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Detecting Surgically Altered Face Images Using CS-LBP and Genetic Algorithm

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Abstract*— In recent years, plastic surgery has become popular world wide. People take facial plastic surgery to correct feature defects or improve attractiveness and confidence. It has been observed that many face recognition algorithms fail to recognize faces after plastic surgery, which thus poses a new challenge to automatic face recognition. 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. The proposed method presents an evolutionary granular computing based algorithm for recognizing faces altered due to plastic surgery procedures. The proposed algorithm starts with generating non-disjoint face granules where each granule represents different information at different size and resolution. Further, feature extractor named center-symmetric local binary pattern (CS-LBP) descriptor is used for extracting discriminating information from each face granules. Finally, different responses are unified in an evolutionary manner using a genetic approach for improved performance. Experimental results demonstrate that the proposed system performs very well. It meets the response time as well as the accuracy requirements.

***Keywords*— Face Recognition, Feature Extraction, Plastic Surgery, Genetic Algorithm .**

I. INTRODUCTION

A facial recognition system is a computer application for automatically verifying or identifying a person from a digital image or a video frame from a video source. It is often used in security systems. There are many difficulties during face recognition such as changes in illumination, head rotation, age-related changes and others. However, due to advances in technology, there are new emerging challenges for which the performance of face recognition systems degrades and plastic surgery is one of them. Plastic surgery is a sophisticated operational technique that is used across the world for improving the facial appearance. For instance to remove acne scars, to become white, to remove dark circles and many more. Plastic surgery can be broadly classified in two different categories such as global plastic surgery and local plastic surgery [3]. Global surgery changes the complete facial structure whereas in local plastic surgery certain parts of faces are changed.

To recognize a face after plastic surgery might lead to rejection of genuine users or acceptance of impostors. These procedures amend the facial features and skin texture thereby providing a makeover in the appearance of face. The nonlinear variation introduced by plastic surgery remains difficult to be modeled by existing face recognition systems. Transmuting facial geometry and texture increases the intra-class variability between the pre-surgery 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. 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 non uniform face transformations. On the other hand, disguise is the process of concealing ones 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.

II. GRANULAR COMPUTING APPROACH FOR FACE RECOGNITION

An Here presents an evolutionary granular computing based algorithm [1] for recognizing faces altered due to plastic surgery procedures. However, the nonlinear variations introduced by plastic surgery remain difficult to be modeled by existing face recognition systems. The proposed algorithm starts with generating non-disjoint face granules where each granule represents different information at different size and resolution. First, feature extractor, named Center symmetric Local Binary Pattern (CS-LBP) [2] and it is used for extracting discriminating information from face granules. Finally, different responses are unified in an evolutionary manner using a genetic approach for improved performance. The proposed algorithm yields high identification accuracy as compared to existing algorithms and a commercial face recognition system.

In the granular approach, as shown in Figure 1, non-disjoint features are extracted at different granular levels. These features are then synergistically combined using evolutionary learning approach 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.

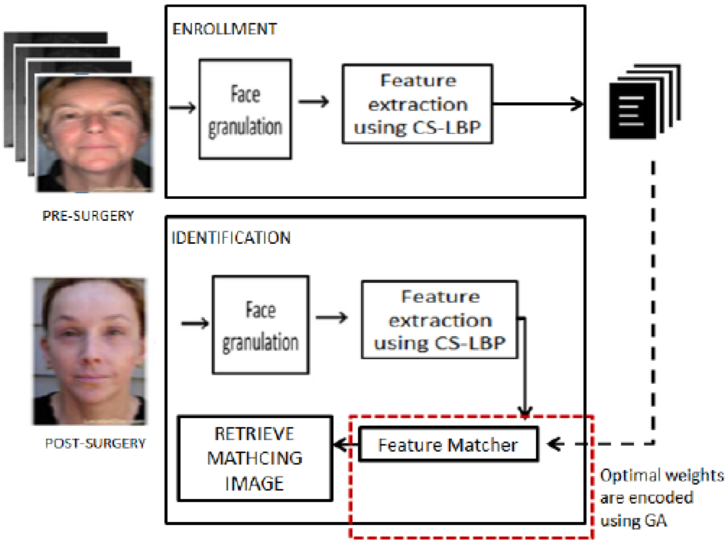

Fig. 1. Block diagram illustrating different stages of the proposed algorithm.

