Recognizing Surgically Altered Face Images Using Multiobjective Evolutionary Algorithm

Himanshu S. Bhatt, *Student Member, IEEE*, Samarth Bharadwaj, *Student Member, IEEE*, Richa Singh, *Member, IEEE*, and Mayank Vatsa, *Member, IEEE*

Abstract—Widespread acceptability and use of biometrics for person authentication has instigated several techniques for evading identification. One such technique is altering facial appearance using surgical procedures that has raised a challenge for face recognition algorithms. Increasing popularity of plastic surgery and its effect on automatic face recognition has attracted attention from the research community. However, the nonlinear variations introduced by plastic surgery remain difficult to be modeled by existing face recognition systems. In this research, a *multiobjective evolutionary granular algorithm* is proposed to match face images before and after plastic surgery. The algorithm first generates non-disjoint face granules at multiple levels of granularity. The granular information is assimilated using a multiobjective genetic approach that simultaneously optimizes the selection of feature extractor for each face granule along with the weights of individual granules. On the plastic surgery face database, the proposed algorithm yields high identification accuracy as compared to existing algorithms and a commercial face recognition system.

Index Terms— Face recognition, plastic surgery, genetic algorithm, granular computing.

I. INTRODUCTION

PLASTIC surgery procedures provide a proficient and enduring way to enhance the facial appearance by correcting feature anomalies and treating facial skin to get a younger look. Apart from cosmetic reasons, plastic surgery procedures are beneficial for patients suffering from several kinds of disorders caused due to excessive structural growth of facial features or skin tissues. These procedures amend the facial features and skin texture thereby providing a makeover in the appearance of face. Fig. 1 shows an example of the effect of plastic surgery on facial appearances. With reduction in cost and time required for these procedures, the popularity of plastic surgery is increasing. Even the widespread acceptability in the society encourages individuals to undergo plastic surgery for cosmetic reasons. Ac-

Fig. 1. Illustrating the variations in facial appearance, texture, and structural geometry caused due to plastic surgery (images taken from internet).

cording to the statistics provided by the American Society for Aesthetic Plastic Surgery for year 2010 [1], there is about 9% increase in the total number of cosmetic surgery procedures, with over 500,000 surgical procedures performed on face.

Transmuting facial geometry and texture increases the intraclass variability between the pre- and post-surgery images of the same individual. Therefore, matching post-surgery images with pre-surgery images becomes an arduous task for automatic face recognition algorithms. Further, as shown in Fig. 2, it is our assertion that variations caused due to plastic surgery have some intersection with the variations caused due to aging and disguise. Facial aging is a biological process that leads to gradual changes in the geometry and texture of a face. Unlike aging, plastic surgery is a spontaneous process and its effects are generally contrary to that of facial aging. Since the variations caused due to plastic surgery procedures are spontaneous, it is difficult for face recognition algorithms to model such nonuniform face transformations. On the other hand, disguise is the process of concealing one's identity by using makeup and other accessories. Both plastic surgery and disguise can be misused by individuals trying to conceal their identity and evade recognition. Variations caused due to disguise are temporary and reversible; however, variations caused due to plastic surgery are long-lasting and may not be reversible. Owing to these reasons, plastic surgery is now established as a new and challenging covariate of face recognition alongside aging and disguise. Singh *et al.* [2] analyzed several types of local and global plastic surgery procedures and their effect on different face recognition algorithms. They have experimentally shown that the nonlinear variations introduced by surgical procedures are difficult to address with current face recognition algorithms. De Marsico *et al.* [3] developed an approach to integrate information derived from local regions to match pre- and post-surgery face images. Recently, Aggarwal *et al.* [4] proposed sparse representation approach on local facial fragments to match surgically altered face images. Though recent results suggest that the algorithms are improving towards addressing the challenge, there is a significant scope for further improvement.

Fig. 2.   Relation among plastic surgery, aging, and disguise variations with respect to face recognition.

Fig. 3.   Block diagram illustrating different stages of the proposed algorithm.

This research presents a multiobjective evolutionary granular computing based algorithm for recognizing faces altered due to plastic surgery procedures. As shown in Fig. 3, the proposed algorithm starts with generating non-disjoint face granules where each granule represents different information at different size and resolution. Further, two feature extractors, namely Extended Uniform Circular Local Binary Pattern (EUCLBP) [5] and Scale Invariant Feature Transform (SIFT) [6], are used for extracting discriminating information from face granules. Finally, different responses are unified in an evolutionary manner using a multiobjective genetic approach for improved performance. The performance of the proposed algorithm is compared with a commercial-off-the-shelf face recognition system (COTS) for matching surgically altered face images against large scale gallery.

II. EVOLUTIONARY GRANULAR COMPUTING APPROACH FOR FACE RECOGNITION

Face recognition algorithms either use facial information in a holistic way or extract features and process them in parts. In the presence of variations such as pose, expression, illumination, and disguise, it is observed that local facial regions are more resilient and can therefore be used for efficient face recognition [7]–[10]. Several part based face recognition approaches capture this observation for improved performance. Heisele *et al.* [7] proposed a component based face recognition approach using different facial components to provide robustness to pose. Weyrauch *et al.* [8] designed an algorithm in which gray-level pixel values from several facial components were concatenated and classification was performed using SVM. Similarly, Li *et al.* [9] proposed an approach where local patches were extracted from different levels of Gaussian pyramid and arranged in an exemplar manner. These exemplar based-local patches were then combined using boosting to construct strong classifiers for prediction. In another approach, a subset selection mechanism was proposed [10] where the most informative local facial locations were used in decision making.

Singh *et al.* [2] observed that a surgical procedure may lead to alterations in more than one facial region. For example, blepharoplasty is primarily performed to amend forehead but it also effects the eyebrows. They also analyzed that with large variations in the appearance, texture, and shape of different facial
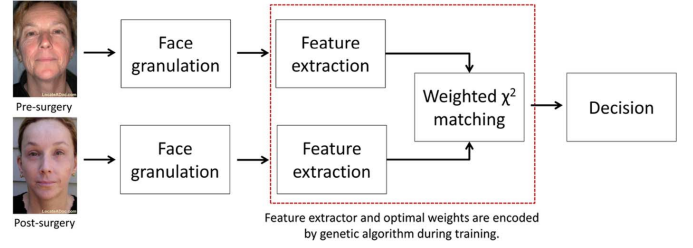
regions, it is difficult for face recognition algorithms to match a post-surgery face image with pre-surgery face images. Previous part-based face recognition approaches may not provide mechanisms to address the concurrent variations introduced in multiple features because these approaches, generally, emphasize on analyzing each feature independently. On the other hand, it is observed that humans solve problems using perception and knowledge represented at different levels of information granularity [11]. They recognize faces using a combination of holistic approaches together with discrete levels of information (or features). Sinha *et al.* [11] established 19 results based on the face recognition capabilities of a human mind. It is suggested that humans can efficiently recognize faces even with low resolution and noise. Moreover, high and low frequency facial information is processed both holistically and locally. Campbell *et al.* [12] reported that inner and outer facial regions represent distinct information that can be useful for face recognition. Researchers from cognitive science also suggested that local facial fragments can provide robustness against partial occlusion and change in viewpoints [11], [13], [14]. To incorporate these observations, this research proposes a granular approach [15], [16] for facial feature extraction and matching. In the granular approach, as shown in Fig. 3, non-disjoint features are extracted at different granular levels. These features are then synergistically combined using multiobjective evolutionary learning to obtain the assimilated information. With granulated information, more flexibility is achieved in analyzing underlying information such as nose, ears, forehead, cheeks, and combination of two or more features. The face granulation scheme proposed in this research helps in analyzing multiple features simultaneously. Moreover, the face granules of different sizes and shapes (as shown in Figs. 4–7) help to gain significant insights about the effect of plastic surgery procedures on different facial features and their neighboring regions.

