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Identify the surgically altered face images using granular-PCA approach

Bincy Baby, M-Tech student and Nurjahan V A, Assistant professor
Computer Science and Engineering Department, Ilahia College of Engineering and Technology, MG university, Kerala, India

Abstract: *Plastic surgery provide a way to enhance the facial appearance. The non-linear variations introduced by the plastic surgery has raised a challenge for face recognition algorithms. In this research we match the face image before and after the plastic surgery. First generate non-disjoint face granules at multiple levels of granularity. The feature extractors are used to extract features from the face granules. The features are then processed by using principal component analysis (PCA) algorithm. Evaluate the weighted distance and match the pre and post surgery images based on weighted distance.*
The proposed system yield high identification accuracy and take less time for recognition as compared to the existing system.
Keywords: *Plastic surgery;face recognition;Granular Computing;PCA Algorithm*

I. Introduction

Plastic surgery is a medical specialty concerned with the correction or restoration of form and function. Though cosmetic or aesthetic surgery is the best-known kind of plastic surgery, plastic surgery is not necessarily cosmetic and includes many types of reconstructive surgery, hand surgery, microsurgery, and the treatment of burns. Plastic surgery of face based on selected cases including burns, accidents, aging etc. The plastic surgery procedures amend the facial features and skin texture thereby providing a makeover in the appearance of face. The changes in the facial geometry and texture introduce variability between pre and post surgery images of the same individual. Therefore, matching post-surgery images with pre-surgery images becomes a complicated task for automatic face recognition algorithms.

Variations caused due to plastic surgery are long-lasting and may not be reversible. Due to these reasons, plastic surgery is now established as a new and challenging problem of face recognition. So many techniques are introduced to address this problem. An approach is a multi-objective evolutionary granular computing based algorithm to match pre-and post surgery face images [1]. A sparse representation approach on local facial fragments to match surgically altered face images [2].Another approach to integrate information derived from local regions to match pre- and post-surgery face images [3]. There is a significant scope for further improvement.

This research presents a principal component analysis (PCA) based algorithm for recognizing faces altered due to plastic surgery procedure. The proposed algorithm starts with generating non-disjoint face granules. Each granule is a representation of different information at different size and resolution. Several part based face recognition approaches capture this observation for improved performance. Face granules are generated pertaining to three levels of granularity. Further, two feature extractors are used for extracting feature information from face granules. Here Extended Uniform Circular Local Binary Patterns [4] and Scale Invariant Feature Transform [5] are used. Both these feature extractors are fast, discriminating, rotation invariant, and robust to changes in gray level intensities due to illumination. 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. Finally feature selection is performed using a principal component analysis algorithm [6]. It is an eigenface approach. Principal Component Analysis examines relationships of variables. Each principal component in Principal Component Analysis is the linear combination of the variables. Using this method we find a subset of principal directions (principal components) in a set of the training faces. Then we project faces into the space of these principal components and get the feature vectors. Face recognition is performed by comparing these feature vectors using different distance measures.

The proposed algorithm provide an improved performance as compared with the genetic algorithm. Also principal component analysis take less time for recognition.

II. Related Works

Sparse representation [2] is a novel approach to address the challenges involved in automatic matching of faces across plastic surgery variations. In the proposed formulation, partwise 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 in the problem we address in this work. The proposed formulation utilizes images from sequestered non-gallery subjects with similar local facial characteristics to fulfill this requirement.

An approach developed by De Marsico [3] integrate information derived from local regions to match pre- and post-surgery face images. Plastic surgery bears on appearance in a non-uniform fashion using a recognition approach that integrates information derived from local region analysis. We implemented and evaluated the performance of two new integrative methods, FARO and FACE, which are based on fractals and a localized version of a correlation index.

Multi-objective evolutionary algorithm [1] is proposed to match both pre and post surgery face images. This algorithm first generates face granules with different size and resolution using different granular approaches. Then feature are extracted from the face granules using feature extractors. EUCLBP and SIFT are used to extract the feature. Weighted Chi square distance is used to compare the descriptors. Face feature selection and weight optimization is performed using genetic algorithm. and take a decision. The search is repeated until the process terminated. The process terminated till there is no improvement in the identification accuracy of the new generation.