The face granulation scheme proposed in this research helps in analysing multiple features simultaneously. Moreover, the face granules of different sizes and shapes help to gain significant insights about the effect of plastic surgery procedures on different facial features and their neighbouring regions. CS-LBP features are computed for each face granules of all pre-surgery images in the database. Weights of each granule are learned using genetic algorithm. Extracted descriptors can be precomputed and stored in a file. During identification, for a given post-surgery image non-disjoint features are extracted at different granular levels. Then extract CS-LBP feature for each granules. Matching is performed by calculating the weighted Chi-Square distance between the extracted descriptors of post-surgery image with stored features of pre-surgery images. Finally retrieve the matching image corresponding to the given post-surgery image from the database.

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. 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, here propose an evolutionary granular computing based algorithm for recognizing faces. 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 analysing underlying information such as nose, ears, forehead, cheeks, or combination of two or more features.

A. Face Image Granulation

Let F be the detected frontal face image of size n x m. Face granules are generated pertaining to three different levels of granularity [1]. The first level of granularity provides global information at multiple levels of resolution. This is analogous to a human mind processing holistic information for face recognition at varying resolutions. 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 Granularity: In Final Stage face granules are generated by applying the Gaussian and Laplacian operators, 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 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.

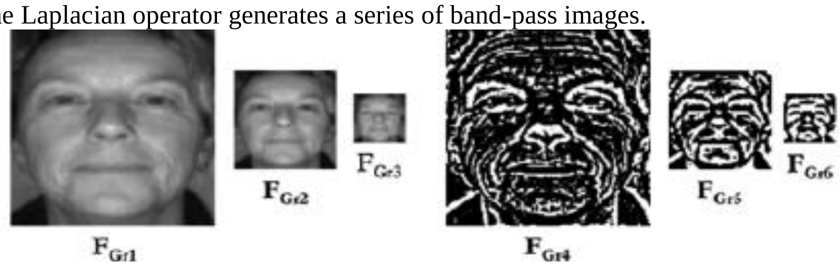

Fig. 2. Face granules in the first level of granularity.

Let the face granules generated by Gaussian and Laplacian operators be represented by FGri, where i represents the granule number. For a face image of size 196 x 224, Figure 2 represents the face granules generated in the first level by applying Gaussian and Laplacian operators. FGr1 to FGr3 are the granules generated by Gaussian operator and FGr4 to FGr6 are the granules generated by Laplacian operator. The size of the smallest granule in the first level is 49 x 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. 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: In the second level of granularity, horizontal and vertical granules are generated by dividing the face image F into different regions as shown in Figure 2 and 3. Here, FGr7 to FGr15 denote the horizontal granules and FGr16 to FGr24 denote the vertical granules. Among the nine horizontal granules, the first three granules i.e. FGr7, FGr8, and FGr7 have the same size (n x m/3). The next three granules, i.e., FGr10, FGr11, and FGr12 are generated such that the size of FGr10 and FGr12 is n x (m/3 - ϵ) and the size of FGr11 is n x (m/3 + 2ϵ). Further, FGr13, FGr14, and FGr15 are generated such that the size of FGr13 and FGr15 is n x (m/3 + ϵ) and the size of FGr14 is n x (m/3 - 2ϵ). Similarly, nine vertical granules FGr16 to FGr24 are generated. This level of granularity provides resilience to variations in different inner and outer facial regions. Figure 3 and Figure 4 show horizontal and vertical granules when the size of face image is 196 x 224.

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

Fig. 4. Horizontall face granules from the second level of granularity

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: 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 .The proposed granulation technique is used to generate 40 non-disjoint face granules from a face image of size 196 x 224.

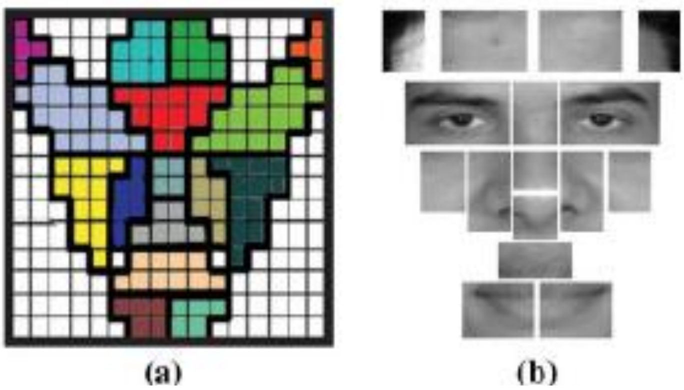

Figure Fig. 5. (a) Golden ratio face template, (b) face granules from third level of granularity.

