Genetic Approach based Recognizing Surgically Altered Face Images for Real Time Security Application

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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 work, 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.

Keywords: Face Recognition, Genetic Approach, Plastic Surgery, Granular computing.

I. INTRODUCTION

An overview of 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. Several part based face recognition approaches capture this observation for improved performance. An approach proposed a component based face recognition approach using different facial components to provide robustness to pose. That designed an algorithm in which gray-level pixel values from several facial components were concatenated and classification was performed using SVM. Similarly, an approach proposed where local patches were extracted from different levels of Gaussian pyramid and arrange Dina exemplar manner.

Faces are recognized using a combination of holistic approaches together with discrete levels of information (or features). 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. An approach 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.

In the granular approach, non-disjoint features are extracted at different granular levels. 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 help to gain significant insights about the effect of plastic surgery procedures on different facial features and their neighbouring regions.

II. MULTI OBJECTIVE EVOLUTIONARY GRANULAR ALGORITHM FOR FACE RECOGNITION

A. *Data Read:*

The surgery and non surgery data are read and obtain basic interference elimination in that raw data using basic detectors.

B. *Granularity Modules:*

The face granularities are obtained using Gaussian operator with both cases like vertical and horizontal granularities with respect to face objects.

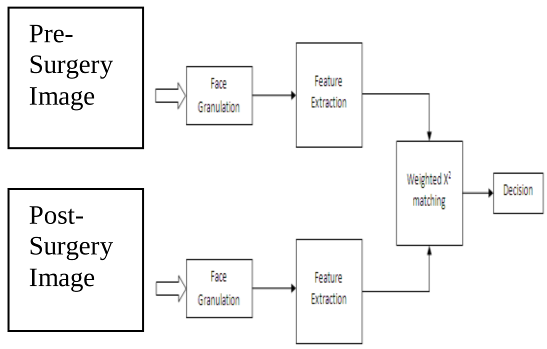


Fig.2: Block diagram of different Stages in proposed algorithm.

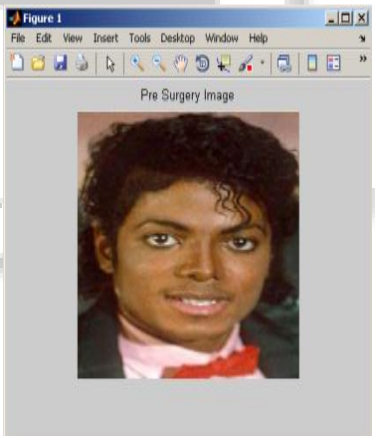
In third level, the face is applied in granularity based on pixel positions with respect to horizontal and vertical wise.
Feature Extraction**:** Various features of face obtained from granulations with SIFT and binary patterns extractions. Based on that features only the face recognition is obtained.
Matching Modules & Decision Modules**:** In this module, the features are matched with both surgery and non surgery data sets. Then using Multi objective evolutionary algorithm (basis of genetic algorithm) decision will obtained.

C. Face Image Granulation

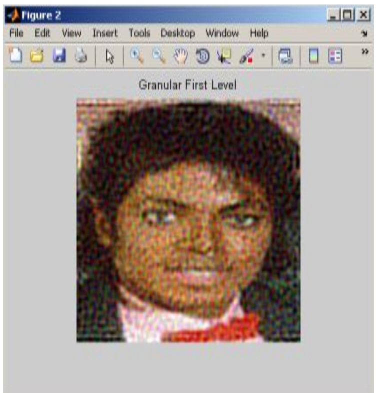
Let the function will detect the frontal face image of size. Face granules are generated pertaining to three levels of granularity. The first level provides global information at multiple resolutions. This is analogous to a human mind processing holistic information for face recognition at varying resolutions. Next, to incorporate the findings of, 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 operator. 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.

1) First Level Of Granularity

In first level, face granules are generated using Gaussian operators. 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.



(a)



(b)

Fig. 1: (a) Input of Pre Surgery Image and (b) Granular First Level

In this fig. 1(a) original image before surgery is given as input data. Then, first granulation technique is performed i.e. Gaussian operator is used in original image for uniform distribution as shown in fig. 1(b).

2) Second Level Of Graularity

Horizontal and vertical granules are generated by dividing the face image into different regions.