III. Problem Domain

In the multi-objective evolutionary approach [1] genetic algorithm is used for face recognition. This algorithm have some drawbacks.

The problem area mainly focused on recognition time. The time that taken by the genetic algorithm for recognition is more as compared with other systems. In case of 32-bit systems the feature points of few images are not initialized in genetic algorithm. Hence an error is generated at the time of recognition.

IV. Proposed System

The proposed method presents a granular-PCA approach for recognizing faces altered due to plastic surgery procedures. The algorithm match both pre-surgery and post-surgery face images. Different stages of proposed system as shown in fig. 1.

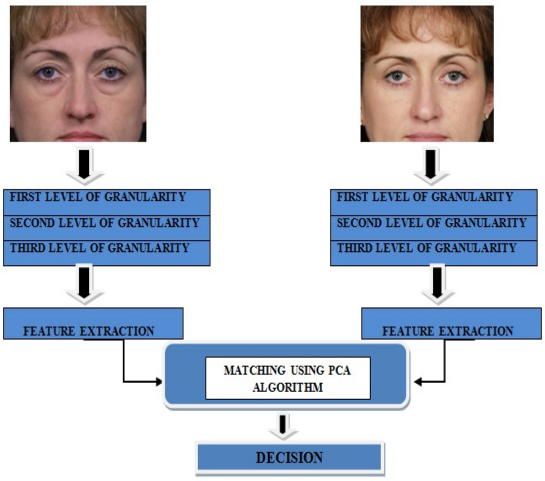

Fig. 1. Block diagram illustrating different stages of the proposed algorithm

The face image used for this approach is of size 196 x 224. This method start with generating face granules at different size and resolution. Face granules are generated by three levels of granularity. The first level provides global information at multiple resolutions. This is done by applying the Gaussian and Laplacian operators [7] in the face images. Inner and outer facial information are extracted at the second level. In this level horizontal and vertical granules are generated by dividing the face image into different region. At the third level, features are extracted from the local facial regions. Local facial features have an important role in face recognition by human mind. The local face regions are eyes, nose and mouth. The local facial regions are extracted using golden ratio template [8] and is utilized in third level of granularity. The three levels of granularity generate 40 face granules with different size and resolution.

The next phase is the face feature extraction. This is done by using two feature extractors. Extended uniform circular local binary pattern (EUCLBP) [4] and scale invariant feature transform (SIFT) [5] are used in this method. EUCLBP is a texture operator. That encode the exact gray level differences. Scale invariant feature transform is a scale and rotation invariant extractor. That generate a compact representation of the image. SIFT transform the image into scale invariant coordinates based on its local features. This approach depends upon the magnitude, orientation and spatial vicinity of the image gradients.

Principal component analysis (PCA) [6] is a very popular face recognition method. Each principal component is the linear combination of variables. In this algorithm face recognition is performed by projecting the face image into a feature space. This feature space is called Face space. That encodes the variation among face images. The face space is defined by Eigen face. This is the Eigen vectors of the set of faces.

PCA algorithm begins with the calculation of Eigen faces using PCA projection and this define the Eigen space. Suppose when a new face is identified, calculate its weight and determine if the image is a face. If it is a face then classify the weight pattern and take a decision.

Assumptions 1:Face space form a cluster in image space.

Based on PCA method find a subset of principal components in a set of face images. Then project the face into the feature space and get the feature vectors. Then compare the feature vectors of both the images using different distance measures. Based on the result of this comparison recognition is performed.

V. Solution Methodology

In the proposed algorithm face recognition is performed by matching the pre and post surgery face images. This approach consists of the following modules:

a) Granular Approach

Image granulation means face image is divided into different parts using different methods. Each parts are known as granules and each granules represent different information. Also each granules have different size and resolution based on the method used for granular approach. An image with size 196 x 224 is used for this algorithm. The face granules can be represented by FGri, where i represent the granule number. In this algorithm granules are generated by using three levels of granularity.

i. First level of granularity

In this level face granules are generated by using two operators. Namely Gaussian and Laplacian operators [7]. Gaussian operator generate low pass filter images. At each iteration the resolution and sample density of face images is reduced. The face granules generated by Gaussian operator is shown in fig. 2.