In figure 5(a), Each of these fragments is a granule representing local information that provides unique features for handling variations due to plastic surgery. Figure 5(b) shows an example of local facial fragments used as face granules in the third level of granularity. Here, the technique is based on fixed structure and no local feature based approach is used for generating granules from frontal face images. Three levels of granularity are designed to address specific variations introduced in local facial regions by different plastic surgery procedures.

B. Facial Feature Extraction

The center-symmetric local binary pattern (CS-LBP) descriptor [2][9], is a new descriptor has several advantages such as tolerance to illumination changes, robustness on _at image areas, and computational efficiency. A good region descriptor can tolerate illumination changes, image noise, image blur, image compression, and small perspective distortions, while preserving distinctiveness. In a recent comparative study the best results were reported for the SIFT-based descriptors. The local binary pattern (LBP) texture operator, on the other hand, has been highly successful for various problems, but it has so far not been used for describing interest regions. The gradient features used by SIFT are replaced with features extracted by a center symmetric local binary pattern (CS-LBP) operator similar to the LBP operator. The CS-LBP descriptor performs significantly better than SIFT for structured scenes, while the difference for textured scenes is smaller.

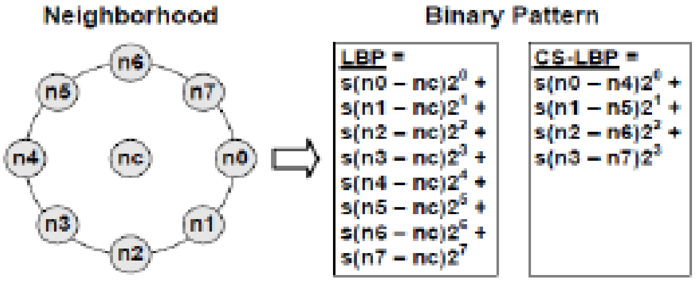

Fig. 6. LBP and CS-LBP features for a neighborhood of 8 pixels.

Center-Symmetric Local Binary Pattern Descriptor (CS-LBP): Which combines the strengths of the well-known SIFT descriptor and the LBP texture operator. The following section provides details on the interest region descriptor CS-LBP.

1). Region Preprocessing: first filter the region with an edge-preserving adaptive noise removal filter. The edge-preserving nature of the filter is essential for good performance, since much of the information comes from edges and other high-frequency parts of a region. Experiments have shown that this filtering improves the performance on average around 5 percent (depending on the test images), and therefore all the experiments presented in this work. Furthermore, the region data is scaled between 0 and 1 such that 1 % of the data is saturated at the low and high intensities of the region. This increases the contrast of the region.

2). Feature Extraction with Center-Symmetric Local Binary Patterns: After preprocessing, extract a feature for each pixel of the region using the center-symmetric local binary pattern (CS-LBP) operator which was inspired by the local binary patterns (LBP). The LBP operator produces rather long histograms and is therefore difficult to use in the context of a region descriptor. To produce more compact binary patterns, compare only center-symmetric pairs of pixels, see Figure 6,here for 8 neighbors, LBP produces 256 different binary patterns, whereas for CS-LBP this number is only 16. Furthermore, robustness on at image regions is obtained by thresholding the gray level differences with a small value T. The value of the threshold T is 1data lies between 0 and 1, T is set to 0.01. The radius is set to 2 and the size of the neighborhood is 8. All the experiments presented in this paper, except the parameter evaluation, are carried out for these parameters (CS-LBP2;8;0:01) which gave the best overall performance for the given test data. It should be noted that the gain of CS-LBP over LBP is not only due to the dimensionality reduction, but also to the fact that the CS-LBP captures better the gradient information than the basic LBP. Experiments with LBP and CS-LBP have shown the benefits of the CS-LBP over the LBP, in particular, significant reduction in dimensionality while preserving distinctiveness.

3). Feature Weighting: Different ways of weighting the features are possible. For example, in the case of SIFT, the bins of the gradient orientation histograms are incremented with Gaussian-weighted gradient magnitudes. A comparison of different weighting strategies, including the SIFT-like weighting, showed that simple uniform weighting is the most suitable choice for the CS-LBP features. This is, of course, good news, as it makes this descriptor computationally very simple.

4). Descriptor Construction: In order to incorporate spatial information into our descriptor, the region is divided into cells with a location grid. The experiments showed that a Cartesian grid seems to be the most suitable choice. For the experiments presented in this work, selected a 4 x 4 Cartesian grid. For each cell a CS-LBP histogram is built. In order to avoid boundary effects in which the descriptor abruptly changes as a feature shifts from one histogram bin to another, a bilinear interpolation is used to distributed the weight of each feature into adjacent histogram bins. The resulting descriptor is a 3D histogram of CSLBP feature locations and values. As explained earlier, the number of different feature values depends on the neighborhood size of the chosen CS-LBP operator.

