Evolutionary Granular Approach for Recognizing Faces Altered Due to Plastic Surgery

Himanshu S. Bhatt, Samarth Bharadwaj, Richa Singh, Mayank Vatsa, and Afzel Noore

Abstract— **Recognizing faces with altered appearances is a challenging task and is only now beginning to be addressed by researchers. The paper presents an evolutionary granular approach for matching face images that have been altered by plastic surgery procedures. The algorithm extracts discriminating information from non-disjoint face granules obtained at different levels of granularity. At the first level of granularity, both pre and post-surgery face images are processed by Gaussian and Laplacian operators to obtain face granules at varying resolutions. The second level of granularity divides face image into horizontal and vertical face granules of varying size and information content. At the third level of granularity, face image is tessellated into non-overlapping local facial regions. An evolutionary approach is proposed using genetic algorithm to simultaneously optimize the selection of feature extractor for each face granule along with finding optimal weights corresponding to each face granule for matching. Experiments on pre and post-plastic surgery face images show that the proposed algorithm provides at least 15% better identification performance as compared to other face recognition algorithms.**

I. INTRODUCTION

Plastic surgery has been recently established as a new and important covariate of face recognition alongside pose, expression, illumination, aging and disguise [17]. Advances in technology have made these procedures affordable and accessible to a much larger audience across all age groups, ethnicity and gender. Facial plastic surgery is a complex subtle process and unlike aging, it is not continuous. In our opinion, such non-uniform face transformations are not generic and difficult to be modeled.

Plastic surgery procedures affect the appearance, texture and shape of different facial regions. Therefore, it is difficult for face recognition algorithms to match a post-surgery face image with a pre-surgery face image. Recently, Singh *et. al.* [17] describe several types of local and global plastic surgery procedures and their effect on different face recognition algorithms. They concluded that the non-linear variations induced by plastic surgery procedures are hard to be addressed using current face recognition algorithms.

Generally face recognition algorithms either use facial information in a holistic way or extract features and process them in parts. On the other hand, cognitive neuroscientists have observed that humans solve problem using perception and knowledge represented at different levels of information granularity [18]. Humans can identify specific facial features and associate a contextual relationship among them to recognize a face even with altered appearances. Inspired from these observations, we propose an evolutionary granular computing based algorithm for recognizing faces. The algorithm starts with generating non-disjoint face granules with each face granule having different information at varying size and resolution. Further, two feature extractors, namely Uniform Circular Local Binary Pattern (UCLBP) [13] and Speeded Up Robust Features (SURF) [6], are used for extracting discriminating information from face granules. Finally, different responses are unified in an evolutionary manner using genetic algorithm for improved performance. Experiments are performed on plastic surgery and non-plastic surgery face databases and results show an improvement of at least 15% over existing algorithms.

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II. GRANULAR COMPUTING APPROACH FOR FACE RECOGNITION

Sinha *et al.* established 19 results based on face recognition capabilities of the human mind [18]. They suggested that humans process high and low frequency facial information holistically as well as locally. Further, Campbell *et al.* reported that different inner and outer facial regions represent distinct information which is helpful for face recognition [8]. It is our hypothesis that if these capabilities can be encoded in an automatic face recognition algorithm, then the recognition performance can be comparable to the performance of human mind for matching faces.

To incorporate the above mentioned research findings, we propose a granular approach [5], [11] for facial feature extraction and matching. In the granular computing approach a unified framework is used to extract non-disjoint features at different granularity levels. These features are then synergistically combined to obtain a more comprehensive information set. With granulated information, more flexibility is achieved in analyzing underlying information such as nose, ears, forehead, cheeks, or combination of two or more features. The proposed granulation process is described as follows:

A. Face Image Granulation

Let F be the detected frontal face image of size $n \times m$. Face granules are generated pertaining to three different levels of granularity. The first level of granularity provides global information at multiple levels of resolution. At the second level of granularity, different inner and outer facial information are extracted. Local facial features play an important role in face recognition, therefore, at the third level of granularity features from the local facial fragments are extracted.

