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Human identification after plastic surgery using region based score level fusion of local facial features

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A R T I C L E   I N F O

Keywords:
Facial recognition after plastic surgery (FRAP'S)
American society of plastic surgeons (ASPS)
Regions of interest (ROIs)
Speeded up robust features (SURF)
K-nearest-neighbour (KNN)
Weighted score level fusion
Expected error rate (EER)
Recognition rate (RR)
Computation time (CT)

A B S T R A C T

Plastic surgery alters original facial features of an individual thereby making Face Recognition after plastic surgery difficult. Cosmetic procedures introduce geometrical deviations which are difficult to analyze by state of the art facial identification procedures. Here a region based score level fusion approach for local facial features is proposed to equalize former and latter surgery images. Steps involved in the recognition process are; firstly identifying the ROIs (areas/regions of interest/concern) of before and after surgery images. ROIs are eyes, nose and mouth regions; feature extraction from identified regions via Speeded Up Robust Features and K Nearest Neighbour techniques; region wise and full face geometrical distance calculation between matched feature vectors of pre and post surgery image samples by a distance metric (sum of squared differences); final recognition rate calculation by weighted score level fusion. The projected procedure gives recognition of 89.7% for local surgical treatment and 87% for global surgery.

1. Introduction

FRAP'S has received considerable notice from researchers of diverse domains such as biometrics, pattern detection and computer vision communities. Synthetic surgery measures provide a skillful and durable way to improve one's external appearance by modifying facial feature defects and improving the texture of facial membrane/skin to get an attractive and youthful appearance. Aside from beautification, synthetic surgical operations are advantageous for patients suffering from diverse physical ailments caused due to extreme enlargement of facial tissues. The geometry of human facial features is altered by these cosmetic procedures [3,14]. American Society of Plastic Surgeons is the world's biggest society of specialized cosmetic medical doctors. It is a leading informative source for visual and reconstructive plastic surgery. A survey according to ASPS for the year 2017 stated that amongst 1.8 million beauty/cosmetic therapies executed in 2017, the peak five were Liposuction (246,354 surgeries, upbeat 5% from 2016), Rhinoplasty (218,924 therapies, downward 2% from 2016), Blepharoplasty (209,571 therapies, more or less the same as in 2016) and Tummy tuck (129,753 surgeries, up 2% from 2016).

Amongst 15.7 million therapies performed in 2017, the top ones were Botox insertions (7.23 million therapies, up by 2% from 2016), Soft Tissue Insertions (2.69 million therapies, up by 3% from 2016), Synthetic Peels (1.37 million surgeries, up by 1% since 2016), Laser hair elimination (1.1 million surgeries, down by 2% from 2016), Micro/Major Dermabrasion (740,287 surgeries, down by 4% from 2016). Tummy tucks, which came down from the peak five most popular synthetic therapies in 2016, were back in 2017. There were approximately 2000 more tummy tuck surgeries in 2017 as compared to 2016. Tummy tucks eradicate surplus fat/skin and refurbish fragile muscles to create a superior abdominal contour. Non-invasive fat therapies and body sculpting are in trend these days. People are choosing more and more to delineate diverse parts of their physique. Techniques to get rid of fat and stiffening of skin tissues are gaining fame, with cellulite treatments nearly up by 20% over the last year. Currently fat reduction and skin tightening therapies are drawing wide attention. Fat elimination therapies that use an unique expertise to "ice over" fat without surgical treatment have an upshot of nearly 7%. Cellulite healing surgeries improved by 19% by using lasers to get rid of unwanted fat. Skin stiffening methods that target fat and firm sagging facial muscles augmented by 9% [2].

Fig. 1 shows an instance of the outcome of synthetic surgical treatment on an individual. Bhatt et al. [3] stated that non-linear deviations introduced by cosmetic therapies make human identification after surgery complex. Varying facial geometry and skin quality in human beings enlarges the intra class changeability amid before and after surgery imagery of the same human being

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Fig. 1. Image samples showing complete facial renovation due to cosmetic surgery [16].

[12]. Thus, matching of before/after surgically treated image samples becomes an arduous task for face detection algorithms [10].

Despite adornment these cosmetic therapies are often undertaken by burglars to conceal their individuality and obligate laws. This makes one's security a critical concern and acknowledgment after therapy a dare. By counterfeiting one's legitimate self identity stern misdeeds are committed by frauds. Medical identity thefts result into great financial loss each year including loss of personal privacy too. This is a serious offense and draws wide attention for research in the biometric recognition and validation domain for development of a robust human detection scheme which is compatible to the constraints offered by cosmetic modifications [5,18].

The manuscript is ordered as follows. Subsequent to the introduction, Section 2 illustrates different types of plastic surgical procedures. Section 3 gives a literature survey on existing FRAP'S recognition techniques. Section 4 projects the anticipated methodology. Section 5 is the result and discussion section. The last section comprises of the conclusion and future prospects in biometric recognition and validation domain.

2. Types of plastic surgery

A medical alteration which restructures human body parts is plastic therapy. Plastic surgeries can recover human disabilities, function and quality of life. Global/local are the two means to transform facial characteristics.

2.1. Texture based surgery (Local in nature)

To rectify defects and perk up skin consistency, local kind of artificial surgical treatment is usually performed. Local plastic surgery is used for different purposes such as rectification of birth defects, healing catastrophe mishaps, or repairing anomalies which are developed due to age. Abnormality modification therapy is used for rectifying jaw, teeth, chin, nose, forehead, eyelids configuration etc. Statistical expanse amid facial traits is customized by local therapy [15,18].

2.2. Structure based surgery (Global in nature)

When synthetic therapy is used for absolute alteration of the facial arrangement it is global therapy. This surgical treatment is very beneficial for acid assaulted sufferers. This surgery involves entire variation of facial characteristics, skin consistency and outward manifestation of a person. The amendments in facial emergence, skin consistency, variation in human facial geometries makes it complex for face identification algorithms to identify faces before and after plastic surgery. Local plastic procedures are competent of giving somewhat moderate detection outcomes because here the entire face geometry is not altered, but for global procedures where the entire face structure undergoes a complete makeover, recognition after plastic surgery still secures a lower score [15,18].

Table 1
A variety of synthetic surgical treatments.