A. Face Image Granulation

Let F be the detected frontal face image of size $n \times m$. Face granules are generated pertaining to three levels of granularity. The first level provides global information at multiple resolutions. This is analogous to a human mind processing holistic information for face recognition at varying resolutions. Next, to incorporate the findings of Campbell *et al.* [12], inner and outer facial information are extracted at the second level. Local facial features play an important role in face recognition by human mind. Therefore, at the third level, features are extracted from the local facial regions.

1) First Level of Granularity: In the first level, face granules are generated by applying the Gaussian and Laplacian operators
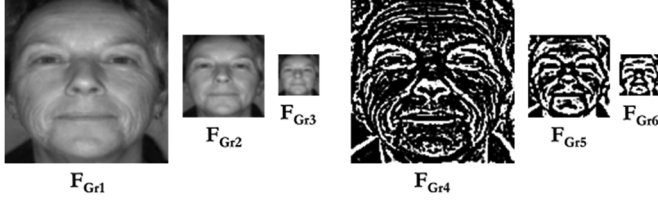
Fig. 4. Face granules in the first level of granularity. F_{Gr1}, F_{Gr2}, and F_{Gr3} are generated by the Gaussian operator, and F_{Gr4}, F_{Gr5}, and F_{Gr6} are generated by the Laplacian operator.

Fig. 5. Horizontal face granules from the second level of granularity ($F_{Gr7} - F_{Gr15}$).

Fig. 6. Vertical face granules from the second level of granularity ($F_{Gr16} - F_{Gr24}$).

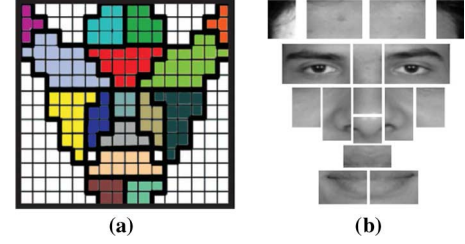Fig. 7. (a) Golden ratio face template [18] and (b) face granules in the third level of granularity ($F_{Gr25} - F_{Gr40}$).

[17]. The Gaussian operator generates a sequence of low pass filtered images by iteratively convolving each of the constituent images with a 2-D Gaussian kernel. The resolution and sample density of the image is reduced between successive iterations and therefore the Gaussian kernel operates on a reduced version of the original image in every iteration. Similarly, the Laplacian operator generates a series of band-pass images. Let the granules generated by Gaussian and Laplacian operators be represented by F_{Gri}, where i represents the granule number. For a face image of size 196×224, Fig. 4 represents the face granules generated in the first level by applying Gaussian and Laplacian operators. The resultant images may be viewed as a 'pyramid' with F_{Gr1} and F_{Gr4} having the highest resolution and F_{Gr3} and F_{Gr6} having the lowest resolution. F_{Gr1} to F_{Gr3} are the granules generated by Gaussian operator and F_{Gr4} to F_{Gr6} are the granules generated by the Laplacian operator. The size of the smallest granule in the first granular level is 49×56. In these six granules, facial features are segregated at different resolutions to provide edge information, noise, smoothness, and blurriness present in a face image. As shown in Fig. 4, the effect of facial wrinkles is reduced from granule F_{Gr1} to F_{Gr3}. The first level of granularity thus compensates for the variations in facial texture, thereby providing resilience to plastic surgery procedures that alter the face texture such as face-lift, skin resurfacing, and dermabrasion.

2) Second Level of Granularity: To accommodate the observations of Campbell *et al.* [12], horizontal and vertical granules are generated by dividing the face image F into different regions as shown in Figs. 5 and 6. Here, F_{Gr7} to F_{Gr15} denote the horizontal granules and F_{Gr16} to F_{Gr24} denote the vertical granules. Among the nine horizontal granules, the first three granules i.e. F_{Gr7}, F_{Gr8}, and F_{Gr9} are of size $n \times m/3$. The next three granules, i.e., F_{Gr10}, F_{Gr11}, and F_{Gr12} are generated such that the size of F_{Gr10} and F_{Gr12} is $n \times (m/3 - \epsilon)$ and the size of F_{Gr11} is $n \times (m/3 + 2\epsilon)$. Further, F_{Gr13}, F_{Gr14}, and F_{Gr15} are generated such that the size of F_{Gr13} and F_{Gr15} is $n \times (m/3 + \epsilon)$

and the size of F_{Gr14} is $n \times (m/3 - 2\epsilon)$. Nine vertical granules, F_{Gr16} to F_{Gr24}, are also generated in a similar manner. Figs. 5 and 6 show horizontal and vertical granules when the size of face image is 196×224 and $\epsilon = 15$.[1] The second level of granularity provides resilience to variations in inner and outer facial regions. It utilizes the relation between horizontal and vertical granules to address the variations in chin, forehead, ears, and cheeks caused due to plastic surgery procedures.

3) Third Level of Granularity: As mentioned previously, human mind can distinguish and classify individuals with their local facial regions such as nose, eyes, and mouth. To incorporate this property, local facial fragments are extracted and utilized as granules in the third level of granularity. Given the eye coordinates, 16 local facial regions are extracted using the golden ratio face template [18] shown in Fig. 7(a). Each of these regions is a granule representing local information that provides unique features for addressing variations due to plastic surgery. Fig. 7(b) shows an example of local facial fragments used as face granules in the third level of granularity.

The proposed granulation technique is used to generate 40 non-disjoint face granules from a face image of size 196×224. Three levels of granularity are designed to address specific variations introduced in local facial regions by different plastic surgery procedures. For example, variations in skin texture due to dermabrasion or skin-resurfacing are more pertinent in F_{Gr1} and F_{Gr4} while texture variations are suppressed in granules F_{Gr2}, F_{Gr3}, F_{Gr5}, and F_{Gr6}. The second level of granularity ($F_{Gr7} - F_{Gr24}$) helps to analyze different combinations of local features that provide resilience to concurrent variations introduced in multiple regions by different plastic surgery procedures (such as blepharoplasty, brow-lift, and rhinoplasty). The third level of granularity ($F_{Gr25} - F_{Gr40}$) independently analyzes each local feature to address the variations in individual facial regions. These 40 face granules are selected based on their capability to address specific variations. The technique used for generating granules is based on fixed structure and no local feature

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[1]In the experiments, it is observed that $\epsilon = 15$ yields the best recognition results when face image is of size 196×224.

based approach has been utilized.[2] For images captured from co-operative users, granulation can be performed according to the features. However, with noncooperative users, identifying features can be challenging and hence feature-based partitioning may not yield accurate results compared to fixed structure partitioning.

B. Facial Feature Extraction

The proposed granulation scheme results in granules with varying information content. Some granules contain fiducial features such as eyes, nose, and mouth while some granules predominantly contain skin regions such as forehead, cheeks, and outer facial region. Therefore, different feature extractors are needed to encode diverse information from the granules. In this framework, any two (complementing) feature extractors can be used; here *Extended Uniform Circular Local Binary Patterns* and *Scale Invariant Feature Transform* are used. Both these feature extractors are fast, discriminating, rotation invariant, and robust to changes in gray level intensities due to illumination. However, the information encoded by these two feature extractors is rather diverse as one encodes the difference in intensity values while the other assimilates information from the image gradients. They efficiently use information assimilated from local regions and form a global image signature by concatenating the descriptors obtained from every local facial region. It is experimentally observed that among the 40 face granules, for some granules EUCLBP finds more discriminative features than SIFT and vice-versa (later shown in the experimental results).

