recognition algorithms on a plastic surgery database that contains face images with both local and global surgeries. To this purpose, six recognition algorithms based on appearance, feature, and texture were considered for evaluation because they are either used as the basis for commercial systems or have reported high accuracy in challenging scenarios: PCA [5], FDA [6], GF [7], LFA [8], LBP [9], GNN [10]. The presented experimental results clearly show that the aforementioned algorithms could not effectively address the variations caused by the plastic surgery procedures. According to these results, the authors believe that more research is required in order to design an optimal face recognition algorithm able to perform.

Singh et al. [11] published a follow up to their first work, expanding and deepening the previous experimental study to quantitatively evaluate the performance of face recognition algorithms on a specifically built plastic surgery database, definitively introducing plastic surgery as a new dimension for face recognition algorithms.

The algorithms selected for the experiments are PCA, FDA, LFA, Circular Local Binary Pattern (CLBP) [12], Speeded Up Robust Features (SURF) [13] and GNN. The results provided showed again the need for algorithms specifically optimized to address the multiple types of variations involved in face plastic surgery. They also suggest that a promising future research direction would be to work on non-visible wavelenghts by using thermal-infrared imagery and compute the thermal differences between pre and post surgery shots. Towards this aim they hope for creating a large face database that contains pre-post operative thermal infrared images.

In [14], Ibrahim et al. present a comparative study whose purpose is to assess the best performing among several face recognition algorithms applied to before-after plastic surgery face images. More in detail, the experiments conducted aimed to evaluating the performance of four feature extraction techniques: principal component analysis (PCA), the Kernel Principal Component Analysis (KPCA) [15], Kernel Fisherfaces Analysis (KFA) [16] and various Gabor-based face representations [17, 18]. These methods were combined to five histogram normalization techniques (normal, rank, exponential, lognormal and histruncate) and to eleven photometric illumination techniques [19]: the single-scale-retinex algorithm (SSR), the multi-scale-retinex algorithm (MSR), the single-scale self quotient image (SSQ), the multi-scale self quotient image (MSQ), the homomorphic-filtering based normalization (HOMO), a wavelet-based normalization (WAV), the DCT-based normalization (DCT), steerable filters (SF), the Gradient-faces approach (GRF), wavelet-denoising-based normalization (WD), adaptive single scale retinex (ASSR). A minimum distance classifier and four distance similarity measures were used. The experiments reported that for face verification, the best illumination technique is Gradient-Face (GRF) normalization technique, the best histogram normalization is the histruncate histogram normalization and the best feature extraction technique is GKFA. For face identification, the best illumination technique is again GRF, and the best feature extraction technique is Gabor principal component analysis (GPCA). For both face identification/verification the minimum distance classifier based on Mahalanobis cosine distance provides the best results.

3.2 Region-based Methods

The common idea developed within this category of approaches is to analyze the face images at a local level or, in some cases, at both global and local scale. The aim is to better discriminate the spatial characterization and the degree of after-surgery changes to improve algorithmic robustness.

De Marsico et al. in [20] and more in deep in [21] were among the first to propose such a kind of approach, based on the assumption that plastic surgery modifies face appearance in a non-uniform fashion, by using a recognition approach that integrates information derived from two complementary regions-of-interest (ROIs) based face analysis methods, FARO [22] and FACE [23], in which local features are fractal and correlation-based through the use of PIFS [24], respectively. The two techniques, which implicitly exploit the relative importance and weight of each face region of interest, are properly integrated for robust matching and recognition. The authors firstly analyzed the level of mutual dependence among facial components by calculating the following correlation index calculated over the AR Face Database [25]:

$$c(A,B) = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}} \tag{1}$$

where n and m are the image dimensions, and A and B are the averages for the corresponding images A and B. It is worth noting that, according to the experimental results, the eyes by themselves contain most of the discriminant information, while the contribution of mouth is secondary yet still significant. Experiments also confirm the expectation that face recognition is indeed challenged by the effects of plastic surgery. However, with regard to face recognition after plastic surgery, both FARO and FACE compare favourably against standard algorithms such as PCA and LDA, with FACE performing better than state-of-the art face recognition methods.

In [26], Aggarwal et al. propose a partwise approach that is based on the intuition that appearance of one or more facial features may not change much across plastic surgery procedures. In such a part-wise framework, the proposed approach exploits recent successes of sparse representations for face matching [27]. Most sparse representation based face matching approaches require several images of each subject in the gallery, though this requirement is rarely satisfied, as it is the case in the plastic surgery database considered for this work. The authors overcome this limitation by using sequestered training face images instead of pre/post surgery images. For each facial feature (eyes, eyebrows, nose, mouth, etc.) of each gallery subject, the proposed method identifies most similar facial parts from the training images, using the public Active Shape Model (ASM) library (STASM) [28] to locate them automatically, and use them in the absence of multiple images per subject in the gallery. Sparse recognition is then performed independently for each facial feature by evaluating the representation error according to:

$$e_i(y) = \|y - A\hat{x}_i\| \qquad (2)$$

where $e_i(y)$ is the representation error for i-th class, A is the training matrix, $\hat{x}_i = \left[0,0,0,\hat{x}_{i,1},,\hat{x}_{i,n_i},0,,0\right]^T$ _$\mathbb{R}^n$ and for a given test sample y the sparse coefficient vector x is obtained solving the optimization problem:

$$x = arg\,\min_{x\in\mathbb{R}^n}\|x\| \text{ subject to } Ax = y \qquad (3)$$

This approach is evaluated on the plastic surgery database introduced in [5]. Following the suggested evaluation protocol for the database, a significant improvement in rank-1 matching accuracy is observed. Effectiveness of the part-wise analysis without the use of sparse representation is also highlighted.

Liu et al. [29] propose a face recognition method, named Ensemble of Gabor Patch Classifiers via Rank-Order List Fusion (GPROF).

