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Sparse Representation Approach on Surgically Altered Face Images Using Evolutionary Algorithm

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Abstract:
Face recognition algorithms have undergone a lot of improvements in the last few years. Even so scope of further improvement is extremely high since current authentication/identification applications are limited to controlled settings, e.g., limited pose and illumination changes, with the user usually aware of being screened and collaborating in the process. Among others, pose and illumination changes are limited. This paper dealt with Multi-objective evolutionary granular algorithm with the aim of recognizing faces even after a surgical procedure, or also in the presence of any variation in appearance, texture and structural geometry.

***Keywords*:** Granular algorithm, Facial recognition, skin disorders.

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

2. Literature Review

De Marsico et al developed an approach to integrate information derived from local regions to match pre- and post-surgery face images where the focus was also on recognizing faces under uncontrolled circumstances like pose and illumination variations. Recently, Aggarwal et al proposed sparse representation approach on local facial fragments to match surgically altered face images. This technique matches an image of a face by comparing it with combinations of individual features from faces already recorded in a database. If the closest matching combination turns out to be made up of features mostly drawn from one person in the database, it is a good bet to say the target image is also of that person. But if the best match combines features pulled from images of many different people then the system has failed to identify the new face. However, to work properly sparse representation requires multiple images of each person in the database, so it does not work with pairs of before and after surgery pictures alone. To overcome this, they used two databases: a general one full of random faces and another containing all of the before surgery pictures. When a target's after surgery picture is analysed, a composite picture as similar as possible is created from the features of people in the general database. All of the before surgery pictures undergo the same process. If the composite picture created using the after-surgery picture matches closely with any of the composite pictures derived from the before surgery pictures, the two are declared a match. The team found that while surgery changes the appearance of a face, many individual features stay the same, and matching based on the nose or eyes alone was actually more accurate than some existing whole-face techniques.

Heisele et al proposed a component based face recognition approach. The main idea of component-based recognition is to compensate for pose changes by allowing a flexible geometrical relation between the components in the classification stage using different facial components to provide robustness to pose. Two global approaches and a component-based approach to face recognition were proposed. It is a system for pose and illumination invariant face recognition that combines 3D morphable models and component-based recognition. A 3D morphable model is used to compute 3D face models from three input images of each subject in the training database. The 3D models are rendered under varying pose and illumination conditions to build a large set of synthetic images. These images are then used for training a

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component-based face recognition system. The face recognition module is preceded by a fast hierarchical face detector resulting in a system that can detect and identify faces in video images as well. Weyrauch et al 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.* 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. This method is proposed to identify the discriminative facial areas for face recognition. Unlike the existing methods that only analyse the given face; the proposed method identifies the distinctive areas of each individual's face by its comparison to the general population. In particular, non-negative matrix factorization (NMF) is extended to learn a localized non-overlapping subspace representation of the facial patterns from a generic face image database. In the learned subspace, the degree of distinctiveness for any facial area is measured depends on the probability of this area is belong to a general face. In another approach, a subset selection mechanism was proposed where the most informative local facial locations were used in decision making. It gives a 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 most discriminative regions of a human face are studied for person identification, instead of assuming a priority for any regions of saliency. The subset selection-based formulation is used to compare three variants of feature selection and genetic algorithms are implemented for this purpose.

3. Methodology:

This paper presents a multi objective 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, two feature extractors, namely Extended Uniform Circular Local Binary Pattern (EUCLBP) and Scale Invariant Feature Transform (SIFT), are used for extracting discriminating information from face granules. Finally, different responses are unified in an evolutionary manner using a multi objective 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.

In modern sciences and technologies, images also gain much broad scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance. Two methods used for Image Processing are Analog and Digital Image Processing. Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst. Association is another important tool in image processing through visual techniques. So analysts apply a combination of personal knowledge and collateral data to image processing. Digital Processing techniques help in manipulation of the digital images by using computers. As raw data from imaging sensors from satellite platform contains deficiencies. To get over such flaws and to get originality of information, it has to undergo various phases of processing. The three general phases that all types of data have to undergo while using digital technique are Pre-processing, enhancement and display, information extraction. It is shown in fig 1.

The purpose of image processing is divided into 5 groups. They are:

- Visualization - Observe the objects that are not visible.
- Image sharpening and restoration - To create a better image.
- Image retrieval - Seek for the image of interest.
- Measurement of pattern – Measures various objects in an image.
- Image Recognition – Distinguish the objects in an image.