5). Descriptor Normalization: The final descriptor is built by concatenating the feature histograms computed for the cells to form a (4 x 4 x 16) 256-dimensional vector. The descriptor is then normalized to unit length. The influence of very large descriptor elements is reduced by thresholding each element to be no larger than 0.2. This means that the distribution of CS-LBP features has greater emphasis than individual large values. Finally, the descriptor is renormalized to unit length.

C. Genetic Algorithm for Weight Optimization

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) [6] are well proven in searching very large spaces to quickly converge to the near optimal solution. Genetic algorithms are a family of computational models belonging to the class of evolutionary algorithms, part of artificial intelligence These algorithms encode a potential solution to a specific problem on a simple chromosome like data structure Uses techniques inspired by natural evolution such as inheritance, mutation, selection and crossover They are often viewed as function optimizers. Terminology:

- Search space/ State space: the space of all feasible solutions.
- Chromosome: a set of genes, a chromosome contains the solution in form of genes.
- Population: a set of solutions (or individuals/chromosomes).
- Generation: the process of evaluation, selection, recombination and mutation.
- Fitness: the value assigned to an individual based on how far or close it is from the solution, greater the fitness value better the solution it contains.

Genetic Encoding: A chromosome is a string whose length is equal to the number of tessellated facial regions. Each unit in the chromosome is a real valued number associated with the corresponding weight of the facial region.

Initial Population: Each generation is populated with 100 chromosomes. In general, the initial population is generated randomly, but for quick convergence in face recognition, weights proportionate to the identification accuracy of each region are used as initial chromosomes. The remaining 99 chromosomes are generated by randomly changing one or more units in the initial chromosome. The weights are normalized such that sum of all weights in a chromosome is 1.

Fitness Function: Each individual chromosome in a generation is a possible solution. To evaluate its effectiveness, recognition is done using the weights encoded by the individual chromosome and weighted Chi square distance measure. Identification accuracy is computed on a training set and 10 best performing chromosomes are selected for mutation to populate the next generation.

Mutation : From best performing chromosomes, again populate a new generation of chromosomes by changing one or more weights by a factor of its standard deviation in the previous best generation. The search process is repeated till convergence, i.e. till the identification accuracy for new generation does not improve. At this point, weights pertaining to the best performing chromosome (i.e. chromosome giving best recognition accuracy on the training data) are used for testing.

Thus, genetic algorithm ends optimal weights for each facial region. It also enables to discard redundant and non discriminating regions whose contribution towards recognition accuracy is very low (i.e. the weight for that region is 0). This leads to dimensionality reduction and better computational efficiency because then do not need to compute texture descriptors for poor performing facial regions during testing.

D. Feature Matching

The descriptors extracted from the given post-surgery image with stored features of post-surgery images are matched using weighted χ^2 distance measure.

E. Retrieve Matching Image From Database

Based on the feature matching performed in the previous step, retrieve image corresponds to the given post-surgery image. Retrieval is performed by considering the distance measure computed. For an image with minimum distance measure will gives the most similar image.

III. PERFORMANCE EVALUATION

The proposed plastic surgery mechanism has been evaluated and compared with an existing surgery detection method in the same scenario. The objective is to evaluate the execution time and accuracy using the proposed technique with respect to a database of surgically altered face images and the corresponding pre-surgery images. All the experiments were conducted on an Intel Core 2.40 GHz PC with 6 GB of memory. All the algorithms were implemented using MATLAB 2012 (64 bit).

Analyzing Computation Time to Solve GA

An analysis is made to check if the proposed method is able to reduce the overall computation time caused by executing genetic algorithm and feature extraction method. Evaluate how much time required for the method to solve genetic algorithm with a given dataset of images. Figure 7 shows how much the execution time is reduced using the proposed method as compared to the existing multiobjective plastic surgery detection method. In figure 7, time required for solving genetic algorithm is represented using different input images.

