Indian Journal of Research in Applied Sciences Engineering (IJRASE)
Vol.2.No.1 2014pp 26-32.
available at: www.goniv.com
Paper Received :05-03-2014
Paper Published:28-03-2014
Paper Reviewed by: 1. John Arhter 2. Hendry Goyal
Editor : Prof. P.Muthukumar

NEURAL NETWORK BASED RECOGNIZING SURGICALLY ALTERED FACE IMAGES FOR REAL TIME SECURITY APPLICATION

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ABSTRACT

Using a Multi-objective 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. In this proposed work, using a morphological fusion algorithm with neural network tool is assimilated to match pre and post surgery face images. It contains training and testing datasets. So it gives optimized result. On the plastic surgery face database, the proposed algorithm yields high identification accuracy as compared to existing algorithms and a commercial face recognition system. Our evaluation results obtained using Genetic algorithm with neural network data sets.

Keywords – SIFT, EUCLBP, Granular, Genetic algorithm, Neural Network

I. INTRODUCTION

Plastic surgery procedures provide a proficient and en-during 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. Figure 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. According to the statistics provided by the American Society for Aesthetic Plastic Surgery for year 2010 [1], there is about 9% in-crease in the total number of cosmetic surgery procedures, with over 500,000 surgical procedures performed on face.

Transmuting facial geometry and texture increases the intra class 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 Figure 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 non-uniform 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.

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

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.

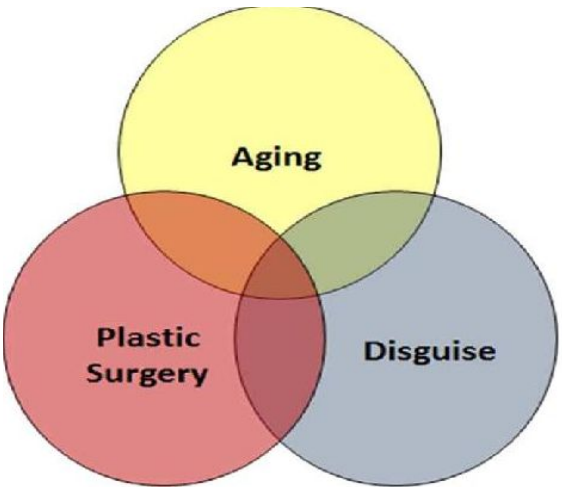


Fig 2: Relation among plastic surgery, aging, and disguise variations with respect to face recognition

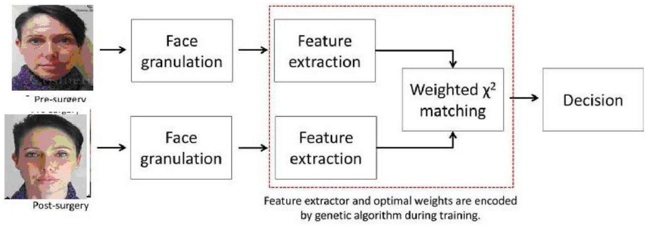


Fig 3: Block diagram illustrating different stages of the proposed algorithm

II. RELATED WORK

The allure for plastic surgery is experienced world-wide and is driven by factors such as the availability of advanced technology, affordable cost and the speed with which these procedures are performed. Facial plastic surgery is generally used for correcting feature defects or improving the appearance, for example, removing birth marks, moles, scars and correcting disfiguring defects. According to the recent statistics released by The American Society for Aesthetic Plastic Surgery for year 2008.

Every year, millions of American individuals undergo cosmetic plastic surgery. There has been an increase of about 162% in the total number of plastic surgeries from 1997 to 2008. In 2008 alone, more than one million facial plastic surgeries they're performed and most common surgical procedures are Liposuction, Blepharoplasty, Rhinoplasty, Chemical peel and Laser skin resurfacing. It is expected that 40% women and 18% men will go for plastic surgery in near future. It is also estimated 29% white Americans and 31% non-white Americans will go for ethnic plastic surgery in near future. Plastic surgery distribution by age: 0-18 years constitute 2% of the total procedures, 19-34 years constitute 22%, 35-50 years constitute 45%, 51-64 years constitute 26%, and 65 years and above constitute 6% of the total plastic surgery procedures. 18% men and 23% women are now more affirmative towards plastic surgery than they are 5 years ago. The statistics clearly indicate the popularity of plastic surgery among all age groups, ethnicity and gender. Similar analysis from different countries illustrates the popularity of plastic surgery.