Their working hypothesis is that local plastic surgery only changes local face appearance, so is safe to assume that it does not corrupt the interior consistency of a face, while also in case of global plastic surgery the interior consistency of face after global plastic surgery can also be preserved as these procedures do not completely change all facial components' identity information. Following these assumptions face is divided into patches, designing one component classifier for each patch, and finally fusing the rank-order list of each component classifier. To this aim, Gabor features [30] together with Fisher LDA [31] are used to design the component classifier. Gabor features have been chosen because they are bio-inspired local features extracting multi-scale and multi-orientation local texture features, and it is particularly appropriate to reveal the interior consistency of human face even after plastic surgery. The discriminative capacity of Gabor feature is further improved by applying PCA and FDA, while rank-order list, a technique proposed for face tagging [32] and face matching [33], is used to represent each face patch. Different patches of the same input face should have similar rank-order lists against a gallery set, due to the interior consistency of face. Finally each patch's rank-order list is fused to compensate for the appearance changes caused by plastic surgery. The authors also explore the possibility of plastic surgery detection (PSD) where, given two face images of the same person, the proposed method can automatically detect the eyelid surgery, nose surgery, forehead surgery and facelift surgery.

Gabor features are also exploited in the work by Lakshmiprabha et al. [34] to implement a multimodal biometric approach using face and periocular biometrics.

The authors start considering that extracting multiple feature information from a single source may provide a satisfactory recognition performance even with a limited number of training images. To this aim they propose to combine face and periocular data extracted from the same image by using Gabor or LBP features. Feature extraction performed, for both face and periocular images, is followed by feature dimension reduction using PCA, while classification is performed using Euclidean distance $\__i$ as follows.

$$\varepsilon_i^2 = \|\Omega_T - \Omega_i\|^2 \qquad (4)$$

where Ω_i is a vector describing the ith face image in the training set. Test image is classified as belonging to image i when the minimum of ε_i is below some chosen threshold value. According to the matching strategy, features from the face images are matched first and when there is a negative result periocular image features are matched.

The experimental results obtained report a measurable advantage of the proposed multimodal biometric approach in terms of recognition accuracy over individual biometric methods. In particular the best performance is achieved by combining periocular region and lips region and this combination results also superior to combining the whole face with periocular region and the whole face with the lips region. Concerning the metrics used, Gabor-PCA and LBP-PCA perform similarly when applied to multimodal descriptors.

The idea of using multimodal biometric techniques is also explored by Mun and Deorankar [35] that propose to use face and periocular biometrics for the recognition of face invariant to plastic surgery. This method exploits different features from face and periocular region to match face images before and after plastic surgery. Features are extracted from both face and periocular region by means of local binary patterns dimensionally reduced through PCA. Euclidean distance is therefore used for classification. If a matching face could not be found, then periocular biometric is used instead. The proposed method is capable of extracting shape as well as texture features and improving the recognition rate using periocular biometric. Experiments conducted using non-surgery face database and plastic surgery face database reported high identification accuracy compared to existing face recognition system.

The approach by Sun et al. [36] is based on the assumption that variations caused by plastic surgeries can be considered as a variety of distortions on the pre-surgery facial images. To properly model these variations an effective image quality tool should correctly interpret the degradation of both texture and structural information. The Structural Similarity (SSIM) index [37] was developed for localized quality measurement and represents such an objective image quality metric. For any two given image signals x and y (aligned with each other) the SSIM index is obtained according to:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (5)$$

where μ_x and μ_y are the mean intensity values of signal x and y, while σ_x and σ_y are their corresponding standard deviations. $\_{xy}$ is the correlation coefficient between x and y. C_1 and C_2 are small positive constants used to avoid instability when the denominator is very close to zero. The authors propose to consider the pre-surgery image as a reference image and the post-surgery image as a distorted one, so that SSIM quality map between the two images can be computed. Further, this quality map is used in a patch level to control the contribution of each patch to the final weighted matching score sc^w calculated according to:

$$sc = \sum_{i \in 1,\dots,n} w_i \times sc_i^O \qquad (6)$$

where w_i is the weight of classifier c_i and sc_i^O results from the following sum rule:

$$sc^O = \sum_{i \in 1,\ldots,n} sc_i^O \qquad (7)$$

In most methods for face recognition across plastic surgery, a background dataset is required to address the problems caused by insufficient gallery images of each individual [38]. A significant advantage of the proposed approach is that neither training process, nor any background information from other databases is required. However, when matching faces of different individuals, lower weights are assigned to regions where the two faces differ most. Experiments were conducted performing both holistic and component-wise matching. For the holistic matching, the whole face image is divided into 8x8 patches. For the component-wise matching, seven facial regions are extracted, including forehead, left ocular, right ocular, nose, left cheek, right cheek and mouth. The results reported highlight the potential of SSIM for matching face images before and after surgeries.

Along a different line of research, El–said et al. [39] proposed a Geometrical approach for Face Recognition after Plastic Surgery (GFRPS). In this approach, recognition is performed through three steps: ROIs are first identified on the post-surgery face image; the distance between the ROI centres is computed on both the post- and pre-surgery images, and a feature vector is composed from the computed distances; the matching score is computed as the distance among feature vectors of pre- and post-surgery images. This algorithm, even if quite simple in its formulation, demonstrated to achieve very good identification performance when compared to algorithms at the state of the art.