Local Surgical Treatment	Global Surgical Treatment
Dermabrasion therapy	Skin peeling/ resurfacing
Brown-lift therapy	Face-uplift surgical procedure
Otoplasty therapy	Facial masculinity alterations (HRT)
Rhinoplasty therapy	
Mentoplasty therapy	
Liposhaving therapy	
Blepharoplasty therapy	

2.3. Types of local and global procedures

The images portrayed in Fig. 2 are taken from the plastic surgery facial dataset. A variety of local and global procedures are explained along the following lines:-

Among all the plastic surgery techniques specified in Table 1 below Cheek Embed therapy, Blepharoplasty, Brow surgical treatment, Rhinoplasty, Otoplasty, Lip escalation etc. are of local type. While on the converse, Rhytidectomy (face lift therapy), hormone substitution treatment (HRT), skin peeling are global in temperament.

Fig. 2(a) shows Dermabrasion therapy which is used to give an inclusive look to the facial skin by transforming skin imperfections due to sun-tans, dark-patches etc. Overall skin texture is recovered by this aesthetic therapy. Brow-lift is basically a surgical treatment for forehead. It is shown in Fig. 2(b). It is undertaken by people who have flagging eyebrows because such eyebrows block vision. It also assists in eliminating wrinkles from the brow region. Fig. 2(c) shows Otoplasty procedure. Otoplasty is a type of ear shape modification therapy. It is used for bringing the ears in close immediacy with the facial structure, reducing the ear volume and thus maintaining appropriate symmetry of the ear structure. Rhinoplasty is a kind of nose contour modification therapy as shown in Fig. 2(d). It is a synthetic therapy to align or taper the nose geometry. Fig. 2(e) illustrates skin whitening treatment in females. Genioplasty/Mentoplasty is a type of chin therapy depicted in Fig. 2(f). It is helpful in reducing bones of the chin with levelling and rounding of the chin region as well. Fig. 2(g) shows Liposhaving therapy which inculcates lip sculpting. Lip augmentation shown in Fig. 2(g) illustrates superficial alteration of lips. It resizes the lip area. Fig. 2(h) shows eyelid therapy. This surgery is used to change both top and base eyelids where a healthy improvement of skin tissues on the eyelids is performed. Skin peeling/resurfacing is shown in Fig. 2(i). To achieve a good quality and silky skin surface resurfacing is done. Rhytidectomy shown in Fig. 2(j) is a synthetic surgical treatment which involves overall facial renovation. This therapy is generally used for curing extreme burns. It can also be employed to augment one's external magnificence. It involves elimination of unnecessary, extreme fat embedded on the facial skin. Hormone replacement therapy shown in Fig. 2(k) is principally gender conversion via substitution of reproductive hormones. These surgeries fluctuate oestrogen and testosterone (reproductive hormones) intensities to change gender.

3. Related work

Singh et al. [20], analyzed identification truthfulness on the plastic therapy facial dataset via six diverse face detection schemes: Neural network based 2-D Log Polar Gabor Transform (GNN), Speeded Up Robust Features (SURF), Local Feature Analysis (LFA), Fisher Discriminant Analysis (FDA), Circular Local Binary Patterns (CLBP) and Principal Component Analysis (PCA). These schemes were implemented because they offered a blend of appearance; feature extraction and consistency based attribute

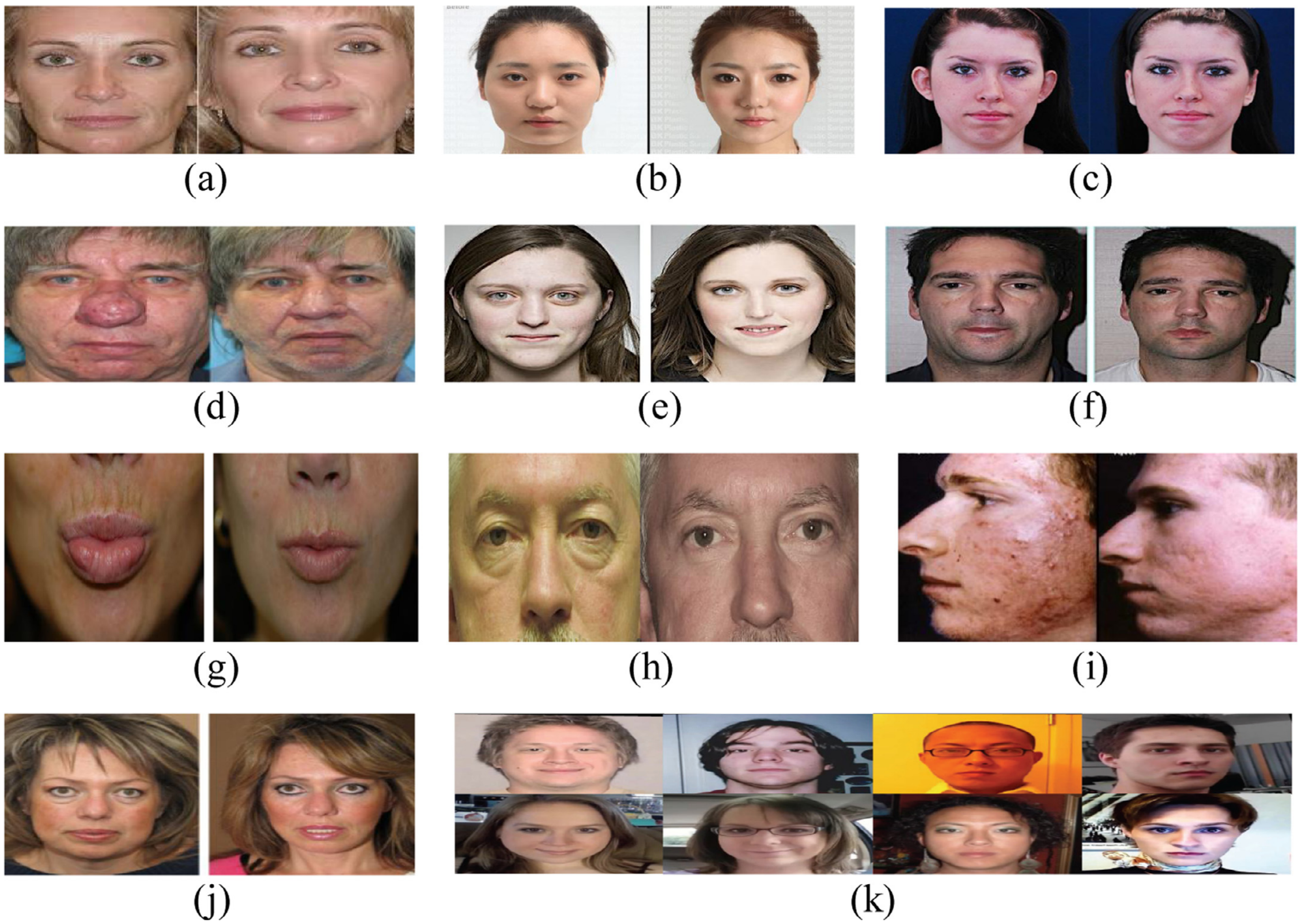

Fig. 2. Before and after images of texture and structure procedures (Plastic surgery facial dataset [16,18].