FGr1 FGr2 FGr3

Fig. 2. Face granules generated by Gaussian operator

Laplacian operator generate a sequence of band pass filter images. The granules generated by Laplacian operator as shown in fig. 3. The granules generated by both operators may be viewed as a pyramid. The facial features at different resolution provide edge information, smoothness, blurriness and noise. This level compensate for the variations in facial texture.

FGr4 FGr5 FGr6

Fig. 3. Face granules generated by Laplacian operator

ii. Second level of granularity

Second level of granularity consists of horizontal and vertical granules generated by divide the face into different regions. The horizontal and vertical granules are shown in fig. 4 and fig. 5.

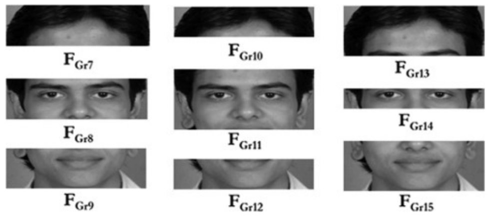

Fig. 4. Horizontal granules

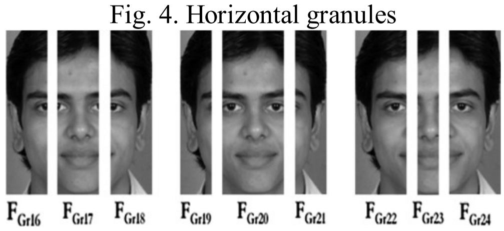

Fig. 5. Vertical granules

There are 9 horizontal granules and 9 vertical granules.FGr7,FGr and FGr9 are of size n x m / 3,where n and m are the horizontal and vertical pixel values. FGr10 and FGr12 are of size n x (m/3-ε) where ε = 15 and FGr11 have n x (m/3+2ε). The size of FGr13 and FGr15 is n x (m/3+ε) and FGr14 is n x (m/3-2ε). Vertical granules are generated in similar manner. This level provide endurance to variations in inner and outer facial regions. It address the variations in chin, forehead, ears, and cheeks caused due to plastic surgery.

iii. Third level of granularity

Human mind can distinguish and understand the local regions such as nose, mouth and eyes. These regions can be fragmented by using third level of granularity. For that here we use golden ratio template [8]. It is a multi-resolution grid that captures partial information. The facial components are defined across eyes and nose, nose and mouth and encode both facial parts. Fig. 6 shows the golden ratio face template. It provide a rough spatial map of the facial features. In this algorithm we get 16 local face region from a face image of size 196 x 224 using golden ratio template.

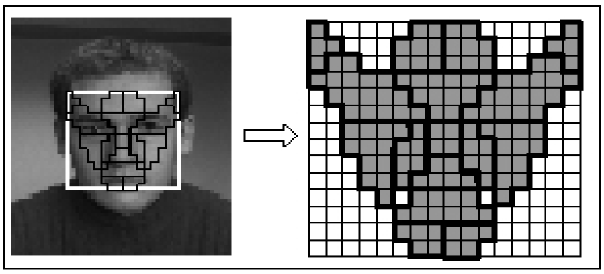

Fig. 6. Granules generated by Golden ratio face template (FGr25 – FGr40)

There are 40 face granules are generated from the three granular approaches. These granules have capability to address specific variations.

b) Feature Extraction

Each granules contain varying information contents. Therefore different feature extractors are used. Here we use two types of feature extractors. Extended uniform circular local binary pattern (EUCLBP) [4] and Scale invariant feature Transform (SIFT) [5].

