Plastic Surgery: A New Dimension to Face Recognition

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***Abstract*—Advancement and affordability is leading to the popularity of plastic surgery procedures. Facial plastic surgery can be reconstructive to correct facial feature anomalies or cosmetic to improve the appearance. Both corrective as well as cosmetic surgeries alter the original facial information to a large extent thereby posing a great challenge for face recognition algorithms. The contribution of this research is 1) preparing a face database of 900 individuals for plastic surgery, and 2) providing an analytical and experimental underpinning of the effect of plastic surgery on face recognition algorithms. The results on the plastic surgery database suggest that it is an arduous research challenge and the current state-of-art face recognition algorithms are unable to provide acceptable levels of identification performance. Therefore, it is imperative to initiate a research effort so that future face recognition systems will be able to address this important problem.**

***Index Terms*—Face recognition, plastic surgery.**

I. Introduction

THE allure for plastic surgery is experienced world-wide and is driven by factors such as the availability of advanced technology, affordable cost, and the speed with which these procedures are performed. Facial plastic surgery is generally used for correcting feature defects or improving the appearance, for example, removing birth marks, moles, scars, and correcting disfiguring defects. The following is according to the recent statistics released by The American Society for Aesthetic Plastic Surgery for year 2008 [1].

- Every year, millions of Americans undergo cosmetic plastic surgery. There has been an increase of about 162% in the total number of plastic surgeries from 1997 to 2008.
- In 2008 alone, more than one million facial plastic surgeries were performed and most common surgical procedures were liposuction, blepharoplasty, rhinoplasty, chemical peel, and laser skin resurfacing.
- It is expected that 40% of women and 18% of men will undergo plastic surgery in the near future.
- It is also estimated that 29% of white Americans and 31% of nonwhite Americans will go for ethnic plastic surgery in the near future.
- Plastic surgery distribution by age: 0–18 years constitute 2% of the total procedures, 19–34 years constitute 22%, 35–50 years constitute 45%, 51–64 years constitute 26%, and 65 years and above constitute 6% of the total plastic surgery procedures.
- 18% of men and 23% of women are now more affirmative towards plastic surgery than they were 5 years ago.

The statistics clearly indicate the popularity of plastic surgery among all age groups, ethnicity, and gender. Similar analysis from different countries illustrates the popularity of plastic surgery. These surgical procedures prove beneficial for patients suffering from structural or functional impairment of facial features, but these procedures can also be misused by individuals who are trying to conceal their identity with the intent to commit fraud or evade law enforcement. These surgical procedures may allow anti-social elements to freely move around without any fear of being identified by any face recognition system. Plastic surgery, results being long-lasting or even permanent, provides an easy and robust way to evade law and security mechanisms. Sometimes, facial plastic surgery may unintentionally cause rejection of genuine users. A recent incidence in China accentuates the intricacies of this covariate. At Hongqiao International airport's customs, a group of women were stopped as all of them had undergone facial plastic surgery and had become so unrecognizable that customs officers could not use their existing passport pictures to recognize them [2].

While face recognition is a well studied problem in which several approaches have been proposed to address the challenges of illumination [3], [4], pose [5]–[7], expression [4], aging [8], [9], and disguise [10], [11], the growing popularity of plastic surgery introduces new challenges in designing future face recognition systems. Since these procedures modify both the shape and texture of facial features to varying degrees, it is difficult to find the correlation between pre- and postsurgery facial geometry. To the best of our knowledge, there is no study that demonstrates any scientific experiment for recognizing faces that have undergone plastic surgery. The major reasons for the problem not being studied are as follows:

- Due to the sensitive nature of the process and the privacy issues involved, it is extremely difficult to prepare a face database that contains images before and after surgery.
- After surgery, the geometric relationship between facial features changes and there is no technique to detect and measure such types of alterations.

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The main aim of this paper is to add a new dimension to face recognition by discussing this challenge and systematically evaluating the performance of existing face recognition algorithms on a database that contains face images before and after surgery. Section II presents a detailed description of different types of facial plastic surgery and Section III presents an analytical study of plastic surgery on face recognition including an experimental evaluation of six face recognition algorithms using a facial plastic surgery database of 900 individuals. Finally, Section IV discusses ethical and engineering challenges in this research domain.

II. Types of Facial Plastic Surgery

In plastic surgery, facial features are reconstructed either globally or locally. Therefore, in general, plastic surgery can be classified into two distinct categories.

