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AN EFFICIENT SELF-UPDATING FACE RECOGNITION SYSTEM FOR PLASTIC SURGERY FACE

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Abstract
Facial recognition system is fundamental a computer application for the automatic identification of a person through a digitized image or a video source. The major cause for the overall poor performance is related to the transformations in appearance of the user based on the aspects akin to ageing, beard growth, sun-tan etc. In order to overcome the above drawback, Self-update process has been developed in which, the system learns the biometric attributes of the user every time the user interacts with the system and the information gets updated automatically. The procedures of Plastic surgery yield a skilled and endurable means of enhancing the facial appearance by means of correcting the anomalies in the feature and then treating the facial skin with the aim of getting a youthful look. When plastic surgery is performed on an individual, the features of the face undergo reconstruction either locally or globally. But, the changes which are introduced new by plastic surgery remain hard to get modeled by the available face recognition systems and they deteriorate the performances of the face recognition algorithm. Hence the Facial plastic surgery produces changes in the facial features to larger extent and thereby creates a significant challenge to the face recognition system. This work introduces a fresh Multimodal Biometric approach making use of novel approaches to boost the rate of recognition and security. The proposed method consists of various processes like Face segmentation using Active Appearance Model (AAM), Face Normalization using Kernel Density Estimate/Point Distribution Model (KDE-PDM), Feature extraction using Local Gabor XOR Patterns (LGXP) and Classification using Independent Component Analysis (ICA). Efficient techniques have been used in each phase of the FRAS in order to obtain improved results.

Keywords:
Facial Recognition System, Self-update Procedure, Active Appearance Model (AAM), Kernel Density Estimate/Point Distribution Model (KDE-PDM), Independent Component Analysis (ICA)

1. INTRODUCTION

In the area of recognizing faces, many techniques have been introduced with the purpose of addressing the issues of illumination, pose, expression, aging and camouflage. However plastic surgery based face recognition is still a lesser explored area. Thus the use of face recognition for surgical faces introduces the new challenge for designing future face recognition system [1]. At a very high level, Facial recognition systems function by the recognition of a human face from the scene and then extracting it. The system thereafter does the measurement of the nodal points on the face, the distance between eyes, shape of the cheekbones and other differentiable features. Face recognition is one among the small number of biometric techniques which has the benefits of both great accuracy and less intrusion. In addition, it renders data regarding the Age, gender, personal identity (physical structure), Mood and emotional state (facial expression) and Interest/attention focus (orientation of gaze). But, still face remains a topic of interest, even after years of research, due to the variations that are noticeable in the face owing to illumination [2], pose, expression and occlusion [3]. One new challenging problem to face recognition is again facial plastic surgery [4]. These types of surgeries changes the facial features to such large extent that often human beings find it tedious to recognize a person face once the surgery is performed. The Fig.1 illustrates an example of the impact of plastic surgery over facial appearances.

After Before

Fig.1. Effect of Plastic Surgery on Facial appearances

There is not much literature available for this challenge. Till now, very less number of researchers has provided contributions to this field. In paper [1], the authors have given the comparative study regarding the various face recognition algorithm for the case of plastic surgery. On the basis of the experimentation conducted by authors, a conclusion has been reached that the face recognition algorithms like PCA, FDA, GF, LLA, LBP and GNN have emerged out with recognition rate which is not more than 40% for local plastic surgery. In addition, for the case of global surgery it was only up to 10%. Among every other algorithm, geometrical feature based technique has proven itself to a greater extent on a comparative basis for local plastic surgery. Because of the advancements in technology, feasibility, and also how fast these procedures are performed, many people go through plastic surgery for the medical causes and few select cosmetic surgery aspiring to look youthful or for the purpose of having a better appearance. These procedures can considerably alter the facial regions both in local and global terms, changing the appearance, facial features and texture. Every facial plastic surgery alters the shape or texture of a specific region of face [5]. It is very hard to have it predicted about which features are not altered (a region with no effects of surgery) with surgery information being unavailable. The challenge is more increased, when an individual goes through more than one surgery. Also, the plastic surgery can get used in wrong ways by individuals who attempt to hide their identity with the intention of committing fraud or escape the enforcement of law. Further, this surgery permits the theft or any terrorist to move freely around without having any fear of being recognized by any of the face recognition system. Also it may result in the rejection to users who are genuine. Hence the newly introduced technique is utilized for recognizing the facial images which have earlier undergone few feature alterations by means of plastic surgery.