1) First Level of Granularity: In the first level, face granules are generated by applying the Gaussian and Laplacian operators [7]. The Gaussian operator generates a sequence of low pass filtered images by iteratively convolving each of the constituent images with a 2D Gaussian filter kernel. The resultant images $I_0, I_1, \ldots, I_A$ may be viewed as a 'pyramid' with I_0 having the highest resolution and I_A having the lowest resolution. Let $\overline{w}(x, y)$ represent the Gaussian kernel of dimension 5×5 and reduction factor 4. The *reduce* operation Re can be written as,

$$Re[F(p,q)] = \sum_{x=1}^{5}\sum_{y=1}^{5} \overline{w}(x,y)F(2p+x, 2q+y) \tag{1}$$

A Gaussian pyramid I_B is defined as,

$$I_B = Re[I_{B-1}], \quad 0 \, < \, B \, < \, A \tag{2}$$

Further, the Laplacian operator generates band-pass images and the process can be summarized as follows:

$$L_B = I_B - Ex[I_{B+1}], \quad 0 \, \le \, B \, < \, A \tag{3}$$

Here, the $Ex[\cdot]$ operator interpolates a low-resolution image to the next higher resolution and can be represented as,

$$Ex[I_{B,D}(p,q)] = 4\sum_{x=-2}^{2}\sum_{y=-2}^{2} \overline{w}(x,y) I_{B,D-1}\left(\frac{p-x}{2}, \frac{q-y}{2}\right) \tag{4}$$

Note that $I_{B,D}$ in Equation 4 denotes 'expanding' I_B D number of times. Let the face 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. 1 represents the face granules generated in the first level by applying Gaussian and Laplacian operators. F_{Gr1} to F_{Gr3} are the granules generated by Gaussian operator and F_{Gr4} to F_{Gr6} are the granules generated by Laplacian operator. The size of the smallest granule in the first 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. This level of granular information thus provides resilience to variations in facial features such as eyes, mouth, and nose.

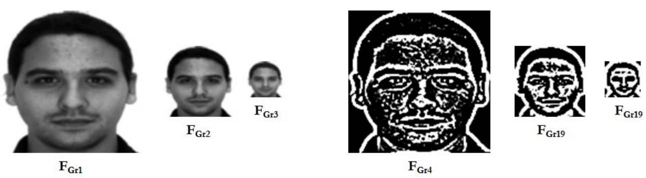

Fig. 1. Face granules in the first level of granularity. $F_{Gr1}, F_{Gr2}, and F_{Gr3}$ are generated by the Gaussian operator, and F_{Gr4}, F_{Gr5}, and F_{Gr6} are generated by the Laplacian operator.

2) Second Level of Granularity: In the second level of granularity, horizontal and vertical granules are generated by dividing the face image F into different regions as shown in Fig. 2 and 3. 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} have the same 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 $n \times (m - \epsilon)$[1] and the size of F_{Gr11} is $n \times (m + 2\epsilon)$. Further, F_{Gr13}, F_{Gr14}, and F_{Gr15} are generated such that the size of F_{Gr13} and F_{Gr15} is $n \times (m + \epsilon)$ and the size of F_{Gr14} is $n \times (m - 2\epsilon)$. Similarly, nine vertical granules F_{Gr16} to F_{Gr24} are generated. This level of granularity provides resilience to variations in different inner and outer facial regions.

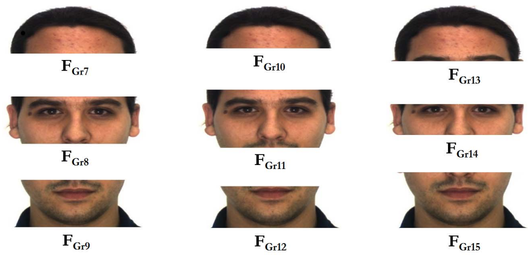

Fig. 2. Horizontal face granules from the second level of granularity.