- *Disease correcting local plastic surgery (Local surgery)*: This is a kind of surgery in which an individual undergoes local plastic surgery for correcting defects, anomalies, or improving skin texture. Local plastic surgery techniques can be applied for possibly three different purposes: 1) to correct by-birth anomalies, 2) to correct the defects that are result of some accident, and 3) to correct the anomalies that have developed over the years. Examples of disease correcting local plastic surgery would be surgery for correcting jaw and teeth structure, nose structure, chin, forehead, and eyelids, etc. Local plastic surgery is also aimed at reshaping and restructuring facial features to improve the aesthetics. This type of local surgery leads to varying amount of changes in the geometric distance between facial features but the overall texture and appearance may look similar to the original face. However, any of the local plastic surgery procedures may be performed in conjunction with one or more such procedures and an amalgamate of such procedures may result in a fairly distinct face when compared to the original face.
- *Plastic surgery for reconstructing complete facial structure (Global surgery)*: Apart from local surgery, plastic surgery can be performed to completely change the facial structure which is known as a full face lift. Global plastic surgery is recommended for cases where functional damage has to be cured such as patients with fatal burns or trauma. Note that global plastic surgery is primarily aimed at reconstructing the features to cure some functional damage rather than to improve the aesthetics. In this type of surgery, the appearance, texture, and facial features of an individual are reconstructed to resemble the normal human face but are usually not the same as the original face. Furthermore, global plastic surgery may also be used to entirely change the face appearance, skin texture, and other facial geometries making it arduous for any face recognition system to recognize faces before and after surgery. Therefore, it can also be misused by criminals or individuals who want to remain elusive from law enforcement and pose a great threat to society despite all the security mechanisms in place.

Under the local and global categories, there are several types of plastic surgery procedures as described below.

1) *Rhinoplasty (nose surgery)*: It is used to reconstruct the nose in cases involving birth defects, accidents where nose bones are damaged, and also to cure breathing problems caused due to the nasal structure. Cosmetic Rhinoplasty is used for those who wish to straighten or narrow their nose to improve their facial appearance. It is also used to prevent the nose structure deformation due to aging.
2) *Blepharoplasty (eyelid surgery)*: The eyelid is the thin skin that covers and protects our eyes. Blepharoplasty may be used to reshape both the upper as well as the lower eyelid in cases where excessive growth of skin tissues on the eyelid causes vision problems.
3) *Brow lift (forehead surgery)*: It is generally recommended for patients above the age of 50 who suffer from flagging eyebrows (due to aging) which obstruct vision. It is also helpful in removing thick wrinkles from the forehead and giving a younger look.
4) *Genioplasty/Mentoplasty (chin surgery)*: It is mostly used to reshape the chin including smooth rounding of the chin, correcting bone damages, and reducing/augmenting chin bones.
5) *Cheek implant*: It is used to improve the facial appearance and it can be divided into two classes, malar and submalar augmentation. In malar augmentation, a solid implant is fitted over the cheek bone whereas in submalar augmentation, implants are fitted in the middle of the cheeks where the person has a recessed (hollow) look.
6) *Otoplasty (ear surgery)*: It involves bringing the ears closer to the face, reducing the size of ears, and orienting/pruning some structural ear elements.
7) *Liposhaving (facial sculpturing)*: It is a technique used to get rid of the excess fat attached to the skin surface on the face, especially in chin and jaw regions. This technique is commonly used to remove the dual chin that grows because of surplus fat below the chin.
8) *Skin resurfacing (skin peeling)*: There are different techniques such as laser resurfacing and chemical peel to treat wrinkles, stretch marks, acne, and other skin damage due to aging and sun burn. Skin resurfacing results in smooth skin with ameliorated texture.
9) *Rhytidectomy (face lift)*: It is used to treat patients with severe burns on face and neck. Face lift surgery can also be employed to fight aging and get a younger look by tightening the face skin and thus minifying wrinkles.
10) *Lip augmentation*: Lips have a pronounced role in an individual's beauty. Cosmetic surgery for lip augmentation involves proper shaping and enhancement of lips with injectable filler substances.
11) *Craniofacial*: This type of surgery is employed to treat by-birth anomalies such as Clift lip and palate (a gap in the roof of mouth), microtia (small outer ear), and other congenital defects of jaws and bones. Some defects may be treated soon after birth but for some (like microtia), the patient may have to wait up to an age of 10–14 years.
12) *Dermabrasion*: It is used to give a smoother texture to the face skin by correcting the skin damaged by sun burns or

Fig. 1. Illustrating the example of (a) lip augmentation, (b) otoplasty or ear surgery, (c) liposubmental chin implant and liposuction of chin/neck, and (d) face resurfacing.

scars (developed as a postsurgery effect), dark irregular patches (melasma) that grow over the face skin, and mole removal.