Bhatt et al. in [40], proposed a complex, multi-resolution approach to analyze the face images at different spatial frequency scales. Non-disjoint face representations are computed, each representation providing spatially disjoint information at different resolution scales. The generated multi-resolution and geometrically diversified representation allows to easily analyzing face granules (i.e. local areas of face), such as nose, ears, forehead, cheeks, or a combination of them. In the first step, both pre- and post-surgery face images are processed to produce face samples at varying resolutions. At the second step the face images are divided into horizontal and vertical stripes of varying size. At the third step the face images are divided into non-overlapping facial regions. The Uniform Circular Local Binary Pattern (UCLBP) [41] and SURF are extracted from the computed representations. The resulting responses are unified in an evolutionary manner using a genetic algorithm. To match the corresponding features extracted from the gallery and probe images, descriptors are first normalized. The dissimilarity score is computed from the weighted □2 distance. The weights assigned to each face granule are learned using a genetic approach as follows:

$$\chi^2(a,b) = \sum_{i,j} \omega_j \frac{(a_{i,j}-b_{i,j})^2}{a_{i,j}+b_{i,j}} \quad (8)$$

where □ and □ are the normalized descriptors (UCLBP or SURF descriptors), □ and □ correspond to the $□^{th}$ bin of the $□^{th}$ face granule and $□_j$ is the weight for the j^{th} face granule.

Face granulation [42] [43] is also exploited in [44] together with a PSO [45] algorithm**.** At the first level of granularity, face granules are generated applying the Gaussian and Laplacian operators while, at the second level, horizontal and vertical granules are generated by dividing the face image into different regions. Feature extraction is then performed by means of both Extended Uniform Circular Local Binary Pattern (EUCLBP) and LBP descriptors. Finally Scale Invariant Feature Transform (SIFT) descriptors [46] computed at the sampled regions are concatenated to form the image signature. Post surgery images and exploited to determine the PSO dimensionality reduction allowing to reconstructing the original face images. Other dimensionality reduction techniques offer solutions that can significantly improve computational efficiency, still yielding reasonable accuracy. Raising issues such as premature coverage and population diversity can be effectively addressed by applying PSO. The experiments show that the choice of PSO over Genetic Algorithms results in a measurable improvement in recognition accuracy.

Verghis et al. [47] postulate that in the human vision system face recognition is performed by analyzing the relation among non-disjoint spatial features, extracted at different granularity levels. Consequently, a multi-objective evolutionary granular algorithm, operating on several granules extracted from a face image, is proposed. At the first level of granularity face images are decomposed into Gaussian and Laplacian of Gaussian multi-resolution image pyramids. At the second level of granularity face images are decomposed into horizontal and vertical face granules of varying sizes. At the third level of granularity discriminating information from local facial regions are extracted. A multi-objective evolutionary genetic algorithm is proposed for feature selection and weight optimization for each face granule. The evolutionary feature selection allows to switch between SIFT and EUCLBP features also facilitating the encoding discriminant information for each face granule. The presented experimental results outperform existing algorithms, including a commercial system for matching surgically altered face images. This is probably due to the contribution of three granular levels and individual face granules which make it possible unifiying diverse information to address the non-linear variations in pre- and post-surgery face images.

All of the methods described above are summarized in Table 2. For a subset of these methods1 the Cumulative Match Characteristic curves, computed over the same facial surgery image dataset (described in the following section), are graphically compared in Figure 12. To improve readability, solid lines are associated to holistic approaches and dashed lines to region-based approaches.

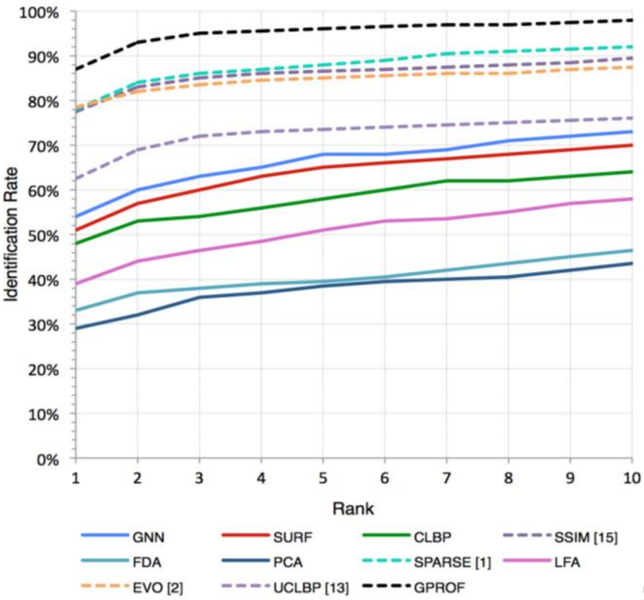


Fig. 12. Comparison of the Cumulative Match Characteristic curves computed from eleven different face recognition algorithms applied to the same plastic surgery database. Dashed lines refer to region-based approaches, while solid lines refer to holistic approaches. To ensure the originally published results are provided, the CMC curves have not been re-computed. Therefore, they are reported only for those methods that included the CMC curves in their original research papers.

3.3 Methods for heterogeneous/counterfeit faces

A different way to look at the problem of recognizing faces after plastic surgery is to consider a surgically altered face as either a heterogeneous variation, or a counterfeit version of the original face. Both issues have been addressed in the literature over the last decade, and involve interesting developments which deserve further attention. The potential impact of these research issues on face recognition in plastic surgery will be further discussed in section 5. Whenever a probe and a gallery image have not been acquired with the same sensor, they can be always treated as heterogeneous images. However, heterogeneous face recognition (HFR) relates to the matching of face images resulting from different capturing technologies. For example, images captured in visible light and NIR/IR images, or mugshots with hand-drawn face sketches.

Li et al [48] in 2009 captured and made publicly available an heterogeneous face database composed of visual (VIS), near infrared (NIR) and three-dimensional (3D) face images known as the HFB Face Database. According to the paper, the database, containing a total of 992 images from 100 subjects (4 VIS, 4 NIR, and 1 or 2 3D facial scans per subject) was aimed at promoting research and development of Heterogeneous Face Biometrics (HFB). The baseline performance of standard PCA and LDA recognition algorithms was also reported. The poor reported results justified the development of more effective methods to address HFR.