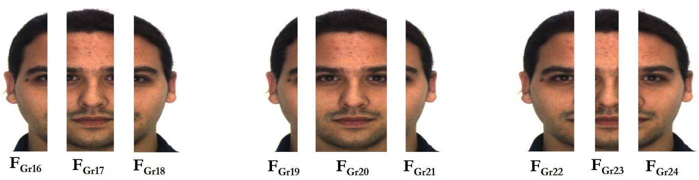

Fig. 3. Vertical face granules from the second level of granularity.

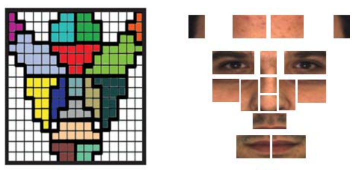

Fig. 4. (a) Golden ratio face template [4], (b) face granules from third level of granularity.

3) Third Level of Granularity: Local facial fragments are extracted and used as face granules in the third level of granularity. Given the eye coordinates, 16 local facial fragments are extracted using the golden ratio face template [4] shown in Fig. 4(a). Each of these fragments is a granule representing local information that provides unique features for handling variations due to plastic surgery. Fig. 4(b) shows an example of local facial fragments used as face granules in the third level of granularity.

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

The proposed granulation technique is used to generate 40 non-disjoint face granules from a face image of size 196×224. Here, we would like to mention that the technique is based on fixed structure and no local feature based approach is used for generating granules from frontal face images.

B. Feature Extraction using UCLBP and SURF

Each face granule is used to extract facial features. In this research, *Uniform Circular Local Binary Patterns* and *Speeded Up Robust Features* are used for facial feature extraction because these are fast, discriminating, rotation invariant and robust to changes in gray level intensities due to illumination. They efficiently use information assimilated from global as well as local facial regions.

1) Uniform Circular Local Binary Patterns: Local binary pattern based descriptor [3], [13] is a widely used texture operator because of its robustness to gray level changes and high computational efficiency. Circular local binary pattern (CLBP) [3], [13] is a feature extractor where the texture descriptor is computed based on the neighboring pixels that are well separated on a circle around the central pixel. CLBP can be further extended to Uniform CLBP [13] to achieve robustness to rotation variations and dimensionality reduction. A binary pattern is called uniform binary pattern if it has at most two bitwise transitions from 0 to 1 or vice-versa. Uniform CLBP is described using Equations 5 and 6.

$$C_{N,R}^{riu2}(p,q) = \begin{cases} \sum_{i=0}^{N-1} f(n_i - n_c)2^i & if \;\; U(C_{N,R}) \leq 2 \\ N+1 & otherwise \end{cases} \quad (5)$$

where,

$$U(C_{N,R}) = \begin{array}{c} \sum_{i=1}^{N-1} |f(n_i - n_c) - f(n_{i-1} - n_c)| \\ +|f(n_{N-1} - n_c) - f(n_0 - n_c)| \end{array} \quad (6)$$

where n_c corresponds to the gray-level intensity of center pixel of the circle and n_i corresponds to the gray-level intensities of N evenly spaced pixels on a circle of radius R. $riu2$ represents the use of rotation invariant uniform patterns. In our experiments, UCLBP is computed with 8 neighboring pixels uniformly distributed on a circle of radius 2. To match two UCLBP features, χ^2 distance measure is used.

2) Speeded Up Robust Features: SURF is a scale and rotation invariant descriptor [6], [9] that generates a compact representation of an image based on the spatial distribution of gradient information around the interest points. Interest points are localized by non-maximum suppression and the descriptor is formed using gradient information assimilated from the neighboring sample points using Haar wavelet responses. To match two SURF descriptors, χ^2 distance measure is used.