13) *Nonsurgical procedures*: There are several nonsurgical procedure for skin resurfacing, wrinkle removal, and acne/scar removal. For example, laser resurfacing for acne scars, photodynamic therapy or photorejuvenation treatments, and BOTOX or filler injections.

Among all the techniques listed above, rhinoplasty, blepharoplasty, forehead surgery, cheek implant, otoplasty, lip augmentation, and craniofacial are purely local surgeries. On the other hand, rhytidectomy (face lift) is purely global plastic surgery whereas liposhaving, skin resurfacing, and dermabrasion can be both local and global. Fig. 1 shows examples of pre- and post-plastic surgery images.[1] In order to protect the identity of the individuals, if possible, only the local facial features that are reconstructed are shown and not the complete face. These procedures usually alter the position of key fiducial points, thus changing the overall appearance of the face. This, in effect, leads to reduced performance of face recognition algorithms. The techniques that modify key fiducial points such as nose, forehead, chin, eyelid, eyebrows, mouth, and lips have a more pronounced effect on face recognition systems than the techniques which deal with ears, mole removal, and dermabrasion.

[1]These images are provided by The American Society for Aesthetic Plastic Surgery.

III. Plastic Surgery and Face Recognition

Most of the existing face recognition algorithms have predominantly focused on mitigating the effects of pose, illumination, and expression, and no attempt has been made to study the effect of local and global plastic surgery on face recognition. As facial plastic surgery procedures become more and more prevalent, face recognition systems will be challenged to recognize individuals after plastic surgery has been performed. In this section, we investigate different aspects related to plastic surgery and face recognition. Specifically, a plastic surgery face database is prepared and the performance of six face recognition algorithms is evaluated.

A. Plastic Surgery Database

One of the major challenges in this research is to prepare a database that contains images of individuals before and after facial plastic surgery. There are several concerns in collecting the database as patients are hesitant in sharing their images. Apart from the issues related to *privacy*, many who have undergone a disease correcting facial surgery would like to be discreet. To

TABLE I
DETAILS OF THE PLASTIC SURGERY DATABASE THAT CONTAINS 1800 IMAGES PERTAINING TO 900 SUBJECTS (FOR EACH INDIVIDUAL, ONE PRESURGERY AND ONE POSTSURGERY IMAGE)

Type	Plastic Surgery Procedure	Number of Individuals
Local	Dermabrasion	32
	Brow lift (Forehead surgery)	60
	Otoplasty (Ear surgery)	74
	Blepharoplasty (Eyelid surgery)	105
	Rhinoplasty (Nose surgery)	192
	Others (Mentoplasty, Malar augmentation, Craniofacial, Lip augmentation, Fat injection)	56
Global	Skin peeling (Skin resurfacing)	73
	Rhytidectomy (Face lift)	308

the best of our knowledge, there is no publically available facial plastic surgery database that can be used to evaluate current face recognition algorithms or develop a new algorithm. However, to conduct a scientific experimental study and to analyze the effect of both local and global surgery on face recognition, it is imperative to collect face images before and after plastic surgery.

Inspired from the data collection procedure of the Public Figures face database [12], we downloaded real-world pre- and post-surgery images mainly from two websites.[2] These websites contain images of face as well as nonface plastic surgery procedures. From these images, we manually filtered nonface images along with occluded or partial face images. In total, the plastic surgery database consists of 1800 full frontal face images pertaining to 900 subjects.[3] The database contains a wide variety of cases such as rhinoplasty (nose surgery), blepharoplasty (eyelid surgery), brow lift, skin peeling, and rhytidectomy (face lift). Table I shows the details of images in the plastic surgery database covering different types of surgery. For each individual, there are two frontal face images with proper illumination and neutral expression: the first is taken before surgery and the second is taken after surgery. The database contains 519 image pairs corresponding to local surgeries and 381 cases of global surgery (e.g., skin peeling and face lift). A Viola Jones face detector [13] is then used to detect the facial region in the images and the size of detected and normalized face images is 200×200.