detection and matching techniques. With these schemes the identification accuracy obtained was low. Bhatt et al. [4], implemented an evolutionary granular technique with CLBP/SURF characteristics to course tessellated facial surgery samples. Aggarwal et al. [1], used a blend of face detection by sparse and parts illustration scheme. Marsico et al. [13], used a correlation scheme for human facial identification on illuminated and pose effected pre processed surgical samples. Said and Atta [19], anticipated geometrical identification/recognition after plastic surgery (GFRAPS). In the primary step of detection process, the regions of concern of the 'post' image were generalized and their middles were identified. The subsequent footstep calculated the geometrical distances amongst the ROI's centers to resolve the post geometrical facial attributes. To evaluate latter facial characteristics of the test image with former facial trait vectors a minimal distance classifier was used. Pre feature vectors that gave maximum resemblance and slightest distance were considered as the ideal contest and its image was chosen as the consequent pre surgery image for the following surgery test image.

3.1. FRAPS based on nature of dataset

Earlier research efforts in the domain of biometric recognition point towards two type of databases i.e. non-surgical and therapeutic datasets (surgical). Non surgical databases contain images at different angles, pose, expression, illumination and occlusion while medically altered databanks contain images of human beings who have undergone either a plastic surgery or hormone replacement therapy. Recognition results obtained from non surgical databases are far better than the values obtained from surgical databases.

3.2. FRAPS based on mode (single/multi mode)

Single mode biometric recognition includes a single human feature for human identification. This approach is not efficient as all performance parameters are dependent on a single human feature. Multimodal biometric recognition is a combination of more than one biometric trait to enhance recognition efficiency. Multimodal biometrics is believed to have additional information between different modalities that increases recognition performance in terms of accuracy. To make use of multimodal biometrics, one has to use a combined scheme that is able to fuse data provided by diverse modalities.

3.3. Fusion based FRAPS

Fusion at score, decision, input, feature level gives more robust recognition results as compared to single mode biometric approach. Fusion of two unlike procedures or two diverse image samples of a particular biometric feature have been used for human identification in the past [7,21]. Punyani et al. [17], stated that multimodal biometric recognition i.e. combination/fusion of two unlike biometric attributes of gait, face etc. images is being used these days for human identification and verification.

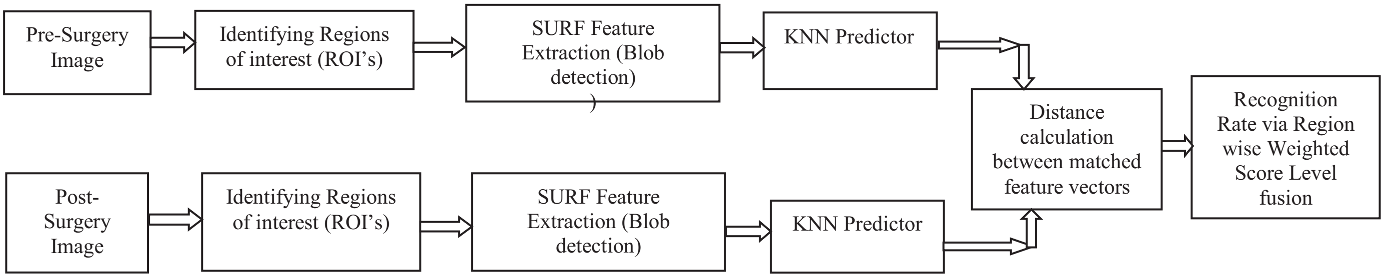

Fig. 3. Block diagram for the proposed FRAPS system.

Fig. 4. Extracted local facial features by SURF for mouth/nose regions.

4. Proposed methodology

The projected recognition scheme is based on a region based score level fusion approach of local facial traits (nose, eyes, and mouth areas) to counterpart face images pre/post synthetic surgical treatment.

Fig. 3 illustrates diagrammatical representation of the anticipated FRAPS recognition scheme. The algorithm proceeds as follows:-

(1) It proceeds firstly by normalizing the facial image samples pre and post surgery to gray scale, and then identifying the ROI's of before and after surgery images i.e. eyes, nose and mouth regions (local facial features). To perform automatic cropping of regions of interest, Viola-Jones face detector is used.

(2) After identification of local facial regions, feature extraction is done by SURF technique by Eqs. (1) and (2).

(3) The most suitable pixel values (feature vectors with maximum details) surrounding the interest points (determined by SURF) are predicted by KNN. It returns extracted features, with their locations from a surgery image.

(4) After this region wise and full face geometrical distance calculation is done between matched feature vectors of pre and post surgery image samples by SSD distance metric. Final recognition rate is calculated by weighted score level fusion i.e. by clubbing the recognition rates received by individual areas of interest (nose, eyes, and mouth) and the entire face.

4.1. SURF

SURF (Speeded Up Robust Features) is moderately adapted from Scale Invariant Characteristic/feature Transform (SIFT). SIFT method identifies and trains data around neighboring key positions that are invariant to scale and directional variations of an image sample. The fundamental edition of SURF is quite faster than other accessible characteristic detectors. This pace is obtained by integral images for image convolutions. In computer vision domain, SURF is a local facial attribute detector. It is used for pattern recognition, image registration, blob extraction, classification and restoration. Blob detection aims at identifying regions in an image that fluctuate in characteristics, such as intensity/colour, compared to neighbouring regions. Blob is an area of an image in which some properties are stable i.e. every single point in a blob can be measured in some logic related to each other.

Fig. 4 shows extracted local feature vectors by SURF. To detect points of interest, this scheme uses an integer approximation of the determinant of Hessian extractor, which can be evaluated by integer functions via pre computed integral image sample. Facial attribute extractor for SURF is based on the computation of Haar wavelet outcome around the area of concern. It advances as follows:-

(1) Extraction

This extraction scheme uses square filters as an estimate of Gaussian smoothing. If the integral image is employed, filtering the image with a square is quite quicker.

$$S(x, y) = \sum_{\substack{0<i<x \\ 0<j<y}} I(i, j) \quad (1)$$

Hessian matrix based blob detector is used to find areas of concern. Hessian matrix determinant is used as a gauge of local alteration about the point of concern. These points are selected when this determinant is maximum. It also uses Hessian determinant for selecting the scale. For a point $p = (x, y)$ in an image I, the Hessian matrix H (p, σ) at point p and scale σ, is given below:-

$$H(p, \sigma) = \begin{pmatrix} L_{xx}(p, \sigma) & L_{xy}(p, \sigma) \\ L_{yx}(p, \sigma) & L_{yy}(p, \sigma) \end{pmatrix} \quad (2)$$

where $L_{xx}(p,\sigma)$ etc., is the convolution of the second order derivative of Gaussian with the image $I(x, y)$ at the point x.