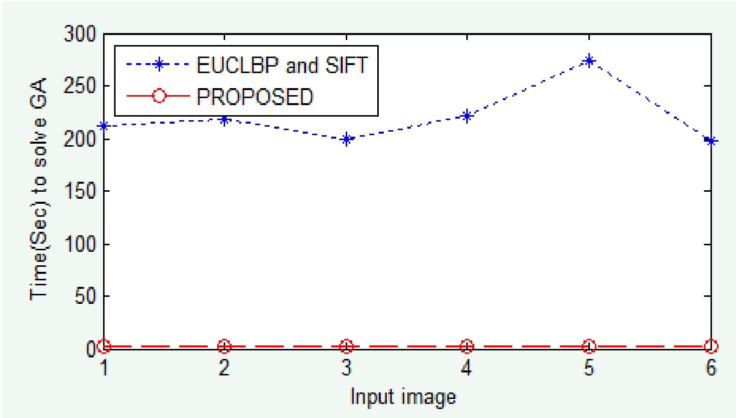

Fig. 7. Comparison of execution time to solve genetic algorithm

A. Analyzing Computation Time to Perform Feature Extraction

An analysis is made on how much time is required for the method to perform feature extraction with a given dataset of images. Figure 8 shows how much the execution time is reduced using the proposed method as compared to the existing multiobjective plastic surgery detection method. In this figure, time required for performing feature extraction is represented using different input images.

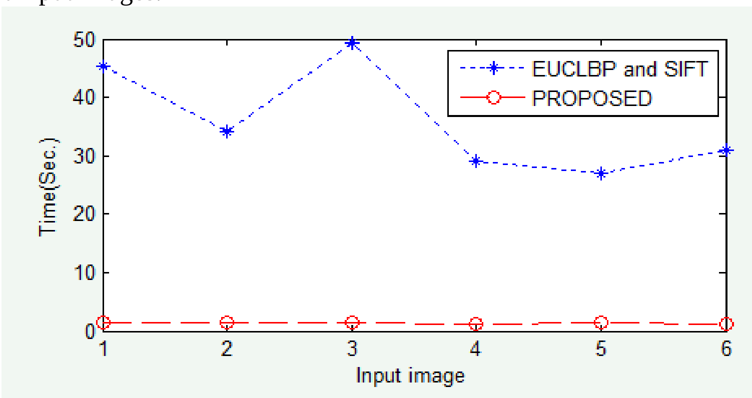

Fig.8. Comparison of execution time to perform feature extraction

B. Accuracy Analysis

The identification accuracy of the proposed method as well as of the existing method was examined by setting different threshold values. The evaluation criterion is based on the number of correct and false matches between a pair of images in the database. The definition of a match depends on the weighted Chi square distance measure. A match is assumed to be correct if the distance measure is less than that of the predefined threshold value. A descriptor can have several matches and several of them may be correct. The results are presented with identification accuracy versus threshold.

$$\text{Accuracy (\%)} = \frac{Number\ \ of\ Correctly\ \ Classified\ \ Images}{Total\ \ Number\ \ of\ Images\ \ Tested}\ X\ 100 \qquad (1)$$

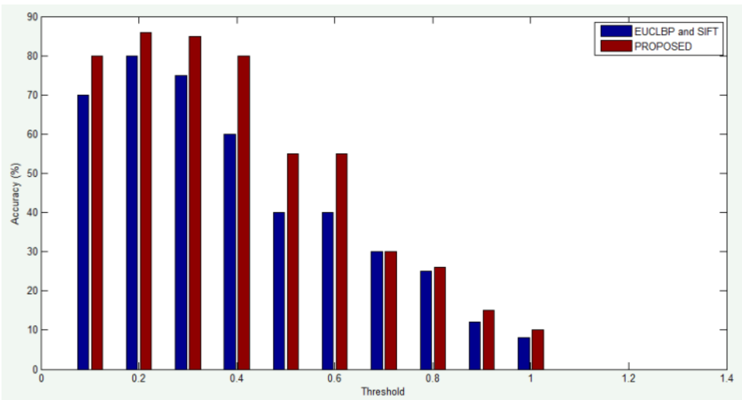

Fig. 9. Comparison of Accuracy Versus Threshold

Figure 9 indicates the identification accuracy of the proposed system along with the existing surgery detection method. This proves that both of the methods yield more beneficial outcomes for a threshold value of 0.2. Among them the proposed algorithm outperforms the existing algorithm by at least 6.22%.

IV. CONCLUSIONS

The proposed method presents an efficient face recognition algorithm for surgically altered face images. The proposed method takes original images as input and found the face recognition with surgical images. This research presents an evolutionary granular algorithm that operates on several granules extracted from a face image. The proposed method starts with generating non-disjoint face granules pretaining to three levels of granularity. 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 in to horizontal and vertical face granules of varying size and information content. The third level of granularity extracts discriminating information from local facial regions. Further, genetic algorithm is proposed for weight optimization 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. The proposed method is compared with EUCLBP and SIFT based multiobjective evolutionary surgery detection algorithm [1]. The experiments show that the proposed method effectively detects surgically altered face images within fraction of time.

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