VI. Extended Uniform Circular Local Binary Pattern(EUCLBP)

Basic local binary pattern (LBP) is a window based texture descriptor. LBP have high computational efficiency and robustness to gray level changes. Circular LBP can be computed in the eqn (1) and (2).

$$C_{N,R}(p,q) = \sum_{i=0}^{N-1} f(n_i - n_c)2^i, \qquad (1)$$

$$f(\cdot) = \begin{cases} 1 & if \;\; n_i - n_c \geq 0 \\ 0 & otherwise \end{cases}, \qquad (2)$$

Where N is the number of neighbors, nc is the gray level intensity of the central pixel and ni is the gray level intensity of N evenly spaced pixels on the circle. CLBP is extended to achieve robustness to rotation variation and dimensionality reduction. Uniform CLBP is computed using Eqn. (3) and (4).

$$C_{N,R}^{riu2}(p,q) = \begin{cases} \sum_{i=0}^{N-1} f(n_i - n_c)2^i & if \ U(C_{N,R}) \le 2 \\ N+1 & otherwise \end{cases} \tag{3}$$

where,

$$U(C_{N,R}) = \begin{matrix} \sum_{i=1}^{N-1} |f(n_i - n_c) - f(n_{i-1} - n_c)| \\ +|f(n_{N-1} - n_c) - f(n_0 - n_c)| \end{matrix} \tag{4}$$

The texture extractor is computed based on neighborhood. Assign a binary value to every neighboring pixel with respect to central pixel. This binary pattern is obtained from neighboring pixels is transformed into gray-level value and is assigned to the central pixel. The concatenation of descriptors from each local patch constitutes the image signature.

VII. Scale Invariant Feature Transform (SIFT)

It is a scale and rotation invariant extractor that generate a compact representation of an image. It is mainly based on magnitude, orientation and spatial vicinity of image. The descriptor is computed in a dense manner around pre- defined interest points. SIFT descriptors computed for the sampled regions are then concatenated to form the image signature.

c) PCA approach for selection of feature extractor and weight optimization

Face recognition using PCA [6] based on information theory approach. It extracts relevant information from the face image and encode as efficiently. First it identifies the subspace of the image space spanned by the training face image data and decorrelates the pixel values. The projection of face images into the principal component subspace achieves information compression, decorrelation and dimensionality reduction to facilitate decision making.

The principal component of the distribution of faces or the Eigen vectors of the covariance matrix of the set of face images is sought by treating, an image as a vector in a very high dimensional face space. Then apply PCA on this database and get the unique feature vectors using the following method.

- The database is rearranged in the form of a matrix where each column represents an image.
- With the help of Eigen values and Eigen vectors covariance matrix is computed.
- Feature vector for each image is then computed.
- This feature vector represents the signature of the image. Signature matrix for whole database is then computed.
- Euclidian distance of the image is computed with all the signatures in the database.
- Image is identified as the one which gives least distance with the signature of the image to recognize.

Eigenfaces can be calculated by collect difference between training images and average face in matrix A (M by N) ,where M is the number of pixels and N is the number of images. The average face calculated by

$$\gamma = \frac{1}{M}\sum_{i=1} T_i$$

The covariance matrix can be represented by

$$C = \frac{1}{M}\sum_{i=1}^{M} \phi_i \phi_i^T$$

Where $\phi_i = T_i - \gamma$

The Eigenvectors of covariance matrix C give the Eigenfaces.

C= AA^T

Instead of calculating Eigenvector, calculate the eigenvalues and corresponding eigenvectors of a much smaller matrix L

L= A^TA

If λi are the eigenvectors of L then A λi are the eigenvectors for C. The eigenvectors are in the descending order of the corresponding eigenvalue. The training face images and new face images can be represented as linear combination of the eigenfaces.

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 χ^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 and are the descriptors computed from face granules pertaining to a gallery-probe pair, and correspond to the bin of the face granule, and is the weight of the face granule. Here, the weights of each face granule are learnt using the genetic algorithm.
4) In identification mode , this procedure is repeated for all the gallery-probe pairs and top matches are obtained based on the match scores.