(2) Positioning of interest points

Scale space is apprehended as a pyramid. A Gaussian filter is used to continually smooth images. These images are sub-sampled to get the consequent elevated levels of the pyramid. Numerous stairs with different measures of the masks are evaluated:

$$\sigma_{\text{approx}} = current\ filter\ dimension \times (fundamental\ filter\ scale / fundamental\ filter\ dimension)$$

After identifying interest points extraction is done. Extraction is followed by comparing the descriptors obtained from diverse image samples and thus matched pairs can be located.

4.2. K nearest neighbour and weighted score level fusion approach

Weighted score level fusion approach is used to unite recognition scores from subsequent regions of interest: (a) full facial region (b) periocular (eye region) (c) mouth region (d) nose region.

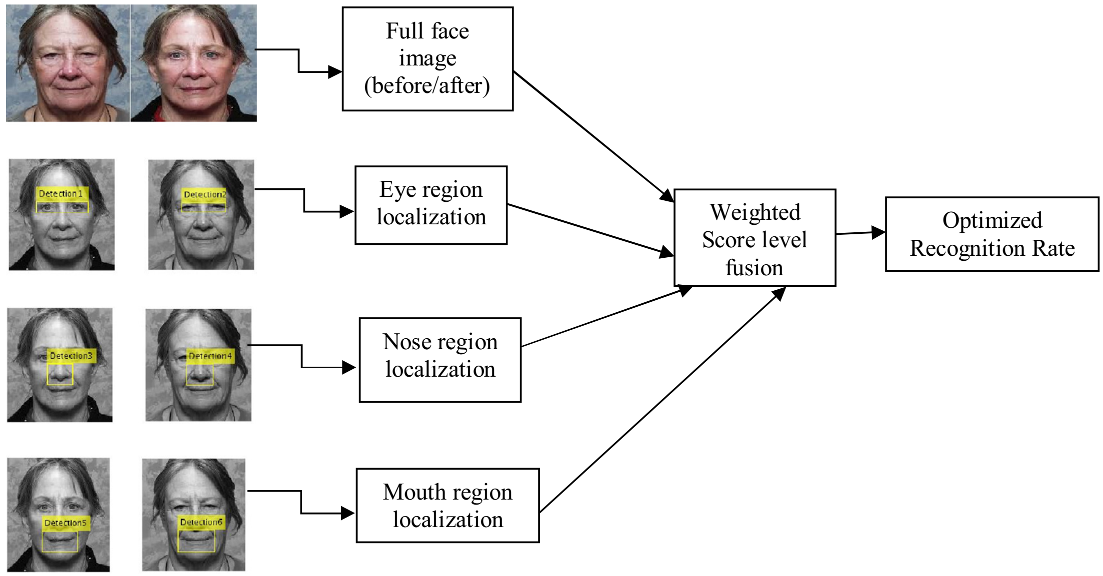

Fig. 5. Schematic demonstration of the projected methodology via fusion.

These pre-processed scores are integrated using the basic sum law with dissimilar weights. For each region of interest facial features are first extracted (localized) using SURF technique, and then by KNN (K nearest neighbor algorithm) the most suitable pixel values surrounding the interest points are determined. KNN predictor returns extracted facial characteristics, with their corresponding positions from a surgery image sample. It obtains descriptors from pixels neighboring a position of concentration. The pixels match features specified by a single point position. Each point specifies the middle position of a neighborhood.

Fig. 5 shows a schematic demonstration of the projected methodology. Liu et al. [11], stated that this scheme takes a pre operational forward facial image as an input. Facial landmarks are then detected and composed as a distance vector. Such a vector is entered into a k-nearest neighbor predictor which is skilled on a set of former and latter surgery facial distance vectors. The basic logic behind the KNN predictor is that similar facial images will have related post operational results after the same plastic surgery technique. The identification outcomes obtained (before/after surgical procedure) clearly state that score level fusion improves overall performance.

5. Results and discussion

5.1. Synthetic surgery facial database

The plastic surgery dataset is a widely available facial database particularly developed for face identification after synthetic surgical treatment, and it is the outcome of the research of Singh et al. [20]. The plastic surgery facial dataset includes eighteen hundred before/after surgery images of nine hundred humans. For every human being, there are two forward facial images with lightning effect and impartial gesture: the former is taken prior to therapy and the latter is taken following therapy. The dataset holds a total of 519 pairs related to local plastic procedures and 381 instances of global therapy: Blepharoplasty (105); Otoplasty (74); Dermabrasion (32); Rhinoplasty (192); Brow lift (60); Other procedures (56); Skin resurfacing (73); Face-uplift (308). All facial image samples in the synthetic therapy database were homogenized and pre-processed. The process included chopping of facial parts of the image samples, changing shading pictures into gray-scale, resizing the clipped ranges to a fundamental facet of 200×200 pixels and then finally normalizing the samples.

5.2. Performance parameters

Performance parameters used for assessment are EER (Expected Error Rate), RR (Recognition Rate) and CT (Computation Time).

(i) EER is defined as, when FAR = FRR. FAR (False Acceptance Rate) is the probability of accommodating false contest between pre/post synthetic therapy samples and FRR (False Rejection Rate) is the probability of declining a false match, before and after a medical alteration.
EER= Σ [Distance between matched points (matched features)] / M, where M is the number of matched feature pairs. Distance between matched points of the two image samples is calculated by SSD (sum of squared differences) distance metric. EER should be low because lesser the value of EER more is the match probability between before and after surgery samples.

(ii) RR is inversely proportional to EER. Lesser the value of EER more the value for RR. RR is the percentage similarity match amid pre/post surgery samples. Higher the recognition higher the match.
RR = (Total number of matches / N) $\times$ 100 where N is total number of image pairs.

(iii) CT (Computation Time) or ‘running time’ is the total processing time in seconds including characteristic extraction and contest.

5.3. Results for Blepharoplasty (eyelids) surgery (Local plastic procedure)

Fig. 6 shows Blepharoplasty samples for pre and post surgery. It is a local plastic procedure used to modify the shape of the eyelids. Fig. 7 shows cropped region-wise templates (i.e. eyes, nose, mouth regions) via Viola Jones face detector. Fig. 8 shows identified eyes, nose and mouth regions i.e. regions of interest. Fig. 9 shows the extracted SURF points for three localized facial regions i.e. eyes, nose and mouth. Extracted SURF points portray recognized facial feature vectors.