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

UCLBP encodes the texture using a detailed histogram whereas SURF encodes the interest points in a concise manner. The uniqueness and distinctness of these features depend on the information present in the granules and it may not be able to efficiently encode some of the granules. Based on this hypothesis, the experiments were conducted to determine the performance of UCLBP and SURF for each of the granule. It is experimentally observed that among the 40 face granules, for some granules UCLBP finds more discriminative features than SURF and vice-versa. It is also observed that SURF interest points cannot be successfully extracted for all face granules. This is mainly because some face granules are not distinctive in terms of SURF features or the small size of some of the face granules typically found in the third level of granularity. In the experiments, there are 14 face granules for which SURF is not able to extract interest points, therefore, UCLBP features are used for those 14 face granules. For the remaining 26 granules, feature extractor for each granule is selected depending on the reliability of the feature for that particular granule. Each face granule has varying contribution towards recognition accuracy therefore giving higher preference to face granules that have more contribution towards the recognition performance should improve the overall accuracy.

Based on the above observations, the next task is simultaneously optimizing the selection of feature extractor and weights associated with every face granule for matching. We propose an evolutionary genetic approach [10] to select feature extractor and corresponding weights for each face granule. Fig. 5 represents the genetic search process to find optimum feature extractor and weights for each face granule. The steps involved are elaborated as follows:

Genetic Encoding: The chromosome is a string whose length is equal to the number of face granules i.e. 40 in our case. We are dealing with simultaneous optimization of two functions, therefore we have two types of chromosomes: 1) for selecting feature extractor (referred to as chromosome $type1$) and 2) for assigning weights to each face granule (referred to as chromosome $type2$). Each unit in chromosome $type1$ is a binary bit 0 or 1 where 0 represents SURF feature extractor and 1 represents UCLBP feature extractor. Chromosome $type2$ has real valued numbers associated with corresponding weights of the 40 face granules.

Initial Population: Initially, there are two generations of 100 chromosomes each corresponding to two different optimization functions.

1) For selecting the feature extractors, we start with half the initial generation i.e. 50 chromosomes with all bits as 1 representing UCLBP as feature extractor for all the 40 face granules. The remaining 50 chromosomes in the initial generation have all permissible bits as 0 representing SURF as feature extractor and 1 representing UCLBP as feature extractor for face granules.
2) For assigning weights to each face granule, a chromosome with weights proportional to the identification accuracy of each face granule (as proposed by Ahonen [3]) is used as the initial chromosome. The remaining 99 chromosomes are generated by randomly changing

one or more units in the initial chromosome. The weights are normalized such that the sum of all weights in a chromosome is 1.

Fitness Function: Each individual chromosome in a generation is a possible solution. Fitness evaluation is performed using the feature extractor selected by chromosome $type1$ and weight encoded by chromosome $type2$ for each face granule. Identification accuracy is computed on a training set and 10 best performing chromosomes are selected for crossover and mutation to populate the next generation.

Crossover: Crossover operation is same for both chromosome $type1$ and chromosome $type2$. The set of uniform crossover operations is performed on 10 best performing chromosomes to populate a new generation of 100 chromosomes as shown in Fig. 5 (b).

Mutation: After crossover, mutation is performed with a probability of 0.02. For chromosome $type1$, mutation is performed by randomly inverting the bits of the chromosome with 2% chance. For chromosome $type2$, mutation is performed by changing one or more weights by a factor of its standard deviation in the previous generation.

The search process is repeated till convergence where the identification accuracy for new generation is better than previous generations. This produces the optimum feature extractor and weights for each face granule pertaining to the best performing chromosomes (i.e. chromosomes giving best recognition accuracy on the training data). Genetic approach also enables to discard redundant and non-discriminating face granules that contributes very little towards the recognition accuracy (i.e. the weight for that face granule is 0). This leads to dimensionality reduction and computational efficiency.