Heterogeneous face images generally result from different skin spectra-optical properties. For this reason, a direct appearance-based matching is not recommended. Liao et al. [49] proposed to perform a Difference-of-Gaussian filtering to normalize the appearance of all heterogeneous faces. An extension of LBP operator is then applied, to encode the local image structures in the transformed domain, and extract the most salient local features to perform classification.

In [50] Klare and Jain proposed to use a common feature-based representation for both NIR images and VIS images exploiting the Histograms of Oriented Gradients (HOG) feature descriptors along with LBP descriptors to extract more discriminant information of the facial structure. LDA is applied on a collection of random subspaces to learn discriminative projections. NIR and VIS images are directly matched using the random subspace projections, and also using a sparse representation-based classification.

Lei et al. [51] presented a coupled discriminant analysis method to improve recognition accuracy. All samples from different modalities were used to represent the coupled projections, whilst the locality information in kernel space is incorporated into the coupled discriminant analysis as a constraint to improve generalization.

More recently, Klare and Jain [52] proposed a generic framework where the probe and gallery images are captured in different modalities and are represented in terms of non-linear kernel similarities for a collection of prototype face images. The similarity is measured against the prototype images from the corresponding modality. The accuracy of the HFR system is improved by computing a linear transformation from the probe to the gallery prototype representation, followed by a projection into a linear discriminant subspace. Degradations due to the small sample size are addressed with a Prototype Random Subspace (PRS) approach. State-of-the-art performance are reported on different heterogeneous images including NIR, photographs, thermal images, viewed and forensic sketches.

Counterfeit face detection algorithms constitute another resource which can be exploited to analyse images of faces altered by plastic surgery. Li et al. [53] proposed an algorithm based on the analysis of Fourier spectra exploiting the structure and motion information of live faces.

In 2011, Määttä et al. [54] proposed an approach for spoofing detection based on the detection of print texture on the face image. The algorithm is based on the detection of image printing quality defects by means of texture features. Multi-scale local binary patterns (LBP) are applied, building a feature space for coupling spoofing detection and face recognition.

Zhang et al. [55] presented a face liveness detection algorithm exploiting the multispectral properties of the human skin. Reflectance data of genuine and false faces, captured at multiple distances, is used for training an SVM classifier to learn the multispectral distribution of genuine and false faces. Even though these algorithms have been specifically developed to analyse heterogeneous or counterfeit facial images, some of the developed models could be adapted to detect specific properties of surgical alterations in face images.

4 Public Face Surgery Datasets

Currently there is only one publicly available face dataset specifically developed for face recognition across plastic surgery, and it is the result of the work of Singh et al. [4] previously cited in section 3. The plastic surgery face database is a real world database containing 1800 pre- and post-surgery images pertaining to 900 subjects. For each individual, there are two frontal face images with diffuse illumination and neutral expression: the first is taken before surgery and the second is taken after surgery. The database contains a wide variety of cases for a total of 519 image pairs corresponding to local surgeries and 381 cases of global surgery (the number among brackets is the total of subjects captured per procedure): Dermoabrasion (32); Brow lift (60); Otoplasty (74); Rhinoplasty (192); Blepharoplasty (105); Others (56); Skin peeling (73); Rhytidectomy (308). The Viola Jones face detector [13] has been applied to detect facial region in the images and the size of the detected and normalized face images is 200x200 pixels. This dataset has been used for experiments by almost all papers included in this survey.

5 Discussion

As explained in the introduction, the practice of facial plastic surgery and other cosmetic procedures are globally expanding. In a cultural model characterized by a great consideration for beauty and aesthetics, these represent a predictable social response to the quest for the best appearance.

TABLE 2

Comparison of algorithms for recognition of faces undergoing surgical procedures. **GLOBAL**: the algorithm is based on a global or holistic analysis of face image; **LOCAL**: the algorithm is based on the analysis of local features extracted from the face image; **TEX**: the algorithm is based on the analysis of the texture extracted from the face image; **3D**: the algorithm is based on the analysis of 3D information extracted from the face image; **RR**%: rank-one recognition accuracy (average value among all surgical procedures).

#	Reference	Dataset	Key Features					Algorithm
			GLOBAL	LOCAL	TEX	3D	RR%	
1	Aggarwal et al. [26]	Plastic Surgery Face Database	N	Y	N	N	*77.9*	Part-wise and Sparse representation
2	Bhatt et al. [40]	Plastic Surgery Face Database	Y	Y	Y	N	*78.6*	Uniform Circular Local Binary Pattern (UCLBP) + Speeded Up Robust Features (SURF) + genetic alghorithm
3	De Marsico et al. [20,21]	Plastic Surgery Face Database	Y	Y	N	N	*70.0*	PIFS + region-based correlation index
4	El–said, Abol Atta [39]	Plastic Surgery Face Database	N	Y	N	N	*76.1*	geometrical descriptors of ROIs + minimum distance classifiers
5	Ibrahim et al. [14]	Plastic Surgery Face Database	Y	N	Y	N	*83.2*	PCA, KPCA, KFA, Gabor
6	Karuppusamy and Ponmuthuramalingam [44]	NA	N	Y	Y	N	-	Extended Uniform Circular Local Binary Pattern (EUCLBP) + SIFT + Particle Swarm Optimization (PSO)
7	Lakshmiprabha et al. [34]	Plastic Surgery Face Database	N	Y	Y	N	*74.4*	Gabor/LBP + PCA + Euclidean Distance
8	Liu et al. [29]	Plastic Surgery Face Database	Y	Y	Y	N	*86.1*	Gabor Patch classifiers via Rank-Order list Fusion (GPROF)
9	Mun and Deorankar [33]	Web available Before/After Surgery photos	Y	Y	Y	N	-	Multimodal biometric featuresPCA (face)+LBP (periocular region)
10	Singh, Vatsa and Noore [4]	NA	Y	Y	Y	N	*40*	PCA, FDA, GF, LFA, LBP, GNN
11	Singh et al. [11]	Plastic Surgery Face Database	Y	Y	Y	N	*40*	PCA, FDA, LFA, CLBP, SURF, GNN