1) Extended Uniform Circular Local Binary Patterns: EU-CLBP [5] is a texture based descriptor that encodes exact gray-level differences along with difference of sign between neighboring pixels. For computing EUCLBP descriptor, the image is first tessellated into nonoverlapping uniform local patches of size 32×32. For each local patch, the EUCLBP descriptor is computed based on the 8 neighboring pixels uniformly sampled on a circle $(\text{radius} = 2)$ centered at the current pixel. The concatenation of descriptors from each local patch constitutes the image signature. Two EUCLBP descriptors are matched using the weighted χ^2 distance.

2) Scale Invariant Feature Transform: SIFT [6] is a scale and rotation invariant descriptor that generates a compact representation of an image based on the magnitude, orientation, and spatial vicinity of image gradients. SIFT, as proposed by Lowe [6], is a sparse descriptor that is computed around the detected interest points. However, SIFT can also be used in a dense manner where the descriptor is computed around predefined interest points. In this research, SIFT descriptor is computed in a dense manner over a set of uniformly distributed nonoverlapping local regions of size 32×32. SIFT descriptors computed for the sampled regions are then concatenated to form the image

signature. Similar to EUCLBP, weighted χ^2 distance is used to compare two SIFT descriptors.

C. Multiobjective Evolutionary Approach for Selection of Feature Extractor and Weight Optimization

Every face granule has useful but diverse information, which if combined together can provide discriminating information for face recognition. Moreover, psychological studies in face recognition [11] have also shown that some facial regions are more discriminating than others and hence, contribute more towards the recognition accuracy. One way to incorporate these observations is utilizing feature selection methods which are used for selective combination of features to combine diverse information for improved performance. Sequential feature selection (SFS) [19] and sequential floating forward selection (SFFS) [19] are widely used feature selection methods that evaluate the growing feature set by sequentially adding (or removing) the features one-at-a-time. On the other hand, a definitive feature selection approach concatenates different features (for example, EUCLBP and SIFT) and performs dimensionality reduction using PCA to yield the final feature set. Other approaches such as genetic search [10] and conditional mutual information (CMI) [20] are also used to find the most informative features. These existing feature selection techniques are single objective functions and may not be sufficient for improving the performance with single gallery evaluations (as in this research).

In this research, feature selection problem embroils around two objectives: 1) select an optimal feature extractor for each granule, and 2) assign proper weight for each face granule. The problem of finding optimal feature extractor and weight for each granule involves searching very large space and finding several suboptimal solutions. Genetic algorithms (GA) are well proven in searching very large spaces to quickly converge to the near optimal solution [21]. Therefore, a multiobjective genetic algorithm is proposed to incorporate feature selection and weight optimization for each face granule. Fig. 8 represents the multi-objective genetic search process and the steps involved are described below.

Genetic Encoding: A chromosome is a string whose length is equal to the number of face granules i.e. 40 in our case. For simultaneous optimization of two functions, two types of chromosomes are encoded: (i) for selecting feature extractor (referred to as chromosome $type1$) and (ii) for assigning weights to each face granule (referred to as chromosome $type2$). Each gene (unit) in chromosome $type1$ is a binary bit 0 or 1 where 0 represents the SIFT feature extractor and 1 represents the EU-CLBP feature extractor. Genes in chromosome $type2$ have real valued numbers associated with corresponding weights of the 40 face granules.

Initial Population: Two generations with 100 chromosomes are populated. One generation has all $type1$ chromosomes while the other generation has all $type2$ chromosomes.

1) For selecting feature extractor ($type1$ chromosome), half of the initial generation (i.e. 50 chromosomes) is set with all the genes (units) as 1, which represents EUCLBP as the feature extractor for all 40 face granules. The remaining 50 chromosomes in the initial generation have all genes as 0

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[2]In our approach, eye-coordinates are detected using the OpenCV's boosted cascade of Haar-like features. Since, the plastic surgery face database contains images with frontal pose and neutral expression, the OpenCV's eye detection is accurate. Using the eye-coordinates, face image is normalized with respect to the horizontal axis and intereye distance is fixed to 100 pixels. Finally, the detected images are resized to 196×224.
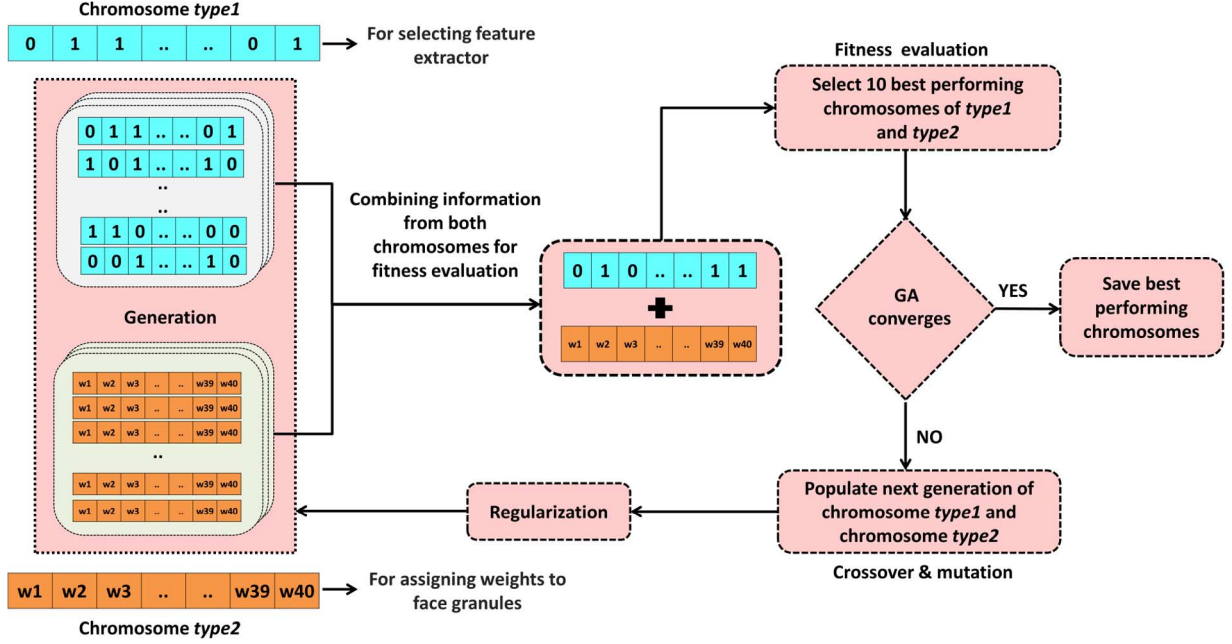
Fig. 8. Genetic optimization process for selecting feature extractor and weight for each face granule.

representing SIFT as the feature extractor for all 40 face granules.

2) For assigning weights to face granules ($type2$ chromosome), a chromosome with weights proportional to the identification accuracy of individual face granules (as proposed by Ahonen [22]) is used as the seed chromosome. The remaining 99 chromosomes are generated by randomly changing one or more genes in the seed chromosome. Further, the weights are normalized such that the sum of all the weights in a chromosome is 1.

Fitness Function: Both $type1$ and $type2$ chromosomes are combined and evaluated simultaneously. Recognition is performed using the feature extractor selected by chromosome $type1$ and weight encoded by chromosome $type2$ for each face granule. Identification accuracy, used as the fitness function, is computed on the training set and 10 best performing chromosomes are selected as *parents* to populate the next generation.