Several experiments are performed to analyze the performance of the proposed algorithm. The performance of the algorithm is compared with the genetic algorithm. Select the pre and post surgery images and preprocess the images into gray scale images. Face granules are generated by three levels of granularity. SIFT and EUCLBP applied on the 40 face granules. Further, evaluate the effectiveness of the multi-objective evolutionary genetic approach for feature selection and compare the result with the feature selection of proposed system.

a) Database

In the proposed system experiments are performed on three databases. Plastic surgery face database, face granules database and gallery_probe database. Plastic surgery face database comprises 25 pre and post surgery image pairs. It consist of different cases of facial plastic surgery such as nose surgery, lip surgery and face lifting. Images are collected from internet. Face granules database is a temporary database. It stores face granules temporarily. This granules are used for further feature extraction and feature selection. There are two gallery_ probe databases. One for Genetic algorithm and the other for PCA algorithm.

b) Analysis

The detected images in the database are first preprocessed to gray scale image. The face images are normalized and resized into 196 x 224. Spacial features are extracted at multiple levels of granularity. Simultaneously optimizing the feature selection and weight computation pertaining to each face granule allows for addressing the nonlinear and spontaneous variations introduced by plastic surgery.

Table I and fig. 6 show rank-1 identification accuracy for the two systems (proposed system and genetic algorithm).

Table I Rank-1 Identification Accuracy of the proposed PCA-Granular Approach and comparison with Multi-Objective Evolutionary Granular Approach

Database	Algorithm	Accuracy
GA-gallery-probe	Multi-Objective Granular Approach	93.33%
PCA-gallery-probe	PCA-Granular Approach	94.41%

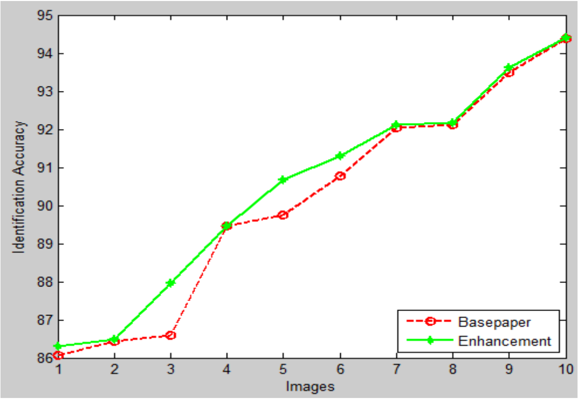

Fig. 6. Identification Accuracy of the proposed PCA-Granular Approach and comparison with Multi-Objective Evolutionary Granular Approach

The main drawback of multi-objective evolutionary algorithm is the time taken for the feature selection. The difference between multi-objective evolutionary algorithm and PCA-granular approach is shown in fig. 7.

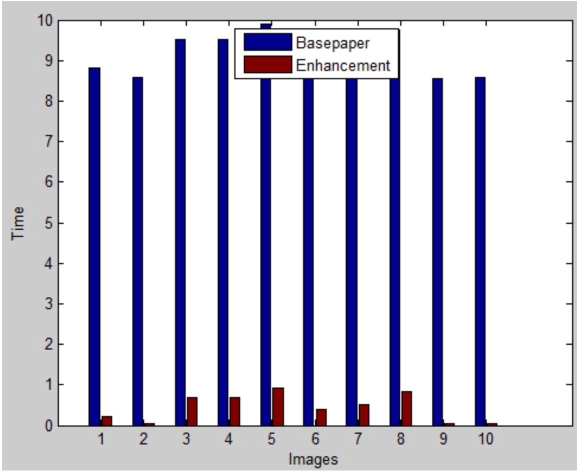

Fig. 7. Time Taken for feature selection

From the following results we can conclude that the performance of the proposed system is higher than the existing system.

VIII. Conclusion and Future Work

Face recognition is now an important method for forensic security. Plastic surgery raised challenge for face recognition system. Variations caused due to plastic surgery can be addressed by using granular-PCA algorithm. Matching both pre and post surgery images using this algorithm. Preprocess both images into gray scale images and apply granular approaches to generate granules of face images. Then extract features from the face granules using EUCLBP and SIFT extractors. Finally face recognition is performed using PCA algorithm. Match gallery-probe pairs using weighted χ^2 distance measure. This algorithm have high identification accuracy and take less time for recognition as compared with the existing system.

In future we are decided to perform face recognition in most accurate manner.

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