D. Combining Face Granules with Evolutionary Learning for Recognition

All the steps of the proposed algorithm are combined as follows:

1) For a given gallery-probe face image pair, 40 face granules are extracted from each image.
2) UCLBP or SURF features are computed for each face granule according to the evolutionary model (learned using the training data).
3) To match the corresponding features extracted from the gallery and probe images, descriptors for each face granule are first normalized. The weighted χ^2 distance measure is used to the compute the dissimilarity score. Here, the weights for each face granule are learned using the genetic approach.

$$\chi^2(a,b) = \sum_{i,j} \omega_j \frac{(a_{i,j} - b_{i,j})^2}{a_{i,j} + b_{i,j}} \tag{7}$$

where a and b are the normalized descriptors (UCLBP or SURF descriptors), i and j correspond to the i^{th} bin of the j^{th} face granule and ω_j is the weight for the j^{th} face granule.
4) In identification mode (1:N), this procedure is repeated for each gallery-probe pair and top matches are obtained based on the dissimilarity scores.

III. Experimental Results

To evaluate the performance of the proposed algorithm two different databases are used: plastic surgery face database [17] and heterogeneous non-plastic surgery database. Section III-A provides details of the databases used in this research and experimental protocol and Section III-B presents the experimental analysis.

A. Database and Experimental Protocol

In this research, publically available plastic surgery face database [17] is used. It comprises of 1800 pre-surgery and post-surgery images for 900 subjects with frontal pose, proper illumination and neutral expression. It is a real world database that consist of different types of facial plastic surgery cases. Further, to analyze the effect of plastic surgery and to obtain a ground truth for the performance of the proposed face recognition algorithm, a non-surgery heterogeneous face database of 900 subjects is used. The database is created by combining two frontal images with proper illumination and neutral expression from different publically available face databases. The heterogeneous database comprises 114 subjects from the AR database [12], 66 subjects from the CMU-PIE database [16], 661 subjects from the FERET database [14], 36 subjects from the Georgia Tech database [1] and 23 subjects from the GTAV database [2].

For each of the following experiments, five times random cross validation is performed where 40% of the database is used for training and the remaining 60% is used for testing. Training data is used to learn the model for selection of feature extractor and weights for each face granule and testing data is used to evaluate the algorithm. Three sets of experiments were performed to evaluate the performance.

1) *Experiment 1:* 1800 pre and post-surgery images pertaining to 900 subjects from the plastic surgery face database are used. Pre-surgery images are used as the gallery and the post-surgery images are used as the probe images.
2) *Experiment 2:* 1800 non-surgery images pertaining to 900 subjects from the non-surgery heterogeneous face database are used.
3) *Experiment 3:* Both plastic surgery and the non-surgery heterogeneous face databases are combined to make a comprehensive database of 3600 images pertaining to 1800 subjects. Using the same experimental protocol, 40% of the database is selected for training and the remaining 60% for testing. It is assumed that the system is completely unaware that it has been trained on any plastic surgery cases. This experiment resembles real world scenario of training-testing.

B. Experimental Results and Analysis

Fig. 6 shows the Cumulative Match Characteristics (CMC) plots pertaining to different experiments and Table I sum-