12	Sun et al. [36]	Plastic Surgery Face Database	Y	Y	Y	N	*77.5*	Structural Similarity (SSIM) index +weighted patch fusion
13	Verghis et Bhuvaneshwari [16]	Plastic Surgery Face Database	Y	Y	N	Y	*87.3*	Evolutionary granular algo-rithm + SIFT and EUCLBP

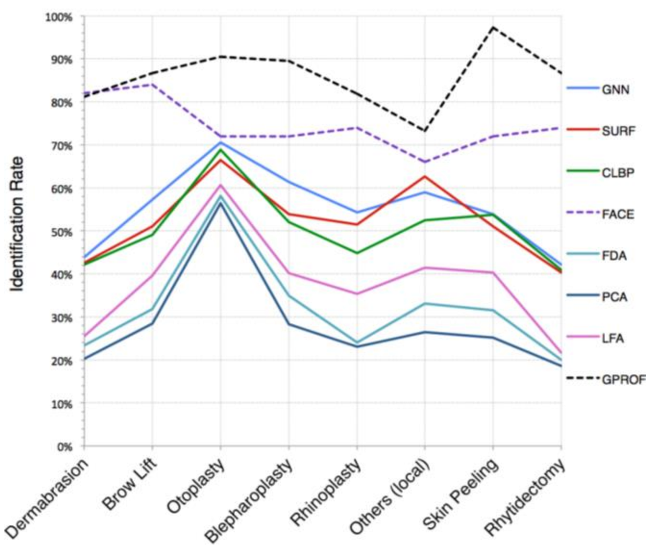
When combined to (or partly favored by) the availability of an ample choice of surgical techniques, with even lower costs compared to the past (particularly for minimally invasive procedures), this fact allows to safely predict a relevant impact on face recognition systems. This trend raises two questions, which are inherently linked to the core of the face recognition problem:

i. *Can a face modified by plastic surgical procedures be still considered as an intra-class variation of the originally captured face sample*?

ii. *What are the required constraints for the distance in the face-space between the post-surgery and the pre-surgery face samples of a given subject to be lower than the distance from a face sample of another subject*?

The answers to these questions require an accurate knowledge of the plastic surgery occurred. This is especially true for subjects affected by serious pathologies or facial traumas. However, the intra-class distance may become quite large even in case of surgical face beautification, as for cheekbone reshaping presented in Fig. 10. As a consequence, the challenge in defining metrics and methods to accurately recognize a face after plastic surgery is not trivial, and it can be very difficult if no information about the applied surgical procedure is available. This is even worse if multiple procedures have been applied over time. The overall change in facial appearance can sometimes be greater than just the summation of each single procedure. As already reported in section 3, over the abundance of research papers published on face recognition, only a relatively small number of papers address the challenge of face recognition after plastic surgery. Moreover, even though many experiements are reported from the same face database described in section 4, only a few of them adopted the same metric and categorized the experimental results by surgical procedure. At present, the best performing approaches achieve fair/good recognition accuracy on individuals to whom minimally invasive procedures (where only high frequency components of the captured face image are affected) were applied. Not surprisingly, the reported experimental results are generally worse when the algorithms are applied to faces undergoing more invasive surgical procedures.

To better understand the sensitivity of face recognition algorithms to aestetic surginal procedures, a comparative analysis has been performed on the algorithms reporting experimental results on the same Plastic Surgery Face Database [14]. The Cumulative Match Characteristic curves, computed from each of the eleven tested algorithms, are reported in Figure 12. As it can be noticed, the five algorithms based on a local analysis of the face (GPROF, FACE, SPARSE, SSIM, EVO) outperform all six algorithms based on an holistic approach (PCA, LFA, GNN, SURF, CLBP, FDA). As illustrated by the sketches in figures 1 to 11, each surgical procedure only changes the appearance of a specific area of the face. Therefore, algorithms based on a local analysis of the face can always exploit the distinctive information from face areas that are not affected by the surgical procedure. On the other hand, as holistic methods require an almost geometrically perfect alignment of the faces being compared, they cannot cope equally well to local changes in the image texture. In fact, every surgical intervention produces either a geometrical or textural distortion of a face area, which is easily captured by holistic approaches. In order to quantitatively evaluate how the performance of the different algorithms is related to a particular surgical procedure, an experiment has been performed where each algorithm was tested on the same