Fig. 10 shows the final match of facial vectors (pre and post surgery) after feature extraction by SURF and prediction by *k*

Table 2
Analysis of Recognition Rate (%) in context to nature of surgery and identification scheme.

Type	Surgery	PCA	FDA	LFA	CLBP	SURF	GNN	Correlation	Granular	Sparse	GFRAPS	Proposed
Local	Dermabrasion	22.7	24.6	25.7	41.6	41.3	43.2	60.96	58.2	57.37	84.6	84.8
	Browlift	31.0	33.0	39.8	48.6	50.0	56.6	60.96	71.6	70.77	83.3	84.0
	Otoplasty	58.9	59.2	61.0	68.3	65.1	69.9	74.26	84.9	84.07	85.4	87.2
	Blepharoplasty	30.8	36.2	40.4	51.6	52.6	60.8	65.16	75.8	74.97	72.7	89.7
	Rhinoplasty	25.6	25.3	35.6	44.3	50.2	53.7	58.06	68.7	67.87	70.8	79.4
Global	Skin peeling	27.7	32.7	40.5	53.2	50.0	53.3	57.66	68.3	67.47	87.2	87.0
	Rhytidectomy	21.1	21.2	21.8	40.4	39.0	41.5	45.86	56.5	55.67	65.0	76.0

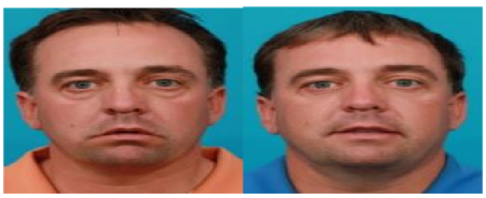

Fig. 6. Facial image before and after Blepharoplasty surgery (http://iabrubric.org/resources.html).

nearest neighbour algorithm. Match process is done separate for local facial features and the entire face. Match process is basically the overlap of before and after surgery image samples. By manipulating distance amid matched feature vectors of pre/post surgery samples the match process is completed. Fig. 10(c). shows no match at the mouth region due to extreme variation of facial geometry at the mouth region due to plastic surgery. Lesser the distance larger the recognition rate. The recognition score obtained for before/after surgery images is taken for all the four images mentioned in Fig. 10. An overall recognition rate of 89.7% is achieved by weighted score level fusion for Blepharoplasty procedure.

5.4. Results for skin peeling surgery (Global plastic procedure)

Fig. 11 shows skin peeling (resurfacing) samples for pre and post surgery. A global procedure results into an almost complete facial renovation. Fig. 12 shows cropped templates for eyes, nose and mouth regions.

Fig. 13 shows identified regions of interest. Fig. 14 shows the extracted SURF points for the facial regions i.e. eyes, nose and mouth. The recognition rate obtained for this global procedure is 87.0% by weighted score level fusion. It can be deduced that for a local plastic procedure recognition rate achieved is higher as discussed above for Blepharoplasty as compared to a global plastic procedure as in the case of Skin peeling.

Fig. 15 shows the final match of facial vectors (pre and post surgery) after feature extraction by SURF and classification by KNN. Fig. 15(c). clearly shows no match at the mouth region due to non linearities introduced by skin peeling procedure. By the proposed approach the recognition rates noticed for both Blepharoplasty surgery (local) and Skin peeling surgery (global) are highest reported till date when compared to existing results in literature.

Table 3
EER analysis against recognition techniques.

Algorithm	EER (%)
PCA	36.42
FDA	26.42
LFA	25.06
CLBP	16.66
SURF	15.00
GNN	12.53
Marsico et al.	12.50
Bhatt et al.	8.33
Aggarwal et al.	7.50
Said et al.	1.30
Proposed method	1.19

Table 2 shows that for global synthetic therapies detection outcomes are not promising and entail more research endeavours while on the contrary local plastic surgeries give pleasing recognition outcomes. The entire facial orientation and geometry is altered for global therapy. For local plastic therapies lesser facial attributes are modified so a higher degree of contest is obtained, while for global therapies scale of match is less.

Fig. 16 graphically demonstrates as to how recognition rate alters according to type of surgery and identification technique Thus we can see that global plastic surgeries such as face-uplift and skin resurfacing show substantial deprivation in RR as judged against other local surgeries such as Otoplasty, Rhinoplasty, Blepharoplasty, browlift, etc.

Table 3 shows EER variation with reference to diverse facial recognition techniques. The proposed methodology gives the lowest value for EER which is a necessity for a robust facial detection algorithm. Fig. 17 illustrates graphically the effect of recognition techniques on EER analysis.

5.5. Performance analysis in context to computation time

Computation time in image processing algorithms quantifies the amount of time taken by an algorithm to run as a function of the extent of the input image sample. Space/memory complexity quantifies the amount of space/memory taken by an algorithm to run as a function of the extent of the input. Time complexity is articulated using Big O notation where n is the input size. Big O notation prohibits coefficients and lower order components and analyses algorithms in terms of overall competence and scalability. For identifying synthetically modified faces computational time can be

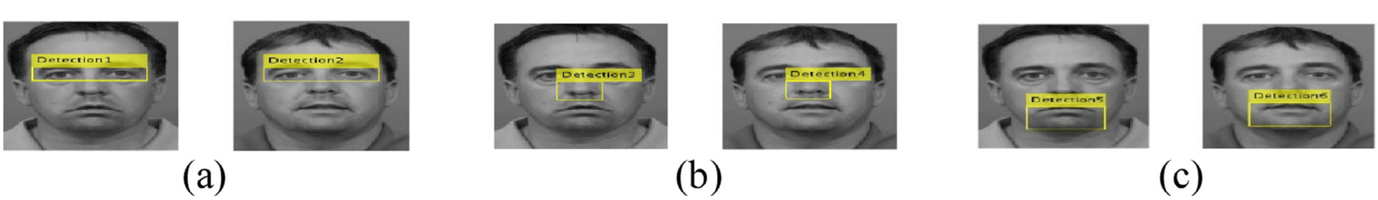

Fig. 7. Detection of local facial regions (eye, nose and mouth templates).

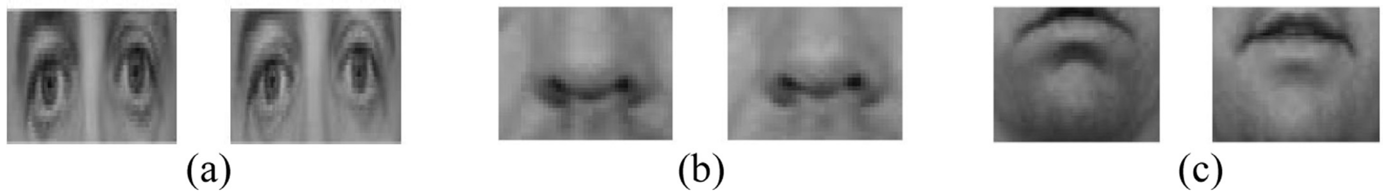

Fig. 8. Identification of regions of interest (eye, nose and mouth regions).