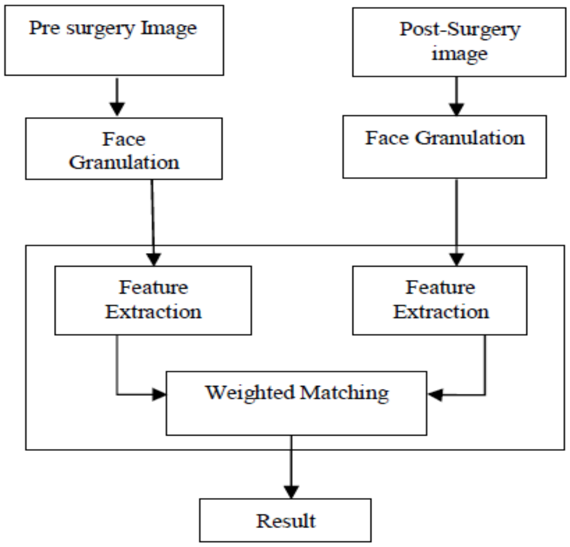

Fig 1 Flow chart of the system.

4. PROPOSED SYSTEM

This research presents a multi-objective evolutionary granular computing based algorithm for recognizing faces altered due to plastic surgery procedures. As shown below 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) and Scale Invariant Feature Transform (SIFT), are used for extracting discriminating information from face granules. Finally, different responses are unified in an evolutionary manner using a multi-objective genetic approach for improved performance.

4.1 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 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) and sequential floating forward selection (SFFS) 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) 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. Therefore, a multi- objective genetic algorithm is proposed to incorporate feature selection and weight optimization for each face granule. Fig. 2 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 type 1) and (ii) for assigning weights to each face granule (referred to as chromosome type 2). Each gene (unit) in chromosome type 1 is a binary bit 0 or 1 where 0 represents the SIFT feature extractor and 1 represents the

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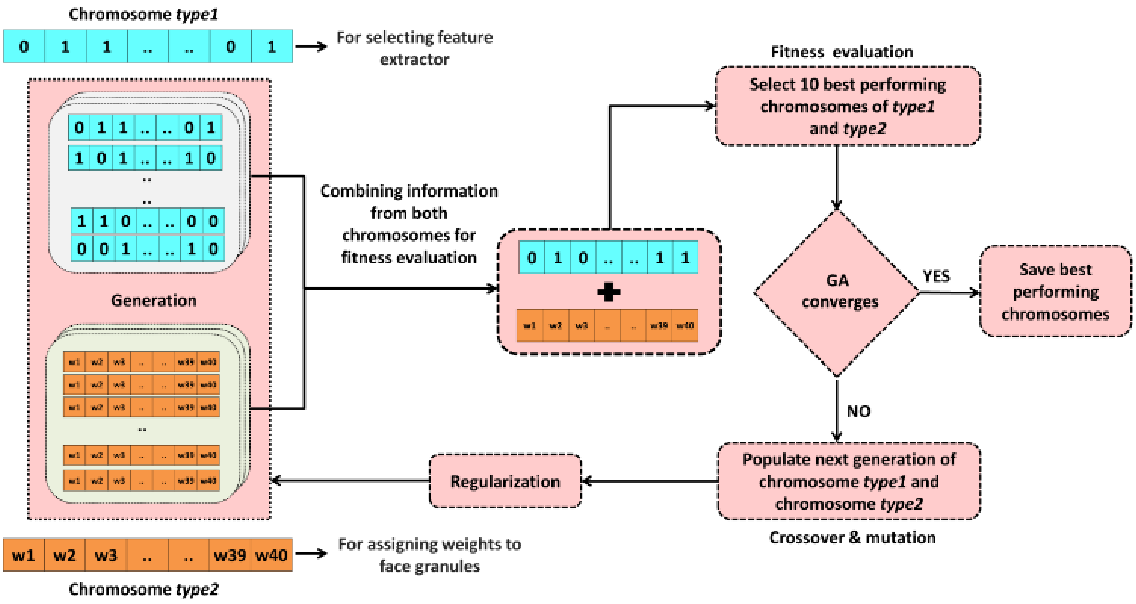

Fig 2 Genetic optimization process for selecting feature extractor and weight for each face granule.