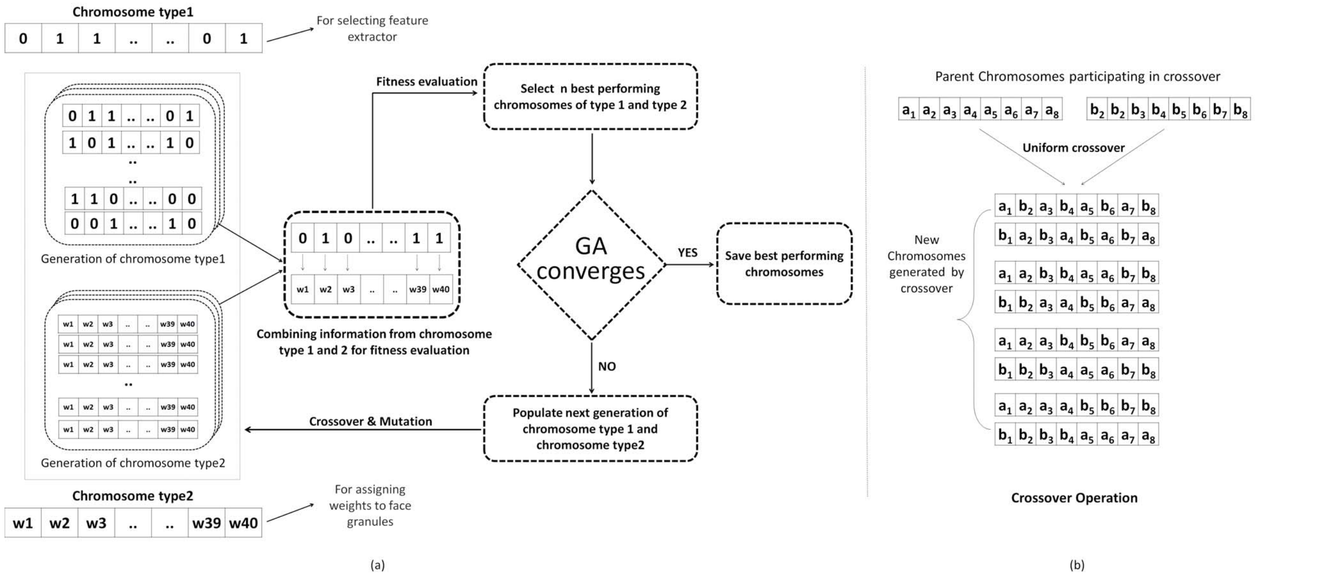

Fig. 5. (a) Genetic optimization process for selecting feature extractor and weight for each face granule, and (b) set of uniform crossover operations used in learning.

TABLE I

RANK-1 IDENTIFICATION ACCURACY OF THE PROPOSED EVOLUTIONARY GRANULAR APPROACH AND OTHER FACE RECOGNITION ALGORITHMS. IDENTIFICATION ACCURACIES AND STANDARD DEVIATIONS ARE COMPUTED WITH 5 TIMES CROSS VALIDATION.

Database	Training/Testing Images	Algorithm	Rank-1 Identification Accuracy	Standard Deviation
Plastic Surgery Face Database	360/540	UCLBP	63.05%	0.73
		SURF	51.35%	1.08
		Granular UCLBP	67.11%	0.64
		Granular SURF	50.16%	1.33
		Sum Rule Fusion	70.05%	0.78
		Proposed	**78.61**%	0.68
Non-surgery Heterogeneous Face Database	360/540	UCLBP	74.61%	0.84
		SURF	77.88%	1.01
		Granular UCLBP	77.80%	0.52
		Granular SURF	75.00%	0.94
		Sum Rule Fusion	80.55%	0.68
		Proposed	**84.44**%	0.61
Combined Face Database	720/1080	UCLBP	69.83%	0.78
		SURF	65.08%	1.28
		Granular UCLBP	72.75%	0.68
		Granular SURF	62.02%	2.03
		Sum Rule Fusion	74.38%	1.06
		Proposed	**78.19**%	0.82