B. Algorithms for Evaluation

To study the effect of plastic surgery on face recognition, we selected six recognition algorithms. These algorithms are: Principal Component Analysis (PCA) [14], Fisher Discriminant Analysis (FDA) [14], Local Feature Analysis (LFA) [15], Circular Local Binary Pattern (CLBP) [16], [17], Speeded Up Robust Features (SURF) [18], and Neural Network Architecture-based 2-D Log Polar Gabor Transform (GNN) [11]. PCA and FDA are appearance-based algorithms, LFA is a feature-based algorithm, SURF is a descriptor-based approach, and LBP and GNN are texture-based algorithms. These algorithms are chosen for evaluation because they cover a spectrum of local and global recognition approaches in face recognition literature.

[2]Available: www.locateadoc.com; www.surgery.org.

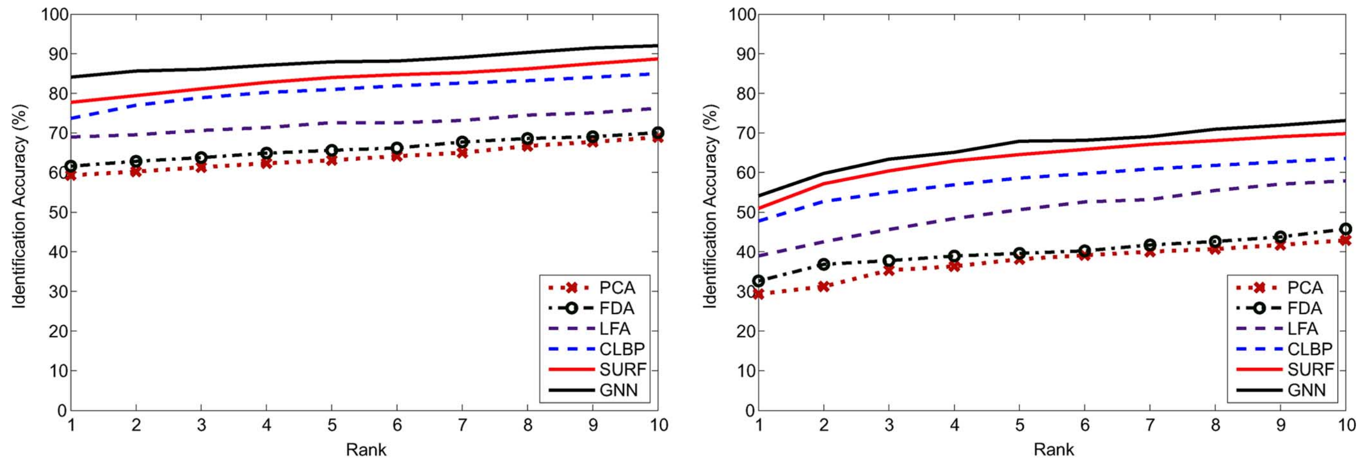
[3]A list of the URL to these images along with a download tool are available at www.iiitd.edu.in/iab.

Fig. 2. Samples from the nonsurgery face database.

C. Experimental Evaluation

The experiments are divided into three sets.

1) **Performance on the Nonsurgery Database:** To analyze the effect of plastic surgery on face recognition algorithms, it is important to have the baseline performance on a dataset that is similar to the plastic surgery database in terms of pose, expression, and illumination and does not have plastic surgery variations. Therefore, the first experiment is performed on face images obtained from publically available nonsurgery databases. We collected 1800 frontal face images with neutral expression, proper illumination, and no occlusion pertaining to 900 subjects from the AR [19], CMU PIE [20], Georgia Tech [21], GTAV [22], and the FERET [23] face databases. A sample of this database is shown in Fig. 2. In most of the real-world applications, face identification systems are first trained on a training database and then the trained system is used to perform recognition on the test database. In such applications, it is highly likely that there is no overlap between the subjects used in the training database and the subjects in the test database. To evaluate the performance of face recognition algorithms in such an application scenario, the database is partitioned into two groups: training and testing. Face images pertaining to 360 subjects (40% of the database) are used to train the face recognition algorithms and the remaining images pertaining to 540 subjects (60% of the database) are used as the test database for performance evaluation. The nonoverlapping train-test partitioning is repeated 10 times and recognition performance is computed in terms of identification accuracy. Cumulative Matching Curves (CMCs) are generated by computing the



(a) (b)

Fig. 3. CMC plots demonstrating the performance of face recognition algorithms on (a) the nonsurgery database and (b) the plastic surgery database.