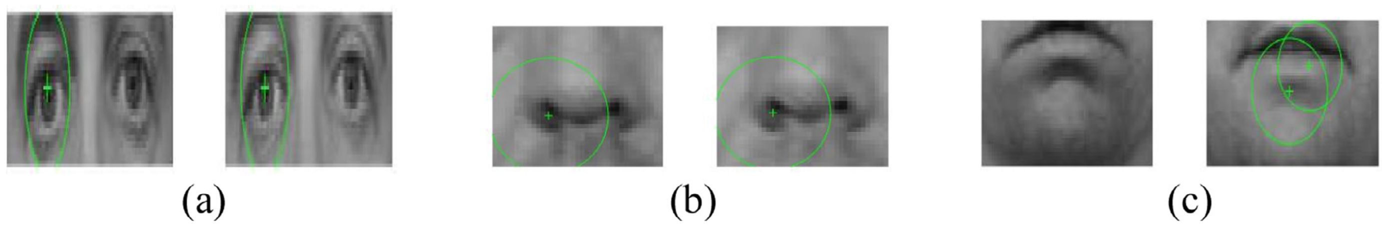

Fig. 9. Feature extraction process (eye, nose and mouth feature vectors).

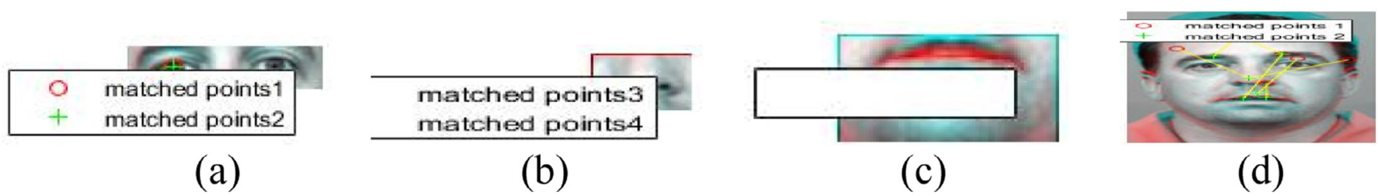

Fig. 10. Matched facial vectors (before and after surgery) for eyes, nose and mouth regions including full face.

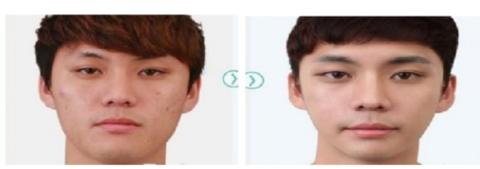

Fig. 11. Facial image pre/post Skin-peeling therapy (http://iab-rubric.org/resources.html).

analysed w.r.t identification technique employed for recognition of pre/post surgical treatment illustrations, type of features extracted (local/global) and the nature of synthetic surgery (partial or complete facial renovation).

Singh et al. [20] reported six diverse face detection schemes namely GNN, SURF, LFA, FDA, CLBP and PCA (Eigen faces) for facial recognition after plastic therapy. LDA/FDA (Fischer faces) preserves class separability and is very popular. Projection functions of LDA are optimized by minimizing the within class covariance and maximizing the between class covariance. It is generally used for pattern recognition. The evaluation of LDA engrosses dense matrices, eigen disintegration which can be computationally complex both in terms of memory and time. LDA has O ($mnt + t^3$) time complexity and entails O ($mn + mt + nt$) memory, where m is the total number of illustrations, n is the total amount of features and $t = \min(m, n)$. It is infeasible to apply LDA when both m and n are huge. The computational time complexity of PCA is defined as O ($p^2n + p^3$) where n is the number of data points and p is the number of features. The execution time of PCA varies linearly with the size of the dataset. When PCA is compared to LDA for small training datasets PCA can surpass LDA whereas PCA is less receptive to diverse training databanks. The Fisher-face approach had EER values lower than the Eigen-face approach and requisites less computation time. For deriving local topographic demonstrations for any class of objects LFA is employed. LFA demonstrations are sparse-disseminated and, hence, are efficiently low-dimensional and retain all the advantages of the compact representations of PCA. But, unlike the global eigen-modes, they give a description of objects in terms of statistically derived local features and their positions. SURF is a local feature extractor with theoretical time complexity defined as O ($mn + k$) where k is the number of extrema found in the previous stage. LBP is computationally simple but if the size of the features increases exponentially with the number of neighbours it leads to an increase in computational complexity in terms of time and space. Highly dense features (local facial attributes) are likely to improve match between before and after surgery samples but have a negative impact on computation time. SURF, LFA, FDA, CLBP and PCA extract local facial features while GNN extracts both (local/global facial traits). Out of all the methods mentioned by Singh et al. [20], GNN gave the highest recognition rate at a cost of increased computation time.

Marsico et al. [13], Bhatt et al. [3], Aggarwal et al. [1] and Said and Atta [19] proposed region based approaches where

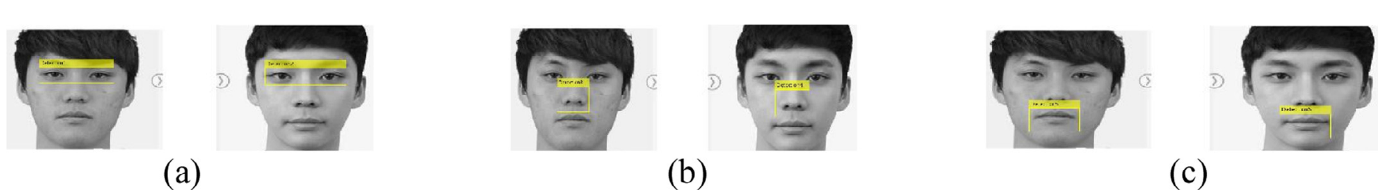

Fig. 12. Detection of local facial regions for Skin-peeling.