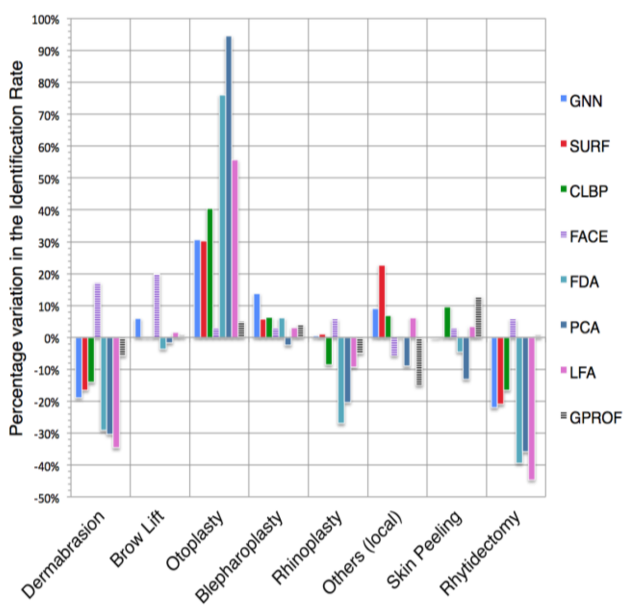


gallery images (i.e. the face images captured before applying the aestethic surgical procedure) from the Plastic Surgery Face Database but partitioning the probe images (i.e. the face images captured after applying the aestethic surgical procedure) according to eight specific surgical procedures. The diagram in Figure 13 reports the identification rate computed at rank 1 for each algorithm, as a funtion of the surgical procedure applied to the subject's face. In order to better highlight the relative performance variability as a function of the surgical procedure, the computed normalized identification rate for each algorithm, is reported in Figure 14. The normalized identification rate has been computed as the ratio between the procedure-specific identification rate (reported in figure 13) and the overall identification rate, as reported in Figure 12 at rank 1. This provides a measurement of the percentage variation in the recognition rate, due to the particular nature of the specific surgical procedure applied to the subject's face. As it can be noticed, also in the procedure-specific experiments, the algorithms performing a local analysis of the face (GPROF, FACE) outperform the holistic algorithms (PCA, LFA, GNN, SURF, CLBP, FDA). However, as suggested by the diagram in Figure 14, the performance degradation is not a simple function of the locality of the matching algorithm. For example, CLBP exhibits a more graceful degradation when varying the applied surgical procedure than FACE. On the other hand, GPROF provides a more stable performance across almost all surgical procedures than FACE.

Fig. 13. Identification error, as reported by eight different recognition algorithms, categorized by eight different surgical procedures. The six leftmost procedures are *local*, while the two rightmost procedures are *global*.

Moreover, holistic methods clearly perform better when processing images of faces where local surgeries were applied, rather than with global surgical procedures, such as Skin Peeling (Resurfacing) and Rhytidectomy (Face Lifting). This is not true for the two region-based methods, GPROF and FACE, for which comparable procedure-wise data is available. Both algorithms well address these two challenging global face surgeries providing performance close or even better than their average identification rate. *Otoplasty* results as the least challenging procedure for all algorithms except FACE. This is due to the fact that most algorithms do not take into account the face areas in proximity of the ears.

Rhytidectomy (face lifting) results as the most challenging procedure for the holistic algorithms and *Other local surgeries* for the region-based algorithms. From the performed comparative analysis, most papers in the literature only report the performance of algorithms applied to images of faces undergoing single facial plastic procedures. No reports are provided on the effect on recognition performance of multiple (or repeated) surgical procedures on the same subject. All compared algorithms have been devised to make the face matching process independent from the deformation in shape and variation in texture due to the plastic surgery. However, to the best of our knowledge, there is no algorithm which explicitly models the shape and texture variations induced by different surgical procedure. A relevant addition to the systems presented in the literature is modeling



the effects of plastic surgeries on the face image to either cancel the photometric alterations from the probe face image or to produce a face representation which is invariant to plastic surgeries. Such representation would require to inferring complex local and global image transformations, which cannot be deterministically computed from the post-surgery face image, without any a-priori knowledge. As

Fig. 14. Comparison of overall vs. procedure-wise performance of eight different algorithms. The reported identification rate is normalized to 1.

surgical procedures mainly produce shape alterations in the face, a 3D face representation would allow to reducing the complexity of the problem by explicitely modeling the shape deformations induced by different plastic surgeries. In some cases, a unique mapping between the pre-surgery and post-surgery face shape could be explicitly computed. To achieve this task it is necessary to either infer 3D data from the available plastic surgery face image datasets, possibly by means of a shape-from-shading or other algorithms, or to build a new dataset by acquiring 3D representations of pre-surgery and post-surgery faces.

As introduced in section 3.3, a surgically altered face image can also be regarded as a kind of heterogeneous face image, so that HFR approaches could possibly be of help on this topic. To this regard, it has to be highlighted that normalization techniques exploited in Heterogeneous Face Recognition approaches may not be sufficient to deal with surgical procedures deeply affecting face shape and/or face proportions. Most HFR algorithms aim to match the common features in heterogeneous face samples of the same subject. This approach may not be applied wherever the surgical procedures deeply modify both the local facial features and its overall proportions. This may be the case of multiple surgical procedures involving key face areas like cheeckbones, eye or nose shape, etc. Therefore, HFR techniques could reasonably be exploited only if the after-surgery face image can be still considered an intra-class variation of the pre-surgery face image.

Another way of looking at a surgically altered face image can be to consider it a counterfeit version of corresponding pre-surgery face image. Therefore, anti-spoofing algorithms may be applied to distinguish between pre- and post-surgery face images, where the surgically altered face represents a counterfeit face image. Toward this end, an explicit modeling of the most frequent facial plastic surgeries is required. This would allow either to synthetically generate the corresponding facial alterations, or to analyze the probe face image to detect the coded alterations. Either processing 2D or 3D face images to detect such alterations, it would be also necessary to determine both the combination of surgeries and the extent of the alteration produced on the original face. In this way, a plastic surgery-specific face-space could be associated to a given probe image, and analyzed to maximize the correspondence to each gallery image. This approach recalls most facial expression recognition algorithms where facial expressions are tagged by facial action units or other part-based and compositional representations of the facial dynamics. As for facial expression recognition, machine learning algorithms (possibly deep learning approaches) could be successfully exploited. The training may require an augmented face-space, including procedurally generated "surgical" variations of each genuine face, simulated at multiple extensions (how far the plastic surgery affected the face shape and texture). The statistical frequency of each surgical procedure and of their combinations, along with face shape and proportion analysis could be exploited to reduce the model space.

6 CONCLUSIONS

Plastic surgery as well as other aestetic procedures are quickly becoming a potential challenge for face recognition in unconstrained environments. This is especially true when dealing with forensic applications where crime perpetuators may purposively alter their facial traits to disguise criminal investigations. Given the large increase in plastic surgeries, even among young people, it may become a challenge also in other scenarios where face recognition is deployed, such as border control or personal authentication on mobile devices. This paper attempted to provide a rigorous analysis of the implications of facial plastic surgeries for automatic face recognition. It also provided an almost complete picture of the state of the art in face recognition after plastic surgery, performing a critical analysis of the inherent issues underneath this challenging topic. This analysis further revealed the need for a deeper understanding of the underlying processes in face recognition. As a result of this effort, we envisage this challenge in face recognition will gain in the short term an increased attention from the academic and industrial communities. Considering the social relevance of plastic surgery in general, and of facial surgery in particular, this study may result in an increased understanding of its impact for the society as well.