TABLE II
RANK-1 IDENTIFICATION ACCURACY OF FACE RECOGNITION ALGORITHMS ON THE NONSURGERY AND PLASTIC SURGERY DATABASES

Algorithm	Non-Surgery Database	Plastic Surgery Database
PCA	59.3%	29.1%
FDA	61.6%	32.5%
LFA	68.9%	38.6%
CLBP	73.6%	47.8%
SURF	77.7%	50.9%
GNN	84.1%	54.2%

identification accuracy over these trials for top 10 ranks. CMC in Fig. 3(a) and rank-1 identification accuracy reported in Table II shows that face recognition algorithms such as SURF, CLBP, and GNN provide accuracy in the range of 73%–84%.

2) **Performance on Plastic Surgery Database:** With the same experimental protocol (as described for Experiment 1), we partition the plastic surgery database in nonoverlapping training (360 subjects) and testing datasets (540 subjects) and compute the identification accuracy of face recognition algorithms. Fig. 3(b) shows the CMC curve and Table II reports rank-1 identification accuracies of this experiment. On the plastic surgery database, it is observed that the best rank-1 identification accuracy is 54% which is about 30% lower when the same algorithm is evaluated with the nonsurgery database.

3) **Performance with Training on Nonsurgery Database and Testing on Plastic Surgery Database:** In general, face recognition algorithms are unlikely to be trained using pre- and postsurgery images. Therefore, in the third experiment, we use 360 subjects from the nonsurgery database for training the algorithms (i.e., training data from experiment 1) and 540 subjects from the plastic surgery database for testing (i.e., testing data for experiment 2). The results of this experiment are documented in Table III. This table also shows a comprehensive breakup of results according to the type of surgeries performed.

The key observations and analysis of the three experiments are summarized below.

- Fig. 3 and Table II show the actual decrement in the identification performance of face recognition algorithms due to plastic surgery. For example, PCA yields 59.3% rank-1 identification accuracy when using the nonsurgery database (face images with neutral expression, proper illumination, and no occlusion). On the other hand, the accuracy decreases by $\sim$30% when evaluated with pre- and postsurgery face images. Similarly, the performance of other face recognition algorithms decreases by 26%–30%. This comparison accentuates that plastic surgery is a very challenging problem and hence the development of algorithms to confound these effects is required.
- As shown in Table III, face recognition algorithms cannot handle global facial plastic surgery such as skin resurfacing and full face lift. With 10 times cross validation, the performance of recognition algorithms varies in the range of 18%–54% which is not acceptable in real-world applications. In most of the global surgery cases, the difference between pre- and postsurgery images of the same individual is very large. In other words, facial features and texture are drastically altered after surgery and hence the algorithms do not yield good performance. For test cases of skin resurfacing that have a relatively closer resemblance in pre- and postsurgery images, most of the recognition algorithms are able to perform correct classification. However, with major skin resurfacing such as surgeries to look younger, none of the algorithms are able to correctly classify the faces. Dermabrasion is another important and common surgical procedure that affects the face recognition performance.
- Among different types of plastic surgery, otoplasty, i.e., ear surgery, has the lowest effect on the performance of face recognition. On the other hand, local facial regions such as nose, chin, eyelids, cheek, lips, and forehead play an important role in face recognition. Any change in one of the regions, in general, affects the identification accuracy. For example, in LFA, nose and eyes play an important role and most of the local features are found close to these regions. Any change in these regions degrades the identification performance.
- Overall, with variations in both global and local surgeries, rank-1 identification accuracies are in the range of 18% (PCA)–61% (GNN). It is to be noted that these results are computed on frontal images with neutral expression and

TABLE III
ANALYZING THE EFFECT OF DIFFERENT TYPES OF PLASTIC SURGERIES ON RANK-1 IDENTIFICATION ACCURACY OF FACE RECOGNITION ALGORITHMS

Type	Surgery	PCA	FDA	LFA	CLBP	SURF	GNN
Local	Dermabrasion	20.2%	23.4 %	25.5 %	42.1%	42.6%	43.8%
	Brow lift (Forehead surgery)	28.5%	31.8%	39.6%	49.1%	51.1%	57.2%
	Otoplasty (Ear surgery)	56.4%	58.1 %	60.7%	68.8%	66.4%	70.5%
	Blepharoplasty (Eyelid surgery)	28.3%	35.0%	40.2%	52.1%	53.9%	61.4%
	Rhinoplasty (Nose surgery)	23.1%	24.1%	35.4%	44.8%	51.5%	54.3%
	Others Local Surgeries	26.4%	33.1%	41.4%	52.4%	62.6%	58.9%
Global	Skin peeling (Skin resurfacing)	25.2 %	31.5%	40.3%	53.7%	51.1%	53.9%
	Rhytidectomy (Facelift)	18.6 %	20.0 %	21.6 %	40.9%	40.3 %	42.1 %
	Overall	27.2%	31.4%	37.8%	47.8%	50.9%	53.7%

proper illumination. If we include other covariates such as pose, expression, and illumination, the performance may further deteriorate.