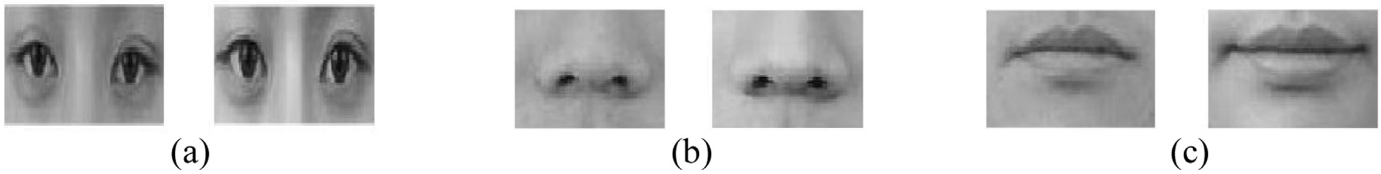

Fig. 13. Identification of regions of interest for Skin-peeling.

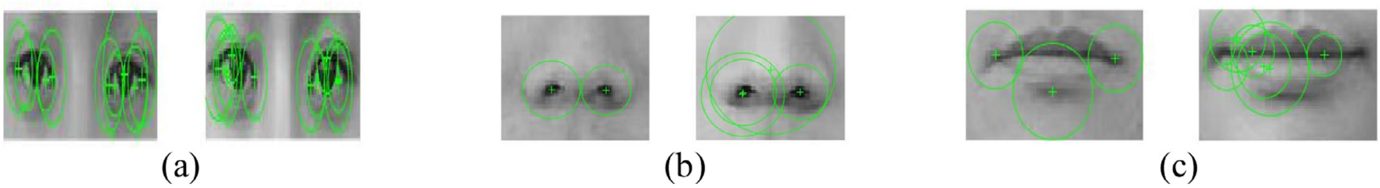

Fig. 14. Feature extraction for Skin-peeling therapy.

Fig. 15. Matched facial traits for Skin-peeling surgery.

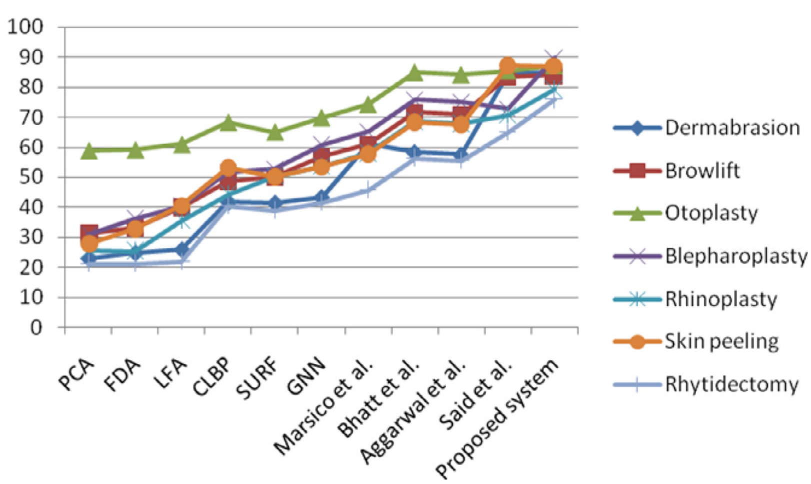

Fig. 16. Performance of face identification methods on plastic surgery facial dataset.

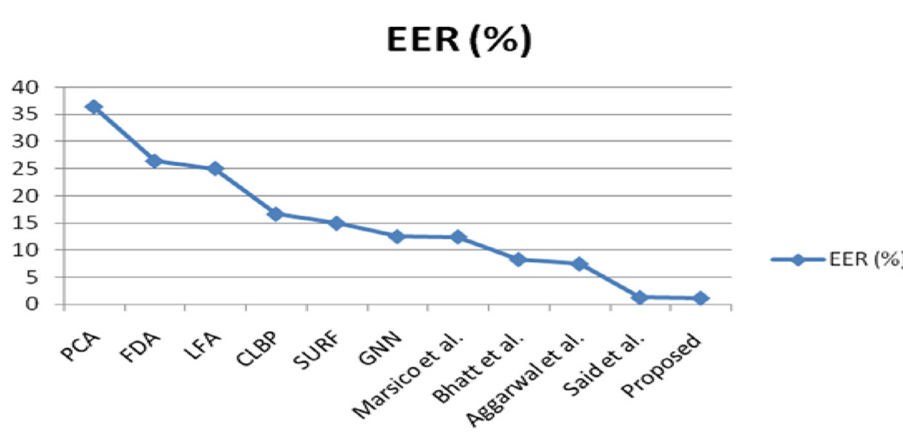

Fig. 17. Graphical illustration for EER (%).

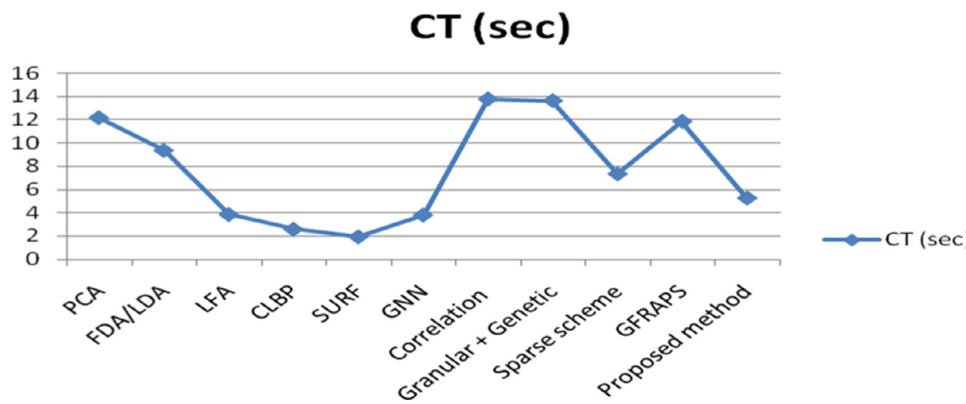

Fig. 18. Graphical analysis of computational complexity.

Table 4
CT analysis against recognition techniques.