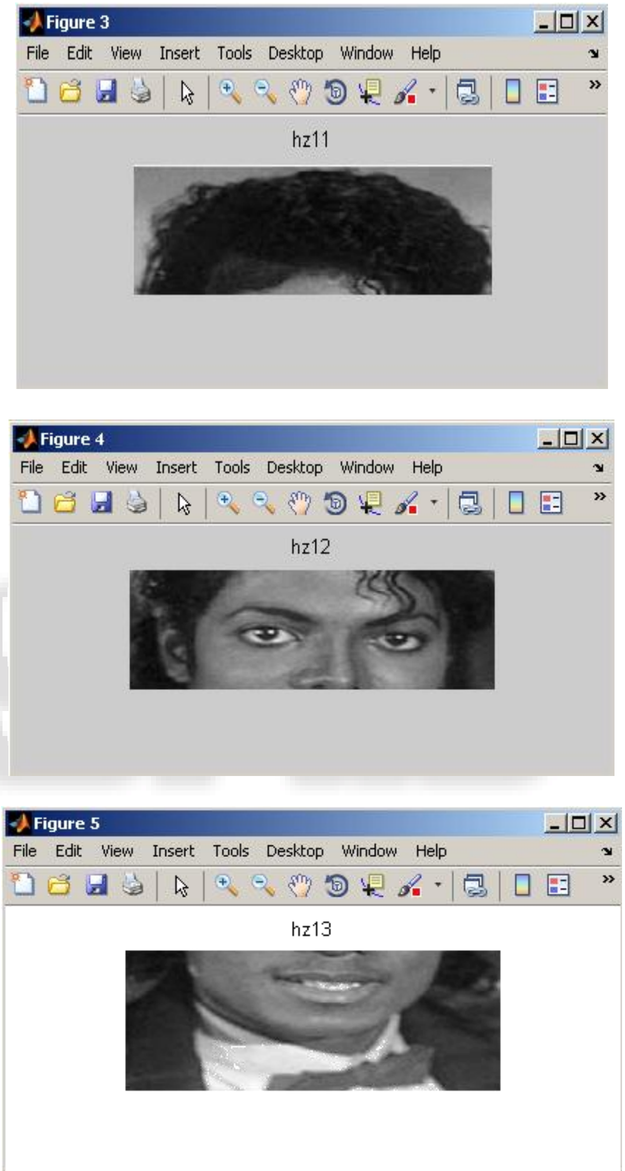


Fig. 2 : Horizontal Face Granules from Second Level of granularity (hz11-hz13)

Horizontal granules are generated by dividing the face image into different regions as shown in Figs. 2.1.2. Here hz11 to hz33 denote horizontal granules. Among the nine horizontal granules, the first three granules i.e. hz11, hz12 and hz13 are of size n × m/3. Like this the next three granules, i.e. hz21, hz22 and hz23 are generated such that the size of hz21 and hz22 is n × (m/3-ϵ) and the size of hz23 is n × (m/3+2ϵ) (hz21-hz23). Further, hz31, hz32 and hz33 are generated such that the size of hz31 and hz33 is n × (m/3+ϵ) and the size of hz32 is n × (m/3-2ϵ) of (hz31-hz33).

Fig. 3: Vertical Face granules from second level of graularity(vz11-vz13)

Vertical granules such as vz11 to vz13 as shown in fig. 2.1.3 are also generated in similar manner. Like this pre and post surgical faces are granulated in ter two different sizesfrom vz21 to vz33.

D. 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. Efficiently the information is assimilated from local regions and forms 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).

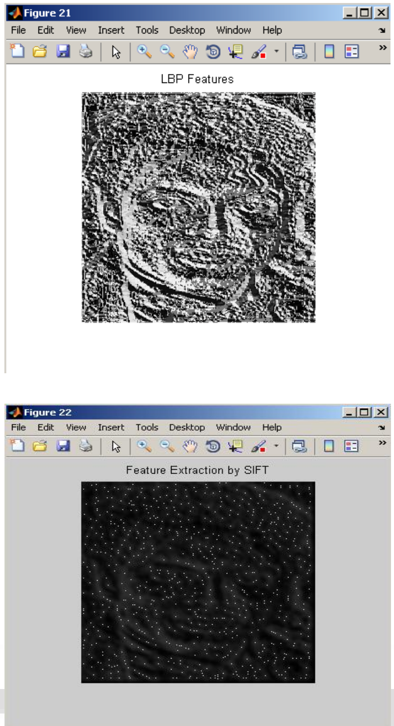


Fig. 4: LBP and SIFT Feature Extraction for Pre Surgery image

In this fig. 4 by using LBP and SIFT feature the pre surgery image is generated based on pixel position with respect to horizontal and vertical granules. SIFT 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 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.

III. RELATED WORKS

As reviewed in [1] G. Aggarwal, S. Biswas, Plastic surgery procedures can significantly alter facial appearance, thereby posing a serious challenge even to the state-of-the-art face matching algorithms. In this work, a novel approach is proposed to address the challenges involved in automatic matching of faces across plastic surgery variations. In the proposed formulation, part wise facial characterization is combined with the recently popular sparse representation approach to address these challenges. The sparse representation approach requires several images per subject in the gallery to function effectively which is often not available in several use-cases, as the problem is addressed in this work. The proposed formulation utilizes images from sequestered non-gallery subjects with similar local facial characteristics to fulfill this requirement. Extensive experiments conducted on a recently introduced plastic surgery database consisting of 900 subjects highlight the effectiveness of the proposed approach.