Crossover: A set of uniform crossover operations is performed on *parents* to populate a new generation of 100 chromosomes. Crossover operation is same for both $type1$ and $type2$ chromosomes.

Mutation: After crossover, mutation is performed for $type2$ chromosomes by changing one or more weights by a factor of its standard deviation in the previous generation. For $type1$ chromosome, mutation is performed by randomly inverting the genes in the chromosome.

The search process is repeated till convergence and terminated when the identification performance of the chromosomes in new generation do not improve compared to the performance of chromosomes in previous five generations. At this point, the feature extractor and optimal weight for each face granule (i.e. chromosomes giving best recognition accuracy on the training data) are obtained. Genetic optimization also enables to discard redundant and nondiscriminating face granules that do not contribute much towards the recognition accuracy (i.e. the weight for that face granule is close to zero). This optimization process

leads to both dimensionality reduction and better computational efficiency.

Evolutionary algorithms such as genetic algorithms often fail to maintain diversity among individual solutions (chromosomes) and cause the population to converge prematurely. This problem is attributed to loss of diversity in a population that decreases the quality of solution. In this research, *adaptive mutation rate* [23] and *random offspring generation* [24] are used to prevent premature convergence to local optima by ensuring sufficient diversity in a population. Depending on population diversity, mutation is performed with an adaptive rate that increases if diversity decreases and vice-versa. Population diversity is measured as the standard deviation of fitness values in a population. Further, random offspring are generated if there is a high degree of similarity among participating chromosomes (parents) during the crossover operation. Combination of such similar chromosomes is ineffective because it leads to offsprings that are exactly similar to parents. Therefore, under such conditions, crossover is not performed and offsprings are generated randomly.

D. Combining Face Granules With Multiobjective Evolutionary Learning for Recognition

The granular approach for matching faces altered due to plastic surgery is summarized below.

1) For a given gallery-probe pair, 40 face granules are extracted from each image.
2) EUCLBP or SIFT features are computed for each face granule according to the evolutionary model learned using the training data.
3) The descriptors extracted from the gallery and probe images are matched using weighted χ^2 distance measure.

$$\chi^2(a, b) = \sum_{i,j} \omega_j \frac{(a_{i,j} - b_{i,j})^2}{a_{i,j} + b_{i,j}} \qquad (1)$$

where a and b are the descriptors computed from face granules pertaining to a gallery-probe pair, i and j correspond to the ith bin of the jth face granule, and ω_j is the weight of the jth face granule. Here, the weights of each face granule are learnt using the genetic algorithm.

4) In identification mode $(1 : N)$, this procedure is repeated for all the gallery-probe pairs and top matches are obtained based on the match scores.

III. EXPERIMENTAL RESULTS

Several experiments are performed to evaluate the performance of the proposed algorithm. The performance of the algorithm is also compared with SIFT and EUCLBP applied on full face image, SIFT and EUCLBP applied on the 40 face granules, sum-rule fusion [25] of SIFT and EUCLBP on face granules, and a commercial-off-the-shelf face recognition system (COTS).[3] Further, to evaluate the effectiveness of the proposed multiobjective genetic approach for feature selection and assimilation, the performance is compared with other feature selection methods, namely, definitive feature selection (referred to as "EUCLBP+SIFT+PCA"), SFS [19], and SFFS [19].

A. Database

In this research, experiments are performed on two databases: (a) plastic surgery face database [2] and (b) combined heterogeneous face database. The plastic surgery face database comprises 1800 pre- and post-surgery images corresponding to 900 subjects with frontal pose, proper illumination, and neutral expression. The database consists of different types of facial plastic surgery cases such as rhinoplasty (nose surgery), blepharoplasty (eyelid surgery), brow lift, skin peeling, and rhytidectomy (face lift). In the real world, it is difficult to isolate individuals who have undergone plastic surgery and use special mechanism to recognize them. Therefore, face recognition algorithms should be robust to variations introduced by plastic surgery even in general operating environments. Considering such generality of face recognition, the second database is prepared by appending the plastic surgery face database with 1800 nonsurgery images pertaining to 900 subjects from other publicly available face databases. This database is termed as the *combined heterogeneous face database* and comprises 3600 images pertaining to 1800 subjects. The nonsurgery images are from the same databases used by Singh *et al.* [2] and consists of two frontal images per subject with proper illumination and neutral expression.

Images in the plastic surgery face database are collected from different sources on internet and have noise and irregularities. The detected images in the database are first preprocessed to zero mean and unit variance followed by applying histogram equalization to maximize image contrast. Further, Wiener filtering is applied to restore the blurred edges. As mentioned previously, the face images are geometrically normalized and the size of each detected face image is 196×224 pixels.

[3]COTS used in our experiments is one of the highly accurate and widely used face recognition software; however the academic license agreement does not allow us to name it in any comparison.

B. Experimental Protocol

To evaluate the efficacy of the proposed algorithm, experiments are performed with 10 times repeated random subsampling (cross validations). In each experiment, 40% of the database is used for training and the remaining 60% is used for testing. The training data is used for selecting EUCLBP/SIFT features for each granule and the corresponding weight, while the unseen testing data is used for performance evaluation. Experimental protocol for all the experiments are described here:

- *Experiment 1*: 1800 pre- and post-surgery images pertaining to 900 subjects from the plastic surgery face database [2] are used in this experiment. Images of 360 subjects are used for training and the performance is evaluated on the remaining 540 subjects. Pre-surgery images are used as the gallery and post-surgery images are used as the probe.
- *Experiment 2*: Out of 1800 subjects from the combined heterogeneous face database, 720 subjects are used for training and the remaining 1080 subjects are used for testing. The training subjects are randomly selected and there is no regulation on the number of training subjects with plastic surgery. This experiment resembles real world scenario of training-testing where the system is unaware of any plastic surgery cases.
- *Experiment 3*: To evaluate the effectiveness of the proposed algorithm for matching individuals against large size gallery, two different experiments are performed. In both the experiments, 6324 frontal face images obtained from government agencies are appended to the gallery of 1800 face images used in *Experiment 2*.
  — Case 1: Training is performed with images of 360 subjects from the plastic surgery face database. The performance is evaluated on post-surgery images from the remaining 540 subjects as probes against the large scale gallery of 7764 subjects.
  — Case 2: Training is performed with images of 720 subjects from the combined heterogeneous face database. The performance is evaluated on images from the remaining 1080 subjects as probes against the large scale gallery of 7404 subjects.

C. Analysis

The proposed algorithm utilizes the observation that human mind recognizes face images by analyzing the relation among non-disjoint spatial features extracted at multiple granular levels. Further, simultaneously optimizing the feature selection and weight computation pertaining to each face granule allows for addressing the nonlinear and spontaneous variations introduced by plastic surgery. Key results and observations from the experiments are summarized below.