Algorithm	CT (s)
PCA	12.17
FDA/LDA	9.37
LFA	3.87
CLBP	2.60
SURF	1.95
GNN	3.82
Correlation	13.77
Granular + Genetic	13.63
Sparse scheme	7.36
GFRAPS	11.85
Proposed method	5.28

human facial image is segmented into various regions of interest to identify prominent facial features. The detection techniques proposed by Marsico et al. [13], Aggarwal et al. [1] and Said and Atta [19] extracted local facial features (eyes, nose, lips etc.) while Bhatt et al. [3] projected a granular scheme followed by genetic algorithm which extracted both local and global facial attributes. Marsico et al. [13] projected recognition after surgery by using FARO (Face Recognition against Occlusions and Expression Variations) which divided the face into appropriate areas (right /left eye, mouth and nose) and then coded them using Partitioned Iterated Function System (PIFS). FACE (Face Analysis for Commercial Entities) was used to compute image association/correlation index. Finally, the Split Face Architecture (SFA) was used to choose the feature extraction method. The experimental results revealed by Said and Atta [19] stated that the GFRPS system is robust, valid for all kinds of facial plastic surgery; works in real time with low hardware requirements and computational time, and the whole process is conducted automatically. Global/local features are vital for face detection after plastic surgery. Global features are structural patterns of facial organs and facial contours. Global attributes are extorted from the full face image by retaining the low frequency coefficients only. Local facial features result into dense matrices (most of the elements are nonzero (high frequency)) while global ones result into sparse matrices (most of the elements are zero (low frequency)). Sparse matrices contain large number of zero valued elements and can save memory and speed up the processing thus lowering the computation time of the algorithm. Aggarwal et al. [1] projected region based sparse illustration approach. Here part-wise facial categorization was united with sparse representation. The projected scheme proceeded by firstly localizing the principal facial features followed by generation of training matrix for each facial part and lastly sparse recognition was accomplished for each facial trait.

Laplacian eigenmaps and LLE (Locally linear embedding) are graph based methods used for non-linear dimensionality reduction (feature extraction) [8,9]. They proceed by building a sparse graph where nodes represent input prototypes and edges signify neighborhood associations. Matrices are created from these graphs whose spectral disintegrations reveal low dimensional compositions. LLE solely preserves local features. Here the local properties are build by writing high-dimensional features as a linear amalgamation of their bordering neighbors. Laplacian eigenmaps compute low-dimensional representations in which the distances amid feature vectors and k nearest neighbours are minimized. Sparse spectral methods (LLE and Laplacian eigenmaps) perform eigen analysis for a $n \times n$ matrix. For these methods the $n \times n$ matrix is sparse, which is advantageous, because it decreases the time for eigen analysis. Eigen analysis of a sparse matrix has time $O\,(pn^2)$, where p is the ratio of non zero elements to the total number of elements in the sparse matrix. The memory time is $O\,(pn^2)$ as well [6]. Computing time can be saved logically by designing a data structure traversing only non-zero elements. One practical drawback of sparse scheme is the need for several image samples. Table 4 illustrates the computation time required by each recognition algorithm.

Table 4 and Fig. 18 portray computation time for diverse recognition techniques listed in literature with respect to the proposed scheme for facial recognition after plastic surgery. Table 4 shows highest CT value for PCA while lowest for SURF. The projected methodology portrays moderate computation time with an enhanced recognition rate and a lower error rate. The nature of plastic procedure is also important in determining computation time of an algorithm. For local plastic therapies the non linearities introduced between pre and post surgery samples are less in comparison to the ones introduced by global therapies, thus resulting into complete facial renovation. It is difficult to model a huge amount of non linearity which in turn increases the computation time.

Table 5 shows computed performance metrics for the anticipated FRAP'S structure. Highest recognition rate is obtained for Blepharoplasty procedure which is a local surgery type. For skin peeling (global plastic procedure) lower recognition rate is achieved. These lower scores may be due to pose, expression, illumination, disguise and occlusion effects. For some regions there is no match between pre and post surgery images due to variation in facial geometry due to plastic procedures. For skin peeling procedure an overall recognition rate of 87% is obtained.

Table 6 shows Rank 1 Recognition Rate's on the synthetic surgery facial dataset. Said and Atta [19], stated that in Rank 1 identification rate the right match is the one that gives utmost resemblance. Let us presume that after comparing the test image sample with each entry in the dataset, the resemblance score for

Table 5
Evaluation of Performance parameters (RR, EER, CC) with the proposed recognition approach.

Surgery type (Local/Global)	Eye region (RR1)	Nose region (RR2)	Mouth region (RR3)	Face region (RR4)	Overall RR (Score level fusion)
Rhytidectomy	No match	74.79	76.2	77.01	76.0
Blepharoplasty	87.68	96.22	No Match	85.29	89.73
Browlift	86.48	79.78	No Match	85.65	84.0
Skin peeling/ resurfacing	83.31	94.42	86.67	83.07	87.0

Table 6
Rank 1 Recognition Rate's for surgery images.

Authors	Algorithm	Rank 1 recognition rate
Singh et al.	Principal Component Analysis	29.1%
	Fisher Discrimnant Analysis	32.5%
	Local Feature Analysis	38.6%
	Circular Local Binary Patterns	47.8%
	Speeded Up Robust Features	50.9%
	2-D Log Polar Gabor Transform	54.2%
Marsico et al.	Correlation scheme	70.6%
Bhatt et al.	Evolutionary granular scheme	78.6%
Aggarwal et al.	Parts/sparse detection	77.9%
Said et al.	Geometrical FRAPS	77.3%
Proposed method	Weighted score level fusion of local facial features	84.0%

each evaluation is 0.7, 0.8, 0.96 and 0.4. The exact matching image is the third one because it gives maximum equivalence score. Thus it can be deduced that presentation metrics depend on a number of aspects such as nature of surgery, database type, predispensation methods, eminence of images, pose, clutter, enlightenment etc.

6. Conclusion and future scope

The proposed research promotes a fusion based design that fuses information from various facial regions and full face to boost up biometric validation for surgically altered facial image samples. The projected method provides an average recognition rate of 89.7% for local surgery (Blepharoplasty) and 87% (Skin Peeling) for global surgery. Compared to existing approaches in literature, the proposed scheme gives highest identification accuracy and lowest EER amid pre/post surgery samples with moderate computation time.

Local/global are the two featured approaches on which face recognition algorithms work. The investigational outcomes show that face detection algorithms give enhanced precision for local surgery as compared to global therapy. Cosmetic therapies of local nature modify the emergence of local facial traits only which in turn leads to better detection after synthetic surgical procedure. The investigational outcomes also state that the projected FRAP'S system is vigorous but has it's own limitations. For some identified regions of interest no match is obtained between before and after surgery images. The proposed system results into slight increase in computation time for some surgical procedures, which is not fruitful for real time applications.

To overcome the above limitations future research directions would be to extract more precise local/global features for an improved contest amid before/after surgery samples. Use of a more precise distance metric can improve the match, recognition rate and computation intricacy. The outcomes of the projected scheme show an enhancement in identification rate and a decline in computation time in context to identification methods stated in literature. In future, the development of new schemes for dimensionality reduction to model non linearity's imposed by plastic therapies can be carried out that do not suffer from the presence of trivial most favorable results. Emphasis on recognition accuracy needs to be balanced with computation time as well. Our experimental results reveal that human identification after cosmetic therapy is a non-trifling task, and requires unremitting research efforts.

Conflict of interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jisa.2019.102373.

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