As reviewed in [4] H. S. Bhatt, S. Bharadwaj, This work presents an efficient algorithm for matching sketches with digital face images. The algorithm extracts discriminating information present in local facial regions at different levels of granularity. Both sketches and digital images are decomposed into multi-resolution pyramid to conserve high frequency information which forms the discriminating facial patterns. Extended uniform circular local binary pattern based descriptors use these patterns to form a unique signature of the face image. Further, for matching, a genetic optimization based approach is proposed to find the optimum weights corresponding to each facial region. The information obtained from different levels of Laplacian pyramid is combined to improve the identification accuracy. Experimental results on sketch-digital image pairs from the databases that show the proposed algorithm can provide better identification performance compared to existing algorithms.

As reviewed in [6] B. Gökberk, M. O. Irfanoglu, A novel is proposed, local feature-based face representation method based on two-stage subset selection where the first stage finds the informative regions and the second stage finds the discriminative features in those locations. The key motivation is to learn the most discriminative regions of a human face and the features in there for person identification, instead of assuming a priori any regions of saliency. The subset selection-based formulation is used and compares three variants of feature selection and genetic algorithms for this purpose. Experiments on frontal face images taken from the FERET dataset confirm the advantage of the proposed approach in terms of high accuracy and significantly reduced dimensionality.

IV. RESULTS

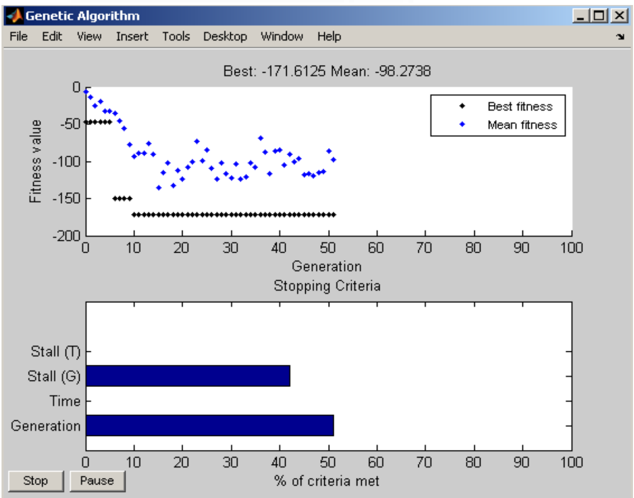


Fig. 5: Decision making for pre and post surgical images

In this fig. 5. genetic algorithm is used to match both pre and post surgery data. It displays the fitness value that represents the value of maximum matching pixel in both data. It also display the percentage of criteria met.

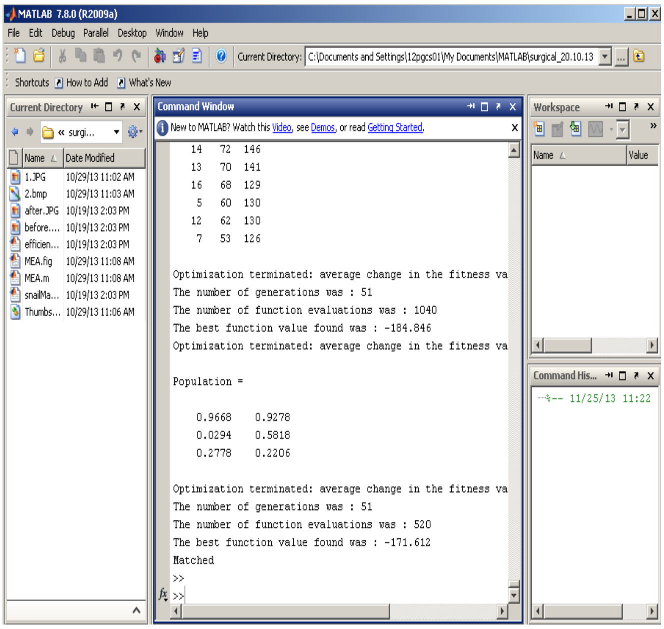


Fig. 6: Matched values of both images

The matched values are shown in fig. 6. that displays the threshold values of both data and maximum fitness values. Then a decision is made that both pre and post surgery images are matched.

V. CONCLUSIONS

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 operators to assimilate in- formation 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. In Future, the features of face is evaluated with classifier like Neural Network classifier to improve the authentication, accuracy and to reduce the execution time for processing.

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