- The CMC curves in Fig. 9 and Table I show rank-1 identification accuracy for Experiments 1 and 2. The proposed algorithm outperforms other algorithms by at least 4.22% on the plastic surgery face database and 4.86% on the combined heterogeneous face database. The proposed algorithm also outperforms the commercial system by 2.66% and 1.93% on the plastic surgery face database and the combined heterogeneous face database respectively.
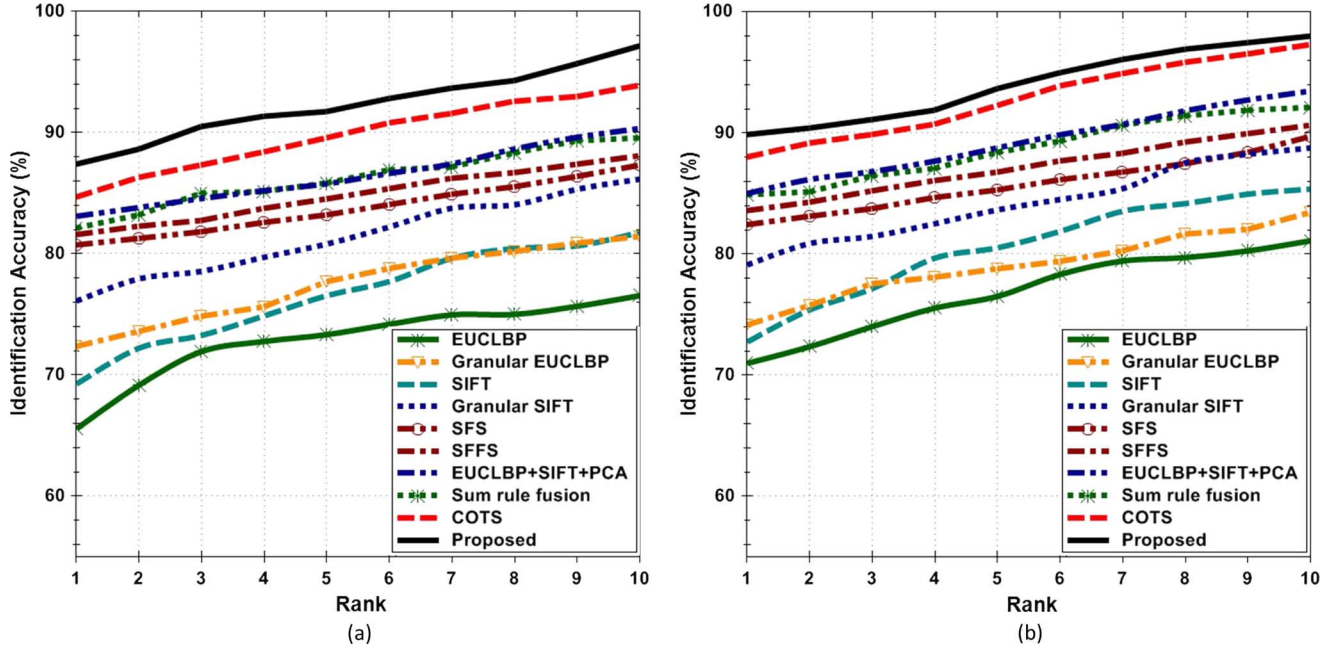
Fig. 9. CMC curves for the proposed and existing algorithms on the (a) plastic surgery face database and (b) combined heterogeneous face database.

TABLE I
RANK-1 IDENTIFICATION ACCURACY (%) OF THE PROPOSED MULTIOBJECTIVE
EVOLUTIONARY GRANULAR APPROACH AND COMPARISON WITH EXISTING
APPROACHES. IDENTIFICATION ACCURACIES AND STANDARD DEVIATIONS
(SD) ARE COMPUTED WITH 10 TIMES CROSS VALIDATION

Database	Algorithm	Accuracy	SD
	Single Algorithm		
	EUCLBP [5]	65.56	1.02
	SIFT [6]	69.26	1.13
Plastic surgery	Granular EUCLBP	72.35	0.85
face database	Granular SIFT	76.11	0.86
	COTS	84.66	0.76
	Match Score Fusion		
(360 Training)	Sum Rule Fusion	82.05	0.90
(540 Testing)	**Feature Selection Approach**		
	SFS [19]	80.66	0.94
	SFFS [19]	81.58	0.96
	EUCLBP+SIFT+PCA	83.10	0.71
	Proposed	**87.32**	**0.64**
	Single Algorithm		
	EUCLBP [5]	70.98	0.92
	SIFT [6]	72.75	0.98
Combined	Granular EUCLBP	74.08	0.78
heterogeneous	Granular SIFT	79.12	0.82
face database	COTS	87.94	0.80
	Match Score Fusion		
(720 Training)	Sum Rule Fusion	84.85	1.16
(1080 Testing)	**Feature Selection Approach**		
	SFS [19]	82.43	0.76
	SFFS [19]	83.59	0.88
	EUCLBP+SIFT+PCA	85.01	0.68
	Proposed	**89.87**	**0.70**

- In Experiment 2, the training-testing partitions have plastic surgery as well as nonsurgery images. It closely resembles the condition which a real world face recognition system encounters in general operating environment. Without the knowledge of specific plastic surgery cases, face recognition system has to be robust in matching surgically altered face images in addition to matching regular face images. Different types of plastic surgery procedures have varying effect on one or more facial regions. The proposed algorithm inherently provides the benefit of addressing the nonlinear variations introduced by different types of plastic surgery procedures.

- CMC curves in Fig. 10 show the performance of the proposed algorithm and commercial system for matching probes against a large gallery (Experiment 3). The proposed algorithm outperforms the commercial system by 4.6% and 2.21% on Case 1 and Case 2 of Experiment 3 respectively. Assimilating discriminating information from different levels of granulation and combining them in an evolutionary manner helps to mitigate the effect of plastic surgery procedures and leads to improved performance.

- Table II shows individual rank-1 identification accuracy of all 40 face granules using EUCLBP and SIFT on the plastic surgery face database. Face granules 4, 7, 19, 21, 29, and 31 yield significantly better recognition performance with EUCLBP as compared to SIFT. On the other hand, face granules 2, 3, 8, 11, 14, 26, 39, and 40 provide better recognition performance with SIFT as compared to EUCLBP. SIFT generally performs better on granules containing fiducial features such as eyes, nose, and mouth, however its performance on predominant skin regions such as forehead, cheeks, and outer facial region is not optimal. Since EUCLBP is based on the exact difference of gray level intensities, it can better encode discriminating micro patterns even from predominant skin regions.

- Multiobjective evolutionary approach for selecting feature extractor using genetic algorithm provides the advantage of choosing better performing feature extractor for each face granule. It is observed in our experiments that on average, SIFT is selected for 22 face granules whereas EUCLBP is selected for 18 face granules.

- To show the improvement due to face granulation, Table I compares the rank-1 identification accuracy of granular
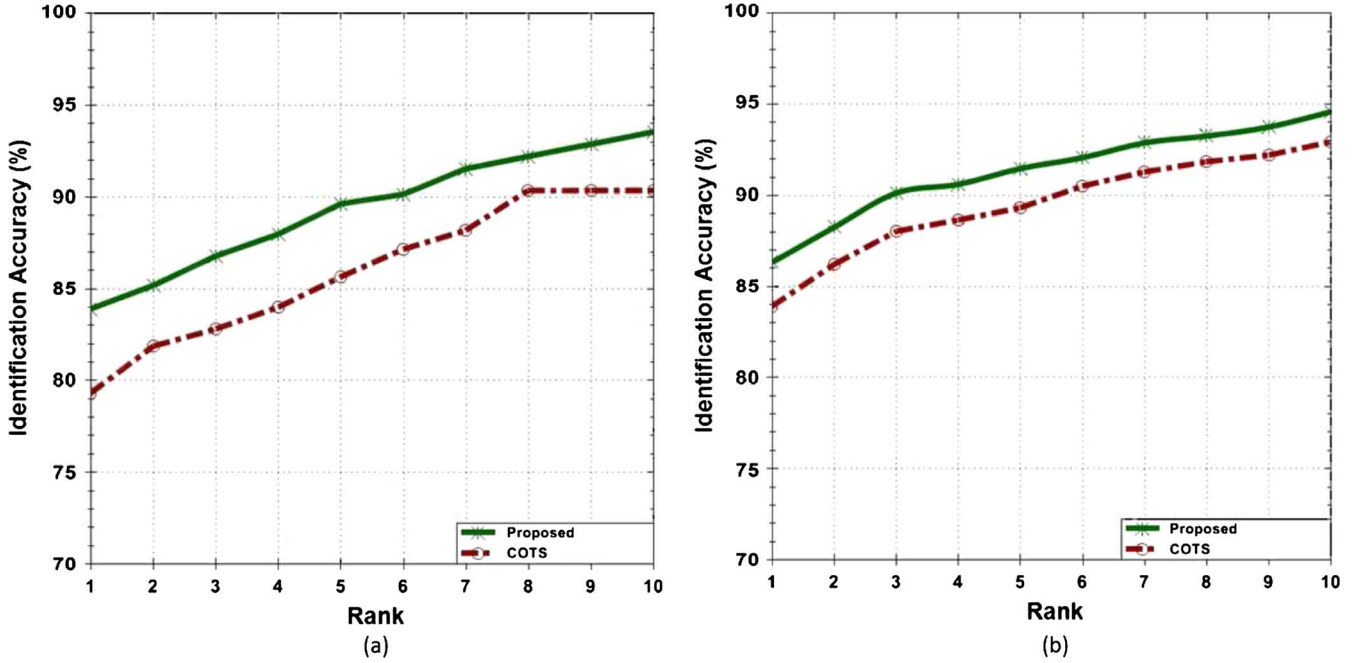
Fig. 10. CMC curves for the proposed and commercial algorithms for large-scale evaluation on probe images from (a) case 1 of experiment 3 and (b) case 2 of experiment 3.