EUCLBP feature extractor. Genes in chromosome type 2 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 type 1 chromosomes while the other generation has all type chromosomes.
1) For selecting feature extractor (type 1 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 representing SIFT as the feature extractor for all 40 face granules.
2) For assigning weights to face granules (type 2 chromosome) ,a chromosome with weights proportional to the identification accuracy of individual face granules 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 and chromosomes type 1 and type 2 are combined and evaluated simultaneously. Recognition is performed using the feature extractor selected by type 1 chromosome and weight encoded by type 2 chromosomes 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 type 1 and type 2 chromosomes.
***Mutation*:** After crossover, mutation is performed for type 2 chromosomes by changing one or more weights by a factor of its standard deviation in the previous generation. For type 1 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 non-discriminating 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* and *random offspring generation* 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 offspring that are

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exactly similar to parents. Therefore, under such conditions, crossover is not performed and offspring are generated randomly.

4.2 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 X^2 distance measure.

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

Where a and b are the descriptors computed from face granules pertaining to a gallery-probe pair, i and j correspond to the i^{th} bin of the j^{th} face granule, and w_j is the weight of the j^{th} face granule. Here, the weights of each face granule are learnt using the genetic algorithm.
3) 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.

5. **IMPLEMENTATION**

The experiments conducted using surgery and no surgery face database. The images available in the face database are collected from different source of internet. Using these images, the plastic surgery face database is created. This plastic surgery face database contains one pre and post-surgery face image with frontal pose, different lighting condition, and various expressions. As well, the resolution of face image is very low. This may also affect performance and accuracy of the face recognition system. Pre-surgery images are used for training purpose and post surgery images as test set.

Main GUI

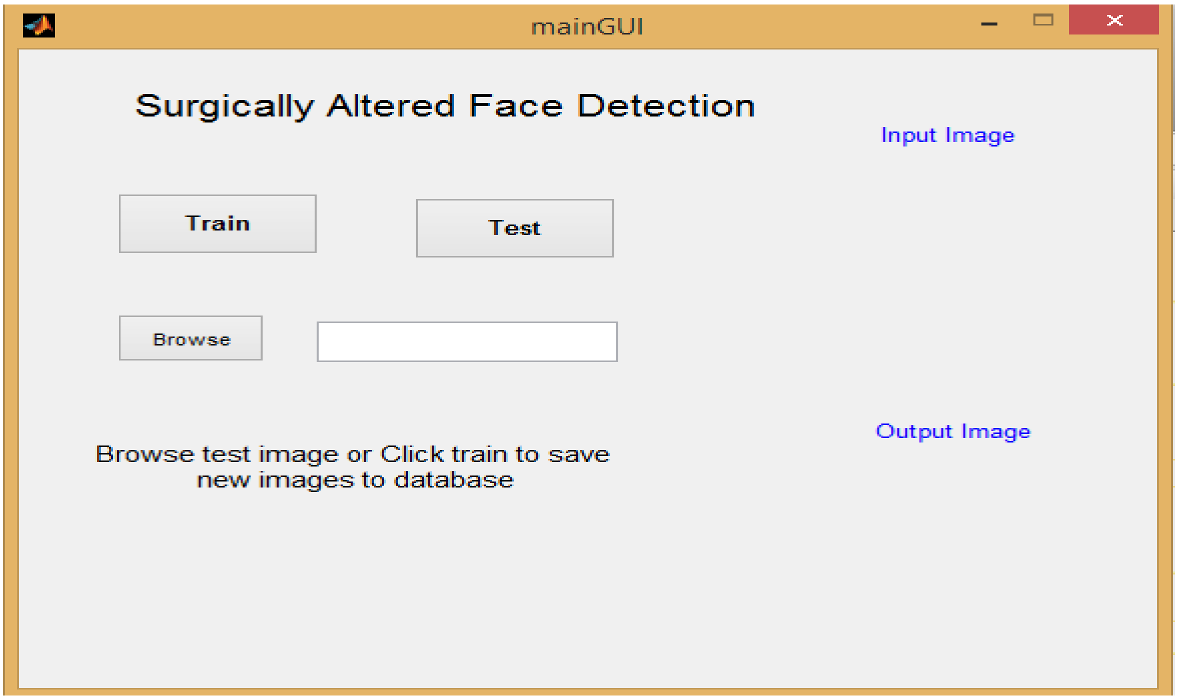

Fig 3: Main GUI of the system

1) Select the path of training database which contain the pre-surgery face image.