- The results of experiments 2 and 3 show that the performance of face recognition algorithms is slightly better when they are trained on pre- and postsurgery images compared to training on the nonsurgery database.
- The correlation analysis of match scores from all six recognition algorithms is performed using the Pearson correlation coefficient. It is observed that the algorithms have limited correlation. The correlation analysis suggests that, for recognizing surgically altered images, these techniques provide complementary information and the performance may improve with effective fusion algorithms.

IV. Discussion

Plastic surgery has been an unexplored area in the face recognition domain and it poses ethical, social, and engineering challenges. Because it is related to the medical history of an individual which is secure under law, *invasion of privacy* is an important constraint in this research. In some cases, facial plastic surgery is performed due to medical reasons and sometimes it is the individual's choice (i.e., cosmetic/aesthetic surgery). In both cases, even though individuals undergoing facial plastic surgery cannot be bound under any legal and social obligations, it is ethical responsibility of the person to get the face image/template updated in the database (i.e., template update).

With the advancement in plastic surgery technology, *identity theft* is another problem. Identity theft can be intentional when a person consciously attempts to resemble someone by undergoing facial plastic surgery procedures or unintentional where he/she may resemble someone else after the surgery. Therefore, face recognition algorithms should be able to distinguish between a genuine and stolen identity, for which the system must include other cross references apart from a recognition algorithm.

Apart from ethical and social issues, several engineering challenges play a vital role in developing algorithms to handle variations due to facial plastic surgery. In our opinion, the first engineering challenge is to develop an algorithm to classify the variations in face due to facial plastic surgery from the variations due to other covariates such as aging and disguise. Even if somehow it is identified that a particular human face has undergone plastic surgery (e.g., manually), matching a postsurgery image with a presurgery face image is an arduous task. Hence, another engineering challenge would be to design an algorithm to correlate facial features in pre- and postsurgery images. Local facial regions such as nose, chin, eyelids, cheek, lips, and forehead play an imperative role in face recognition and small variations affect the recognition performance. Further, a combination of local plastic surgery procedures may result in a fairly distinct face from the original face. To develop an algorithm that assess such nonlinear variations in pre- and postfacial plastic surgery images makes the engineering challenge even more difficult. It is our assertion that these challenges should receive immediate attention from the research community to develop efficient face recognition algorithms that can account for nonlinear variations introduced by facial plastic surgery procedures. Here, it is important to note that plastic surgery poses fundamental issues that cannot be solved by engineering solutions alone.

V. Conclusion and Future Research Directions

The popularity of plastic surgery has increased many folds over the past few years and the statistical data shows that it is growing. Due to advancements in technology, affordability, and the speed with which these procedures can be performed, some people undergo plastic surgery for medical reasons and some choose cosmetic surgery to look younger or improve the appearance. The procedures can significantly change the facial regions both locally and globally, altering the appearance, facial features, and texture, thereby posing a serious challenge to face recognition systems. Existing face recognition algorithms generally rely on local and global facial features and any variation can affect the recognition performance. This paper introduces plastic surgery as a new dimension to face recognition. The contribution of this research is two-fold: 1) we have prepared a plastic surgery face database of 900 individuals that contains images before and after surgeries, and 2) we have presented an experimental study to quantitatively evaluate the performance of face recognition algorithms on the plastic surgery database. The study shows that appearance-, feature-, and texture-based algorithms are unable to effectively mitigate the variations caused by plastic surgery procedures. Based on the results, we believe that more research is required to design optimal face recognition algorithms that can account for the challenges due to plastic surgery. It is our assertion that the results of this work would inspire further research in this important area. One possible future research direction would be to use thermal-infrared imagery and compute the thermal differences between pre- and postsurgery images. However, such an approach first requires creating a large face database that contains pre- and postoperative thermal infrared images.

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