TABLE II
RANK-1 IDENTIFICATION ACCURACY (%) OF FACE GRANULES USING SIFT AND EUCLBP

Granule	SIFT	EUCLBP	Granule	SIFT	EUCLBP
F_{Gr1}	69.26	65.56	F_{Gr21}	14.12	22.08
F_{Gr2}	51.42	42.26	F_{Gr22}	19.25	23.96
F_{Gr3}	46.18	21.32	F_{Gr23}	23.64	19.25
F_{Gr4}	22.86	36.20	F_{Gr24}	20.88	23.94
F_{Gr5}	20.15	25.75	F_{Gr25}	9.72	5.50
F_{Gr6}	16.26	19.50	F_{Gr26}	19.36	8.85
F_{Gr7}	10.46	19.38	F_{Gr27}	18.12	12.50
F_{Gr8}	39.06	28.64	F_{Gr28}	9.22	7.25
F_{Gr9}	17.85	23.42	F_{Gr29}	17.36	22.50
F_{Gr10}	13.14	19.64	F_{Gr30}	8.54	6.48
F_{Gr11}	41.43	32.38	F_{Gr31}	18.52	22.86
F_{Gr12}	28.20	24.44	F_{Gr32}	14.24	6.48
F_{Gr13}	16.88	22.02	F_{Gr33}	13.16	11.24
F_{Gr14}	33.06	23.84	F_{Gr34}	11.35	5.65
F_{Gr15}	30.56	24.68	F_{Gr35}	10.75	7.94
F_{Gr16}	15.76	21.84	F_{Gr36}	15.10	13.54
F_{Gr17}	33.12	25.50	F_{Gr37}	12.64	6.28
F_{Gr18}	15.64	21.28	F_{Gr38}	12.20	10.38
F_{Gr19}	11.82	20.10	F_{Gr39}	22.86	12.82
F_{Gr20}	51.60	44.40	F_{Gr40}	24.92	11.18

EUCLBP and granular SIFT with EUCLBP and SIFT applied on the full face. The results show that applying EUCLBP and SIFT on face granules improves the rank-1 accuracy by at least 3% as compared to a full face image. The ability to encode local features at different resolutions and sizes (face granules) allows the proposed algorithm to be resilient to the nonlinear variations introduced by plastic surgery procedures.

- To show the efficacy of the multiobjective evolutionary approach, the performance is compared with sum-rule fusion [25] of SIFT and EUCLBP on face granules. Table I shows that the proposed algorithm outperforms sum-rule fusion by at least 5% on both the databases.

- While comparing with existing feature selection approaches, SFS and SFFS algorithms are used to select either EUCLBP or SIFT features for each face granule based on the identification accuracy (optimization function). The dimension of selected features is empirically decided based on the best performance achieved during training. In SFS, the best performance is achieved with all 40 face granules. However for feature selection using SFFS, the best performance is obtained with 32 face granules. Unlike SFS and SFFS algorithms, the proposed multiobjective evolutionary granular algorithm allows for simultaneous optimization of feature selection and weights for each face granule. As shown in Table I, the proposed algorithm outperforms SFS by at least 6.66% and SFFS by at least 5.74% in rank-1 identification accuracy on both the databases.

- In definitive feature selection (EUCLBP+SIFT+PCA), PCA is used for dimensionality reduction in which top Eigen vectors are retained to preserve 95% of the total energy of the distribution. Unlike the multiobjective genetic optimization, PCA based dimensionality reduction does not allow assigning distinct weights to different face granules and therefore the proposed algorithm outperforms definitive feature selection by at least 4.22%.

- Recently, Aggarwal et al. [4] proposed a sparse representation based approach to match surgically altered face images in a part-wise manner. The proposed granular algorithm outperforms the sparse representation based approach [4] by 9.4% on the plastic surgery face database under the same experimental protocol.

- From nonparametric rank-ordered test (Mann-Whitney test on the ranks obtained from the algorithms), it can be concluded that there is a statistically significant difference between the proposed algorithm and COTS. Further, at 95%

TABLE III
RANK-1 IDENTIFICATION ACCURACY (%) ON DIFFERENT TYPES OF LOCAL AND GLOBAL PLASTIC SURGERY PROCEDURES

| Type	Surgery	No. of Cases	PCA	FDA	LFA	CLBP	SURF	GNN	Periocular	Proposed
Local	Browlift	60	28.5	31.8	39.6	49.1	51.1	57.2	34.42	89.22
	Dermabrasion	32	20.2	23.4	25.5	42.1	42.6	43.8	44.56	77.89
	Otoplasty	74	56.4	58.1	60.7	68.8	66.4	70.5	47.25	92.25
	Blepharoplasty	105	28.3	35.0	40.2	52.1	53.9	61.4	30.96	91.42
	Rhinoplasty	192	23.1	24.1	35.4	44.8	51.5	54.3	40.71	88.85
	Other	56	26.4	33.1	41.4	52.4	62.6	58.9	35.81	89.17
Global	Rhytidectomy	308	18.6	20.0	21.6	40.9	40.3	42.1	37.27	71.76
	Skin peeling	73	25.2	31.5	40.3	53.7	51.1	53.9	45.83	85.09
	Overall	**900**	**27.2**	**31.4**	**37.8**	**47.8**	**50.9**	**53.7**	**40.11**	**87.32**
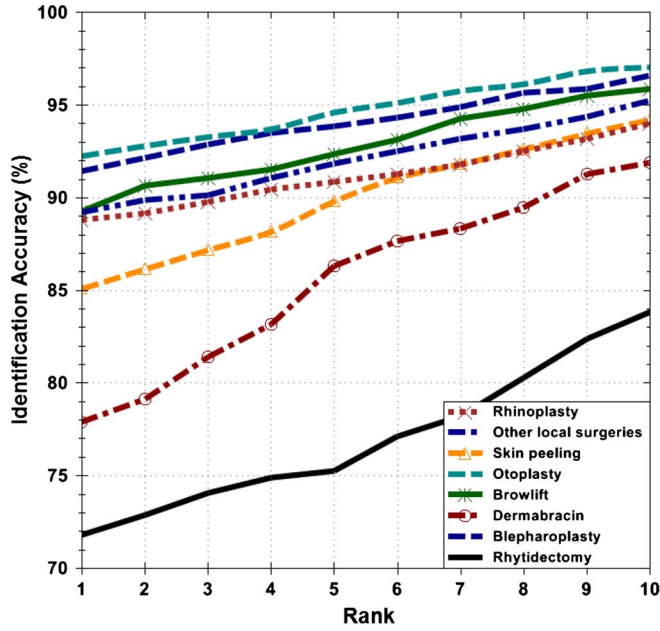
Fig. 11. CMC curves on different types of local and global plastic surgery procedures for the proposed algorithm.

confidence level, parametric t-test (using the match scores) also suggests that the proposed algorithm and COTS are statistically different.