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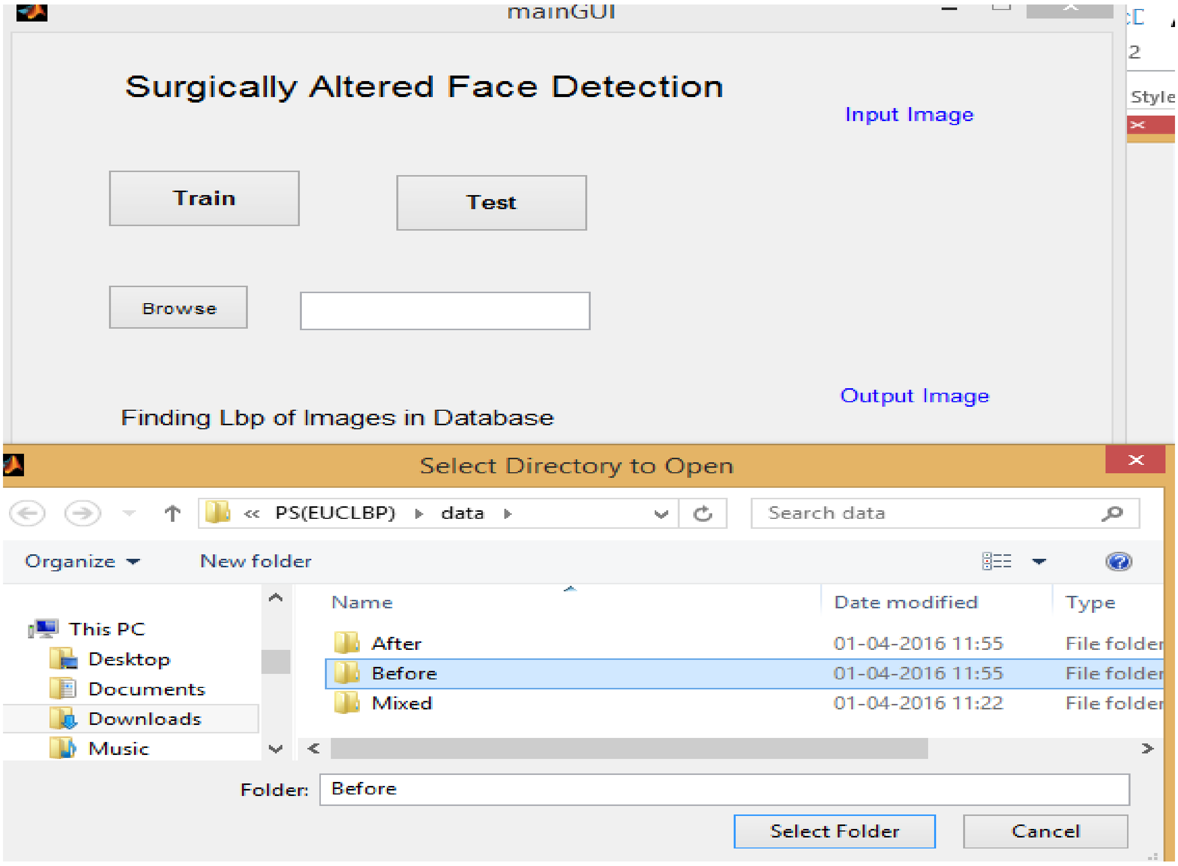

Fig 4 training database

2) Select the path of testing database which contains the post-surgery face image.