These surgical procedures prove beneficial for patients suffering from structural or functional impairment of facial features, but these procedures can also be misused by individuals who are trying to conceal their identity with the intent to commit fraud or evade law enforcement. These surgical procedures may allow anti-social elements to freely move around without any fear of being identified by any face recognition system. Plastic surgery, results being long lasting or even permanent, provide an easy and robust way to evade law and security mechanism. Sometimes, facial plastic surgery may unintentionally cause rejection of genuine users. A recent incidence in China accentuates the intricacies of this covariate. At Hongqiao International airport's customs, a group of women they're stopped as all of them had undergone facial plastic surgery and had become so unrecognizable that customs officers could not use their existing passport pictures to recognize them. While face recognition is a they all studied problem in which several approaches have been proposed to address the challenges of illumination, pose , expression , aging and disguise the growing popularity of plastic surgery introduces new challenges in designing future face recognition systems. Since these procedures modify both the shape and texture of facial features to varying degrees, it is difficult to find the correlation between pre and post surgery facial geometry.

To the best of our knowledge, there is no study that demonstrates any scientific experiment for recognizing faces that have undergone local or global plastic surgery. The major reasons for the problem not being studied are:

1. Due to the sensitive nature of the process and the privacy issues involved, it is extremely difficult to prepare a face database that contains images before and after surgery.
2. After surgery, the geometric relationship between facial features changes and there is no technique to detect and measure such type of alterations

III. PROPOSED WORK

We present a multiobjective evolutionary granular computing based algorithm for recognizing faces altered due to plastic surgery procedures. As shown in Figure 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.

3.1 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. 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. 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 arrange Dina 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 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. Figure 3. Block diagram illustrating different stages of the proposed algorithm facial regions, it is difficult for face recognition algorithms to match a post-surgery face image with pre-surgery face images. They recognize faces using a combination of holistic approaches together with discrete levels of information (or features). Singh *et al* [2]. 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. 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.

To incorporate these observations, propose approach for facial feature extraction and matching. In the granular approach, as shown in Figure 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.

3.2 FACE IMAGE GRANULATION

Let be the detected 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.

First Level of Granularity: In the first level, 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 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.

Second Level of Granularity: To accommodate the observations of Marsico *et al* [3]. Horizontal and vertical granules are generated by dividing the face image into different regions.

Third Level of Granularity: To incorporate this property, local facial fragments are extracted and utilized as granules in the third level of granularity.

3.3 FACIAL FEATURE EXTRACTION

The proposed granulation scheme results in granules with varying information content. Some granules contain fiducially 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: EUCLBP** [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 non overlapping uniform local patches of size 32. For each local patch, the EUCLBP descriptor is computed based on the 8 neighboring pixels uniformly sampled on a circle 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 distance.

2) **Scale Invariant Feature Transform: 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, as proposed by Lowe *et al* [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 no overlapping local regions of size 32 x 32. SIFT descriptors computed for the sampled regions are then concatenated to form the image C.

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 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 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

(ii) For assigning weights to each face granule (referred to as chromosome). Each gene (unit) in chromosome is a binary bit 0 or 1 where 0 represents the SIFT feature extractor.

3.4 NEURAL NETWORK CLASSIFIER

Neural network tool is used to,

1. Recognize the pattern,
2. Image matching,
3. Feature extraction.

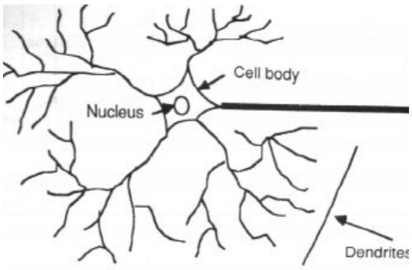


Fig 4: Neural network classifier diagram

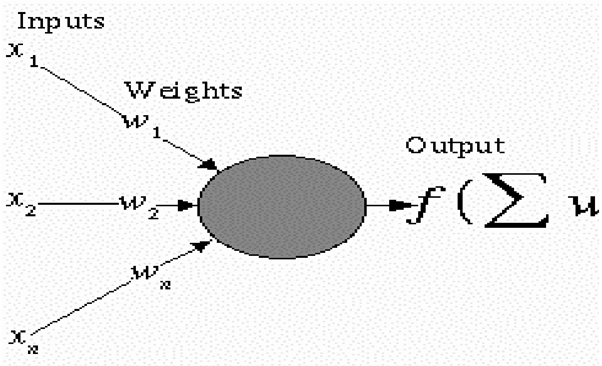


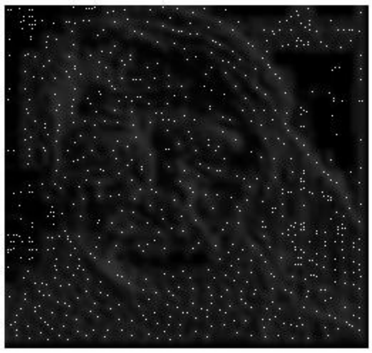
Fig 5: Feature Extraction diagram

The data set, consisting of 129 firms, was partitioned into a training set and a test set. The training set of 74 firms consisted of 38 that went bankrupt and 36 that did not. The needed ratios were computed and stored in the input file to the neural network and in a file for a conventional discriminate analysis program for comparison of the two techniques. It extracts the images in (i) Testing dataset, (ii) Training data sets, (iii) Regression process.