D. Identification Performance With Different Plastic Surgery Procedures

According to Singh *et al.* [2], plastic surgery procedures can be categorized into *global* and *local* plastic surgery. **Global plastic surgery** completely transforms the face and is recommended in cases where functional damage is to be cured such as patients with fatal burns or trauma. In these kind of surgeries, facial appearance, skin texture, and feature shapes vary drastically thus making it arduous for any face recognition system to recognize pre- and post-surgery faces. Rhytidectomy (full face-lift) is used to treat patients with severe burns on face and neck. It can also be used to reverse the effect of aging and get a younger look, thus modifying the appearance and texture of the whole face. Analogous to rhytidectomy, skin peeling procedures such as laser resurfacing and chemical peel alter the texture information thus affecting the performance of face recognition algorithms. These procedures are used to treat wrinkles, stretch marks, acne, and other skin damages caused due to aging and sunburns. These two global plastic surgery procedures severely impact the performance of the proposed algorithm that yields rank-1 identification accuracy of 71.76% and 85.09% for cases

with rhytidectomy and skin peeling respectively, as shown in Fig. 11 and Table III.

On the other hand, **local plastic surgery** is meant for reshaping and restructuring facial features to improve the aesthetics. These surgical procedures result in varying amounts of change in the geometric distance between facial features but the overall texture and appearance of the face remains similar to the original face. Dermabrasion is used to give a smooth finish to face skin by correcting the skin damaged by sunburns or scars (developed as a post-surgery effect), dark irregular patches (melasma) that grow over the face skin, and mole removal. Among all the local plastic surgery procedures listed in [2], dermabrasion has the most prominent effect on the performance of the proposed algorithm as it drastically changes the face texture. As shown in Fig. 11 and Table III, the proposed approach yields rank-1 identification accuracy of 77.89% for dermabrasion cases. Other local plastic surgery procedures also affect the performance of the proposed algorithm to varying degrees. Since plastic surgery procedures increase the difference between pre- and post-surgery images of the same individual (intraclass variations), they drastically reduce the performance of existing face recognition algorithms. The performance of the proposed algorithm with various global and local plastic surgery procedures is also shown in Table III and CMC curves in Fig. 11. These results show that the proposed algorithm provides improvement of at least 21.7% compared to existing algorithms[4] across different plastic surgeries.

E. Analysis of Different Granularity Levels

To understand the contribution of different granularity levels for recognizing face images altered due to plastic surgery, a detailed experimental study of individual granular levels is performed. The correlation analysis of all three levels of granularity is reported in Table IV. The complimentary information vested in different levels is utilized by the proposed algorithm for efficiently matching surgically altered face images. Table V shows the identification accuracy of individual levels of granularity for the two databases. The first level of granularity has different Gaussian and Laplacian pyramids that assimilate discriminating information across multiple resolutions. Pyramids at level-0 contain minute features whereas the pyramids at level-1 and level-2 provide high level prominent features of a face. Several psychological studies have shown that humans use different inner and outer facial features to identify

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[4]Since the experimental protocol and sample distribution across different validation trials in [2] and the current research are same, the results of PCA, FDA, LFA, CLBP, SURF, and GNN are directly compared.
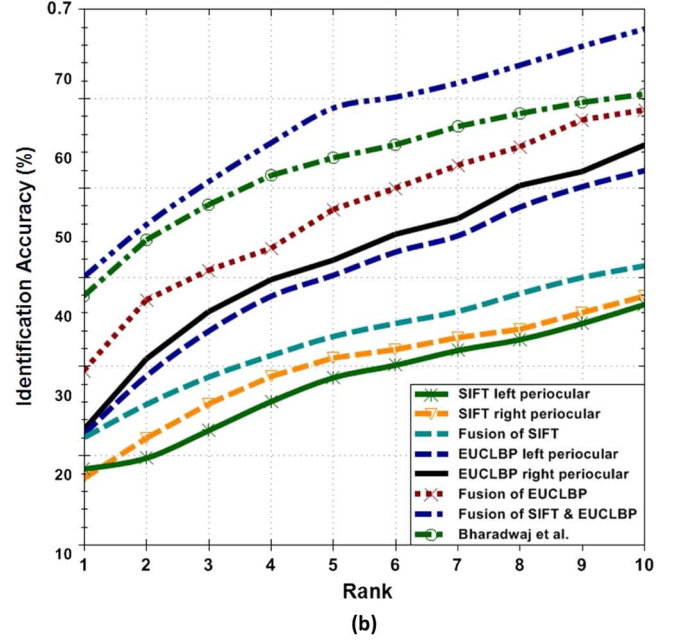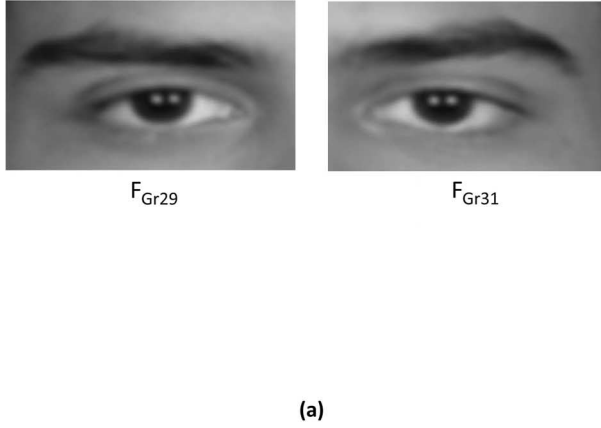
Fig. 12. (a) F_{Gr29} represents the right periocular region and F_{Gr31} represents the left periocular region; (b) CMC curves comparing the performance of different algorithms for matching periocular region on the plastic surgery face database.

TABLE IV
PEARSON CORRELATION COEFFICIENT BETWEEN DIFFERENT GRANULAR LEVELS ON THE PLASTIC SURGERY FACE DATABASE

Database	Granules	Genuine correlation	Impostor correlation
Plastic surgery face database	Level 1 - Level 2	0.67	0.59
	Level 1 - Level 3	0.43	0.21
	Level 2 - Level 3	0.63	0.55
Combined heterogeneous face database	Level 1 - Level 2	0.81	0.78
	Level 1 - Level 3	0.38	0.20
	Level 2 - Level 3	0.42	0.26

TABLE V
RANK-1 IDENTIFICATION ACCURACY (%) OF DIFFERENT LEVELS OF GRANULES AND THEIR COMBINATIONS ON THE PLASTIC SURGERY AND THE COMBINED HETEROGENEOUS FACE DATABASE

Database	Granular level	Accuracy
Plastic surgery face database	Granular level 1	78.3
	Granular level 2	82.7
	Granular level 3	58.4
	Granular levels 1 and 2	80.1
	Granular levels 2 and 3	82.8
	Granular levels 1 and 3	85.0
	Proposed	**87.3**
Combines Heterogeneous face database	Granular level 1	80.7
	Granular level 2	84.1
	Granular level 3	61.5
	Granular levels 1 and 2	83.2
	Granular levels 2 and 3	84.4
	Granular levels 1 and 3	86.9
	Proposed	**89.8**

individuals [26]. The inner facial features include nose, eyes, eyebrows, and mouth while the outer facial region comprises face outline, structure of jaw/chin, and forehead. The second level of granularity therefore extracts information from different inner and outer facial regions representing discriminative information that is useful for face recognition. Local facial fragments such as nose, eyes, and mouth provide robustness to variations in local regions caused due to plastic surgery procedures. Human mind can efficiently distinguish and classify individuals with their local facial fragments. Therefore, the third level of granularity assimilates discriminating information from these regions. The proposed granular approach unifies diverse information from different levels that are useful for recognizing faces altered due to plastic surgery.