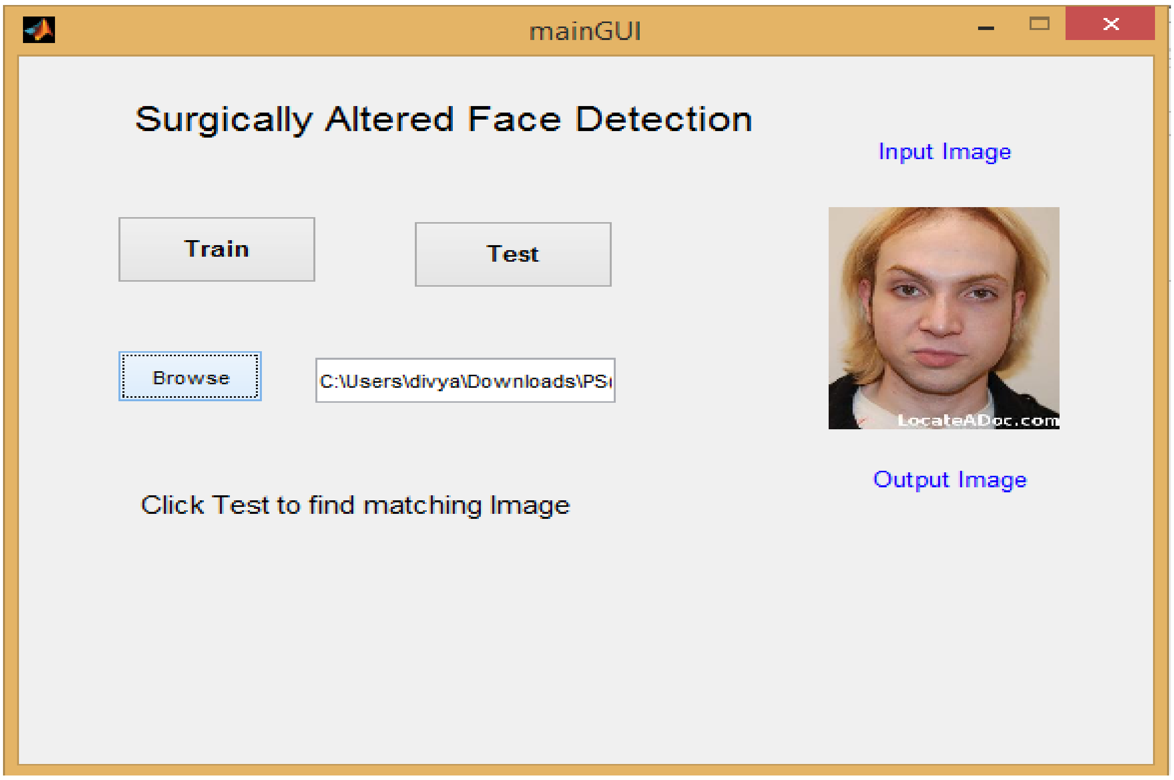

Fig 5 Testing the image

3) Result of propose method on Plastic-surgery face image.

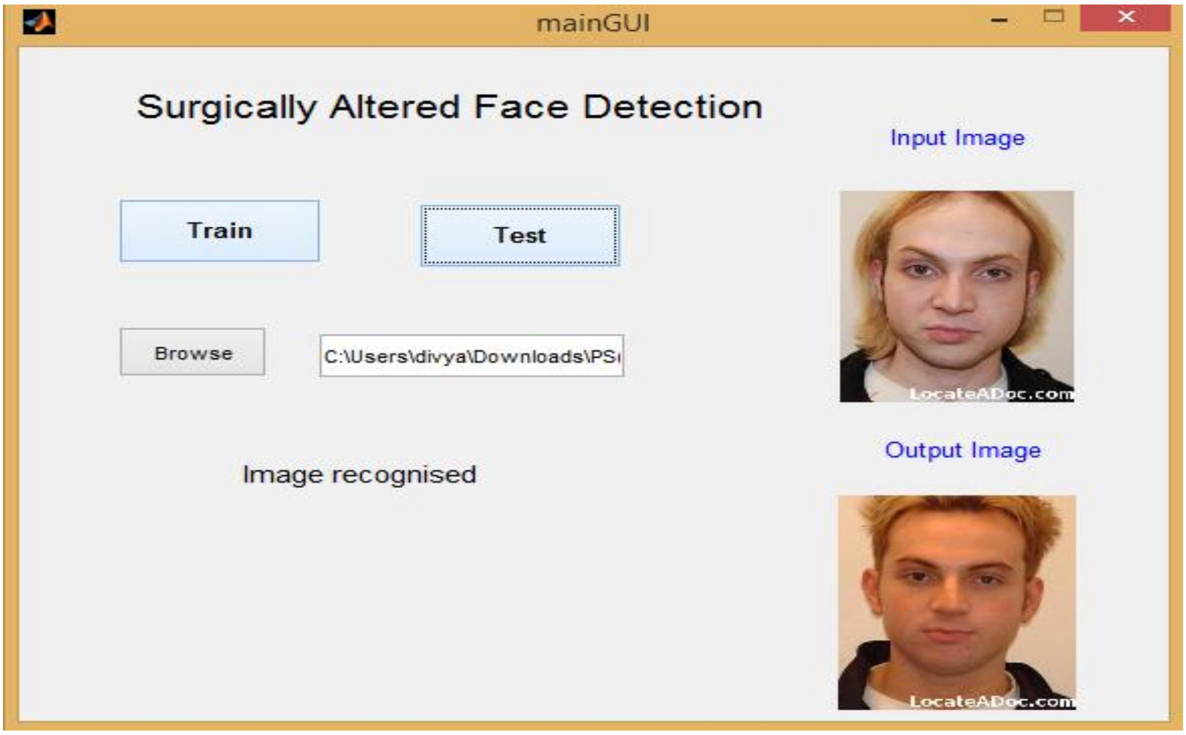

Fig 6 Result of the system

6. 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 paper presents a multi- objective 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 multi-objective 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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