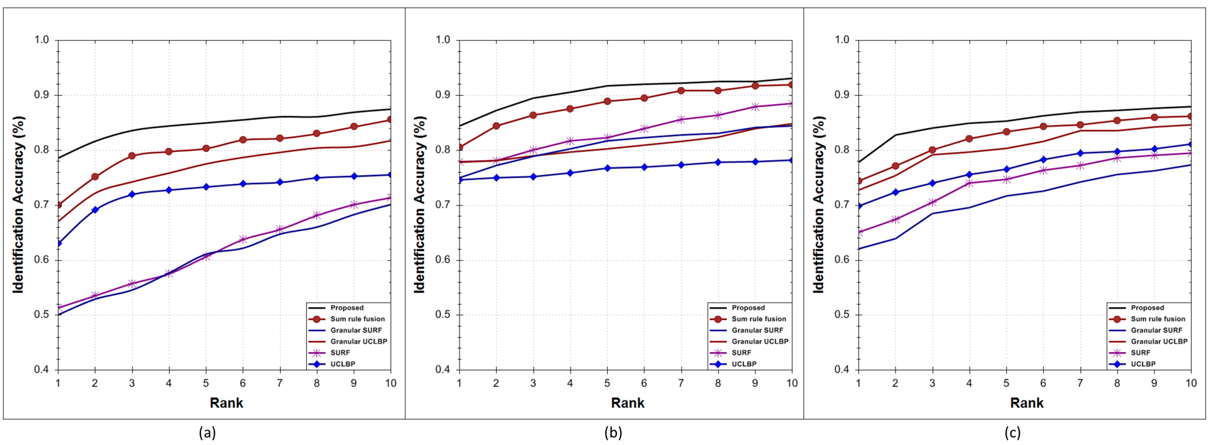

Fig. 6. CMC curves for the proposed and existing algorithms on face databases: (a) Plastic surgery, (b) Non-surgery heterogeneous, and (c) Combined.

marizes the identification accuracies. The key results and analysis are listed below:

- The CMC in Fig. 6 shows rank 1 identification accuracy of all the algorithms. The proposed granular approach with evolutionary learning outperforms existing algorithms in all three experiments. The proposed algorithm yields rank 1 identification accuracy of 78.6% on the plastic surgery face database [17]. On the other hand, the proposed algorithm gives rank 1 identification accuracy of 84.4% on the heterogeneous face database and 78.19% on the combined database.
- We compare the performance of UCLBP when it is applied on full face and when it is applied on face granules. Results show that, by applying UCLBP on face granules, the rank 1 accuracy is improved by $4-5\%$ as compared to UCLBP applied on a full face image only. This improvement in recognition accuracy can be attributed to the discriminating information obtained from face granules varying in size and resolution.
- Performance of SURF [6], [9], on the other hand, reduces when applied on face granules. The reduction in performance can be attributed to the small size of several face granules where SURF is not able to find the interest points. These small face granules may not have discriminating SURF interest points but may have very discriminating information that can be exploited by UCLBP descriptor.
- To show the efficacy of evolutionary approach for selecting feature extractor and weight optimization using genetic algorithm, it is compared with Sum Rule Fusion [15] of SURF and UCLBP on face granules. The proposed method significantly outperforms the sum rule fusion on all three databases.
- Evolutionary approach for selecting feature extractor using genetic algorithm provides the benefit of choosing better performing feature extractor for each face granule. It is observed that, in all the experiments, out of 26 possible cases for selection of feature extractor, SURF was selected for 14 face granules while UCLBP was selected for 12 face granules. For the 14 small-sized face granules, UCLBP was fixed as the feature extractor.
- Experimental results strengthen our assertion that local information based approaches such as face granules can handle the variations introduced by plastic surgery procedures. The ability to encode local features at different resolution and size allows the proposed algorithm to be resilient to such non linear variations.

IV. CONCLUSIONS

Generally, face recognition systems and algorithms are designed to recognize faces of cooperative individuals in a controlled environment. However, it becomes a challenging problem when faces are altered using plastic surgery procedures. In this research, we proposed an evolutionary granular approach for matching surgically altered face images. The proposed algorithm utilizes the observation that human mind recognizes face image by analyzing the relation among non-disjoint spatial features extracted at different granular levels. The evolutionary approach for selecting the most appropriate feature extractor and associated weights allows switching between two feature extractors (SURF and UCLBP) that help in encoding discriminating information conforming to the content of each face granule. The performance is evaluated on different face databases and the proposed evolutionary granular algorithm outperforms existing face recognition algorithms.

V. ACKNOWLEDGMENTS

Authors are thankful to A. Martinez, F. Tarrs, P.J. Philips, T. Sim and A.V. Nefian for providing the face databases used in this research.

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