Given the large variability of available plastic surgeries and the produced changes in the face shape, recognition becomes an ill-posed problem. This requires appropriate constraints and-or optimization strategies to be adopted. These, in turn, may take into account the available information on the physical implications in altering the face traits by means of different aestetic procedures. For most facial surgeries always exist areas within the face where the facial traits remain un-altered. Therefore, even without exploiting non-facial information, such as the iris, it is always possible to locate and exploit facial traits to be matched against pre-surgery face images. It is envisaged that different strategies, tailored to specific plastic surgery procedures, may be adopted and concurrently applied to post-surgery facial images. However, a considerable effort is still needed to achieve a truly "plastic surgery invariant" face representation and matching approach to be deployed in real world scenarios.

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REFERENCES

[1] American Society of Plastic Surgeons (ASPS) website: http://www.plasticsurgery.org/about-asps.html

[2] Y. Eisenthal, G. Dror, E. Ruppin, Facial Attractiveness: Beauty and the Machine, Neural Computation 18, 2006, pp. 119–142.

[3] T. Leyvand, D. Cohen-Or, G. Dror, D. Lischinski, Data-Driven Enhancement of Facial Attractiveness, in: ACM Transaction on Graphics (TOG), 2008, Vol. 27, No. 3, article 38.

[4] R. Singh, M. Vatsa, A Noore, "Effect of plastic surgery on face recognition: A preliminary study", in: Proceedings Workshops of Computer Vision and Pattern Recognition (CVPRW), 2009, pp. 72 – 77.

[5] W. Zhao, A. Krishnaswamy, R. Chellappa, D. L. Swets, J. Weng, "Discriminant analysis of principal components for face recognition". In Face Recognition, Springer Berlin Heidelberg, 1998, pp. 73-85.

[6] S. Mika, G. Ratsch, J. Weston, B. Scholkopf, and K. R. Muller, "Fisher discriminant analysis with kernels". Neural networks for signal processing, 1999, IX, 1, 1, pp. 41-48.

[7] I.J. Cox, J. Ghosn, and P.N. Yianilos, "Feature-based face recognition usingmixture-distance", in Proceedings of International Conference on Computer Vision and Pattern Recognition, 1996, pp. 209–216

[8] P. Penev and J. Atick, "Local feature analysis: a general statistical theory for object representation", Network: Computation in Neural Systems, vol. 7, 1996, pp. 477–500.

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

[10] R. Singh, M. Vatsa, and A. Noore, "Face recognition with disguise and single gallery images", Image and Vision Computing, 2009, vol. 27, no. 3, pp. 245–257.

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

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

[13] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Surf: Speeded up robust features". Computer Vision and Image Understanding 2008, 110 (3), pp. :346–359.

[14] R. M. Ibrahim, F.E.Z Abou-Chadi and. A. S. Samra, "Plastic Surgery Face Recognition: A comparative Study of Performance", IJCSI International Journal of Computer Science Issues, 2013, Vol. 10, Issue 5, No 2.

[15] P. N. Bellhumer, J. Hespanha, and D. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection," IEEE Trans. Pattern Anal. Mach. Intell., 1997, vol. 17, no. 7, pp. 711–720.

[16] Ming Hsuan Yang, "Face Recognition Using Kernel Methods", http://www.face-rec.org/ algorithms/ kernel /nips01.pdf.

[17] V. Štruc, and N. Pavešić, "The Complete Gabor-Fisher Classifier for Robust Face Recognition", EURASIP Journal on Advances in Signal Processing, Vol. 2010. No. 31.

[18] L. Shen and L. Bai, "Information theory for Gabor feature selection for face recognition," EURASIP Journal on Applied Signal Processing, vol. 2006, Article ID 30274, 11 pages.

[19] M. Leszczyński, "Image Preprocessing for Illumination Invariant Face Verification", journal of telecommunication and information technology, Vol. 2010, No.4, pp.19.

[20] M. De Marsico, M. Nappi, D. Riccio, H. Wechsler, "Robust Face Recognition after Plastic Surgery Using Local Region Analysis", in: Proceedings of International Conference on Image Analysis and Recognition - ICIAR 2011, June 22-24, 2011, Burnaby, BC, Canada, LNCS 6754/2011, 191-200

[21] M. De Marsico, M. Nappi, D. Riccio, H. Wechsler, "Robust Face Recognition after Plastic Surgery Using Region-Based Approaches", Pattern Recognition, Elsevier, accepted paper.

[22] M. De Marsico, M. Nappi, D. Riccio, "FARO: FAce Recognition against Occlusions and expression variations", IEEE Transactions on Systems, Man, and Cybernetics — Part A: Systems and Humans 40 (1)(2010), pp. 121-132.

[23] M. De Marsico, M. Nappi, D. Riccio, "FACE: Face analysis for commercial entities", in: Proceedings of International Conference on Image Processing (ICIP), 2010, Honk Kong, pp. 1597-1600.

[24] Y. Fisher, "Fractal Image Compression: Theory and Application", Springer-Verlag, 1994.

[25] Martinez, A.M. "Recognizing imprecisely localized, partially occluded, and expression variant faces from a single sample per class". IEEE Transaction on Pattern Analisys and Machine Intelligence, 2002, vol. 24, no. 6, pp. 748–763.

[26] G. Aggarwal, S. Biswas, P. J. Flynn, K. W. Bowyer, "A Sparse Representation Approach to Face Matching Across Plastic Surgery", in: Proceedings of IEEE Workshop on Applications of Computer Vision, January 2012, Colorado Springs, CO, pp. 113-119

[27] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma., "Robust face recognition via sparse representation". IEEE Transactions on Pattern Analysis and Machine Intelligence, 2009, vol 31, no. 2, pp. 210–227.