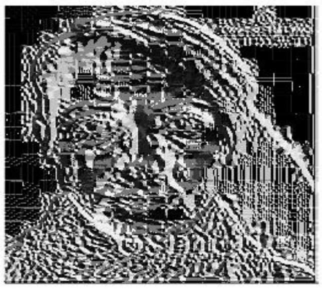
IV. IMPLEMENTATION

Post Surgery

Feature Extraction by SIFT

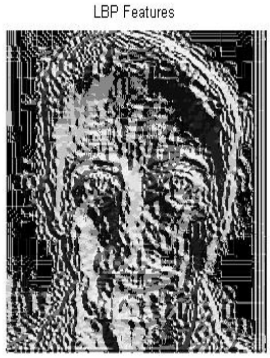


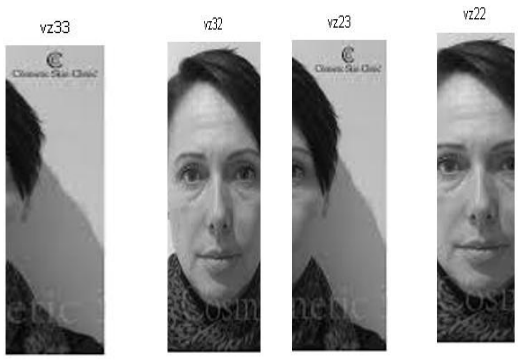
LBP Features

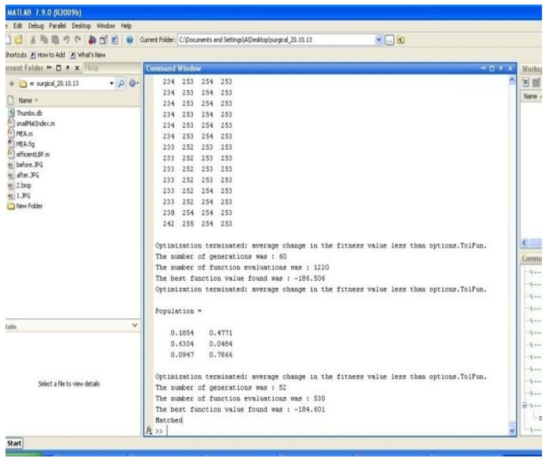


Granular First Level


Granular First Level


LBP Features


vz33
vz32
vz23
vz22

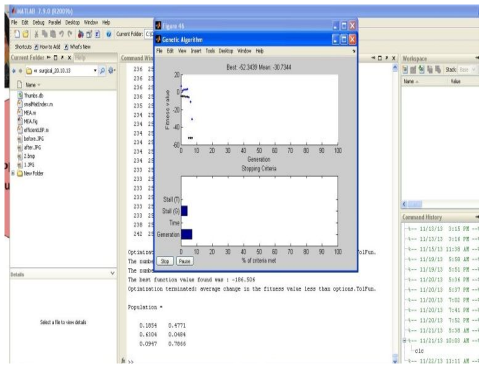


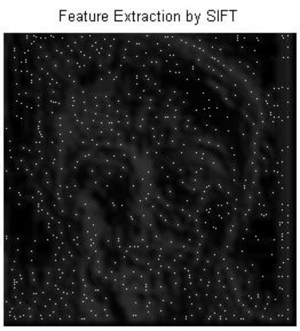

hz33

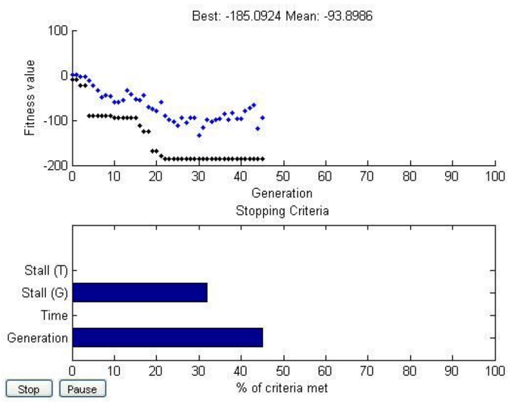

hz32


hz31


hz23




Feature Extraction by SIFT


Best: -185.0924 Mean: -93.8986
Fitness value
Generation
Stopping Criteria
Stall (T)
Stall (G)
Time
Generation
% of criteria met
Stop
Pause

V. CONCLUSION AND DISCUSSIONS

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 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, 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 reduce the execution time for processing.

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