To analyze the complimentary information provided by different granularity levels, the performance is evaluated for different combinations. The performance of the proposed multiobjective evolutionary granular approach is optimized for a particular level of granulation or their combination by assigning null weights to the face granules corresponding to other levels of granulation during genetic optimization. Table V also shows the results for different combinations of granular levels on the two databases.

According to the statistics provided by American Society for Aesthetic Plastic Surgery [1], blepharoplasty (eyelid surgery) is

identified as one of the top five surgical procedures performed in 2010. Eyelid is the thin skin that covers and protects our eyes and is a major feature in periocular recognition algorithms. Blepharoplasty is used to reshape upper and lower eyelids to treat excessive growth of skin tissues obstructing vision. Some other global plastic surgery procedures such as rhytidectomy or skin peeling may also affect the periocular region. Periocular region can be used as a biometric when the face is occluded [27] and/or the iris cannot be captured [28]. Recently, Juefei-Xu et al. [29] proposed using periocular region for age invariant face recognition and reported substantial improvements in both verification and identification performance. Driven by the robustness of periocular biometrics against occlusion and aging, this research also evaluates the performance of periocular biometrics for recognizing surgically altered face images. In the proposed granulation scheme, F_{Gr29} and F_{Gr31} represent the right and left periocular regions as shown in Fig. 12(a). Experiments are performed using the protocol of Experiment 1 in Section III-B. CMC curves in Fig. 12(b) show the performance of periocular

region for matching surgically altered faces from the plastic surgery face database. The performance is computed individually for the left and right periocular regions using SIFT and EUCLBP. Sum-rule fusion [25] of SIFT on the left and right periocular regions (fusion of SIFT) and sum-rule fusion of EUCLBP on the left and right periocular regions (fusion of EUCLBP) is also reported. Finally, the overall performance of periocular region is computed based on the sum-rule fusion of SIFT and EUCLBP on left and right periocular regions (fusion of SIFT and EUCLBP). The performance is also compared with an existing periocular based recognition algorithm, referred to as Bharadwaj *et al.* [28]. Experiments are also performed to analyze the effect of different global and local plastic surgery procedures (especially blepharoplasty) on the periocular region. Table III reports rank-1 identification accuracy of periocular region for matching faces altered due to specific types of plastic surgery. Blepharoplasty alters the periocular region thereby affecting the performance of periocular biometrics. It is also observed that the performance of periocular biometrics is reduced when a local region neighboring the periocular region (such as nose and forehead) is transformed due to plastic surgery. This is mainly because modifying local features also transmits some vicissitudes in the adjacent facial regions. The results suggest that although, periocular biometrics has shown robustness to aging and occlusion, plastic surgery is an important challenge.

IV. CONCLUSION

Plastic surgery has emerged as a new covariate of face recognition and its allure has made it indispensable for face recognition algorithms to be robust in matching surgically altered face images. This research presents a multiobjective evolutionary granular algorithm that operates on several granules extracted from a face image. The first level of granularity processes the image with Gaussian and Laplacian operators to assimilate information from multiresolution image pyramids. The second level of granularity tessellates the image into horizontal and vertical face granules of varying size and information content. The third level of granularity extracts discriminating information from local facial regions. Further, a multiobjective evolutionary genetic algorithm is proposed for feature selection and weight optimization for each face granule. The evolutionary selection of feature extractor allows switching between two feature extractors (SIFT and EUCLBP) and helps in encoding discriminatory information for each face granule. The proposed algorithm utilizes the observation that human mind recognizes faces by analyzing the relation among non-disjoint spatial features extracted at different granularity levels. Experiments under different protocols, including large scale matching, show that the proposed algorithm outperforms existing algorithms including a commercial system when matching surgically altered face images. Further, experiments on several local and global plastic surgery procedures also show that the proposed algorithm consistently outperforms other existing algorithms. Detailed analysis of the contribution of three granular levels and individual face granules corroborates the hypothesis that the proposed algorithm unifies diverse information from all granules to address the nonlinear variations in pre- and post-surgery images.

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Himanshu S. Bhatt (S'10) received the Bachelor in Technology degree in information technology in 2009 from the Jaypee Institute of Information Technology, Noida, India. He is currently working toward the Ph.D. degree from the Indraprastha Institute of Information Technology (IIIT) Delhi, India.

His research interests include image processing, machine learning, and their applications in biometrics. He is a recipient of IBM Ph.D. fellowship 2011–13, best poster awards in IEEE BTAS 2010 and IJCB 2011.

Samarth Bharadwaj (S'10) received the Bachelor in Technology degree in information technology in 2009 from the Jaypee Institute of Information Technology, Noida, India. He is currently working toward the Ph.D. degree from the Indraprastha Institute of Information Technology (IIIT) Delhi, India.

His main areas of interest are image processing, pattern classification, and their application in the field of facial and ocular biometrics. He is also recipient of best poster awards in BTAS 2010 and IJCB 2011.

Richa Singh (S'04–M'09) received the M.S. and Ph.D. degrees in computer science in 2005 and 2008, respectively, from the West Virginia University, Morgantown.

She is currently an Assistant Professor at the Indraprastha Institute of Information Technology (IIIT) Delhi, India. Her research has been funded by the UIDAI and DIT, India. She is a recipient of FAST award by DST, India. Her areas of interest are biometrics, pattern recognition, and machine learning. She has more than 100 publications in refereed journals, book chapters, and conferences. She is also an editorial board member of *Information Fusion*, Elsevier.

Dr. Singh is a member of the CDEFFS, IEEE, Computer Society and the Association for Computing Machinery. She is also a member of the Golden Key International, Phi Kappa Phi, Tau Beta Pi, Upsilon Pi Epsilon, and Eta Kappa Nu honor societies. She is the recipient of 11 best paper and best poster awards in international conferences.

Mayank Vatsa (S'04–M'09) received the M.S. and Ph.D. degrees in computer science in 2005 and 2008, respectively, from the West Virginia University, Morgantown.

He is currently an Assistant Professor at the Indraprastha Institute of Information Technology (IIIT) Delhi, India. He has more than 100 publications in refereed journals, book chapters, and conferences. His research has been funded by the UIDAI and DIT. He is the recipient of FAST award by DST, India. His areas of interest are biometrics, image processing, computer vision, and information fusion.

Dr. Vatsa is a member of the Computer Society and Association for Computing Machinery. He is also a member of the Golden Key International, Phi Kappa Phi, Tau Beta Pi, Sigma Xi, Upsilon Pi Epsilon, and Eta Kappa Nu honor societies. He is the recipient of 11 best paper and best poster awards in international conferences. He is an area editor of *IEEE Biometric Compendium*, 2012, Program co-chair of IAPR International Conference on Biometrics, 2013, and IEEE/IAPR International Joint Conference on Biometrics, 2014.