[28] S. Milborrow and F. Nicolls. "Locating facial features with an extended active shape model". In Proceedings of European Conference on Computer Vision, 2008, pp. 504-513.

[29] [26] X. Liu, S. Shan, and X. Chen. "Face recognition after plastic surgery: A comprehensive study". In Asian Conference on Computer Vision, 2012, pp. 565-576.

[30] C. Liu, H. Wechsler, "Gabor feature based classification using the enhanced Fisher linear discriminant model for face recognition". Image Processing, IEEE Transactions on, 2002, vol 11, no. 4, pp. 467-476

[31] P. Belhumeur, J. Hespanha, D. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection". Pattern Analysis and Machine Intelligence, IEEE Transactions on, 1997, vol. 19, no. 7, pp. 711-720.

[32] C. Zhu, F. Wen, J. Sun, "A rank-order distance based clustering algorithm for face tagging." In: Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on, IEEE, 2011, pp. 481-48

[33] F. Schroff, T. Treibitz, D. Kriegman, S. Belongie, "Pose, illumination and expression invariant pairwise face-similarity measure via doppelg-anger list comparison". In: Computer Vision (ICCV) IEEE International Conference on, 2011, pp. 2494-2501

[34] N. Lakshmiprabha, J. Bhattacharya, S. Ma jumder, "Face recognition using multimodal biometric features". In: Image Information Processing (ICIIP), 2011 International Conference on, IEEE, 2011, pp. 1–6.

[35] M. Mun and A. Deorankar, "Implementation of Plastic Surgery Face Recognition Using Multimodal Biometric Features", IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5, no. 3 , 2014, pp. 3711-3715

[36] Y. Sun, M. Tistarelli, D. Maltoni, "Structural Similarity based image quality map for face recognition across plastic surgery", Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on, 2013, pp, 1-8.

[37] Z. Wang, B. A.C, H. Sheikh, and E. Simoncelli. Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, 2004, vol. 13, no. 4, pp. 600–612.

[38] L.Wolf, T. Hassner, and Y. Taigman. "Similarity scores based on background samples". In Asian Conference on Computer Vision, 2009, pp. 88–97.

[39] S. A. El–said, H. M. Abol Atta. "Geometrical face recognition after plastic surgery". International Journal of Computer Applications in Technology, Inderscience Publishers, 2014, Volume 49, no. 3–4, pp. 352-364.

[40] H. Bhatt, S. Bharadwa, R. Singh, M. Vatsa, A. Noore, "Evolutionary granular approach for recognizing faces altered due to plastic surgery". In: Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on, IEEE, 2011, pp. 720–725.

[41] T. Ojala, M. Pietikainen, and T. Maenpaa. "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns". IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002, vol. 24, no. 7, pp. 971–987.

[42] A. Bargiela and W. Pedrycz. "Granular computing: An introduction". Kluwer Academic Publishers, Boston, 2002.

[43] T. Lin, Y. Yao, and L. Zadeh. "Data mining, rough sets and granular computing". Physica-Verlag, 2002.

[44] P. Karuppusamy, P. Ponmuthuramalingam, "Recognizing Pre and Post Surgery Faces Using Multi Objective Particle Swam Optimization", International Journal of Advanced Research in Computer Science and Software Engineering, 2013, vol. 3, no. 10, pp. 316-320.

[45] J. Kennedy and R. C. Eberhart, "Swarm Intelligence", Morgan Kaufmann Publishers, San Francisco, Calif, USA, 2001.

[46] D. G. Lowe, "Distinctive image features from scale-invariant keypoints". International journal of computer vision, 2004, vol. 60, no. 2, pp. 91-110.

[47] T. J. Verghis, S. Uma, P. Bhuvaneshwari, "A Multi-Objective Evolutionary Approach to Face Matching Across Plastic Surgery". COMPUSOFT, An international journal of advanced computer technology, 2014, vol. 3, no. 2. pp. 529-532.

[48] S. Z. Li, Z. Lei, M. Ao, "The HFB face database for heterogeneous face biometrics research". In 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 2009, pp. 1-8.

[49] S. Liao, D. Yi, Z. Lei, R. Qin, S. Z. Li, "Heterogeneous face recognition from local structures of normalized appearance". In International Conference on Biometrics, 2009, Springer Berlin Heidelberg, pp. 209-218

[50] B. F. Klare, A. K. Jain, "Heterogeneous face recognition: Matching nir to visible light images". In Pattern Recognition (ICPR), 2010, IEEE, pp. 1513-1516.

[51] Z. Lei, S. Liao, A. K. Jain, S. Z. Li, "Coupled discriminant analysis for heterogeneous face recognition". IEEE Transactions on Information Forensics and Security, vol. 7, no. 6, 2012, pp. 1707-1716.

[52] B. F. Klare, A. K. Jain, "Heterogeneous face recognition using kernel prototype similarities". IEEE transactions on pattern analysis and machine intelligence, 2013, vol. 35, no. 6, pp. 1410-1422.

[53] J. Li, Y. Wang, T. Tan, A. K. Jain, "Live face detection based on the analysis of fourier spectra". In Defense and Security, International Society for Optics and Photonics, 2004, pp. 296-303.

[54] J. Määttä, A. Hadid, M. Pietikäinen, "Face spoofing detection from single images using micro-texture analysis". In Biometrics (IJCB), 2011 international joint conference on, 2011, pp. 1-7.

[55] Z. Zhang, D. Yi, Z. Lei, S. Z. Li, "Face liveness detection by learning multispectral reflectance distributions". In Automatic Face & Gesture Recognition (FG 2011) IEEE International Conference on, 2011, pp. 436-441.

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HIGHLIGHTS

- A survey about Face Recognition After Plastic Surgery is presented.
- Approaches to the problem and to related topics are resumed and discussed.
- Results reported in literature are compared and analyzed.