This research work develops a novel FRAS which comprises of various modules like Face Detection, Face segmentation, Face Normalization, Feature extraction, Classification and Selection. In this proposed approach, Face segmentation is carried out using Active Appearance Model (AAM), Face Normalization is performed using Kernel Density Estimate/Point Distribution Model (KDE-PDM), Feature extraction using local Gabor XOR Patterns (LGXP) and Classification is based Independent Component Analysis (ICA).

2. RELATED WORK

A probabilistic type of approach utilizing part-based matching has been introduced for expression invariant and occlusion tolerant recognition of the frontal faces. The global techniques and a component-based strategy for the face recognition and the evaluation of their reliability against pose variations have been studied. The global technique comprises of a straight forward face detect or that does the extraction of the face from an input image and then propagate it to a set consisting of SVM classifiers which conducts the face recognition [6].

Explain about a semi-automatic alignment step combined with the Support Vector Machine (SVM) classification. Because of self-occlusion, the automatic alignment procedures will fail eventually to calculate the accurate correspondences for huge pose differences between the input and reference faces. Combination of view-specific classifiers have also been employed to face detection. A probabilistic based approach making use of part-based matching has been introduced for expression invariant and occlusion tolerant recognition of the frontal faces. There are two global techniques and component-based strategy for face recognition and their reliability against pose variations has been evaluated. The first global technique comprises of a practical face detector that acquires the face from an input image and then propagates it to a group of SVM classifiers which carry out the face recognition. By exploiting a face detector, translation and scale invariance is achieved [7].

In the recent research that merely pursues a lesser error rate in face recognition cannot be as considerable as it might have been anticipated earlier, since various types of errors result in multiple amount of losses. Face recognition is formulated to be a multi-class cost-sensitive learning job and under such a kind of formulation, the total cost is tried to be minimized instead of the overall error rate itself. As far the knowledge for the best is concerned, this is the first and foremost study over cost-economic face recognition [8].

Normalized Linear Discriminant Analysis (NLDA) is proposed in [9] for use in self-updating systems. Based on the simulation results in various data bases, it is observed that Normalized cross-correlation is better than semi-supervised linear discriminant examination. But, this technique does not acknowledge the corruption of training data due to misclassified examples.

3. PROPOSED METHODOLOGY

The Face Recognition Authentication System (FRAS) used in this research work is shown in Fig.2 and it has six main building blocks namely face detection, segmentation, normalization, classification and selection block for automatic learning. In the following sub-sections, the algorithms used in each block are described.

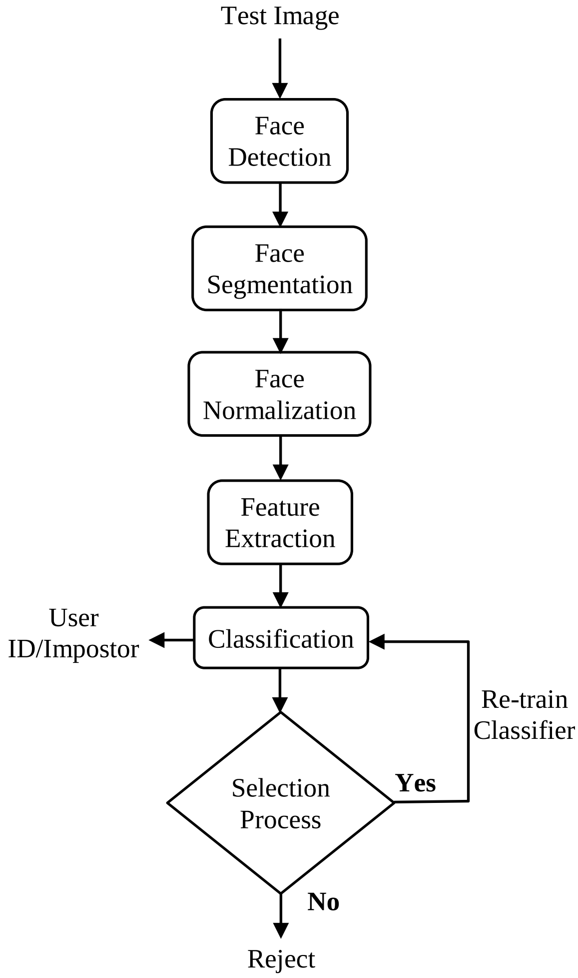

Fig.2. Flowchart of Proposed FRAS

3.1 FACE DETECTION

The face detection block identifies whether there are face(s) in an image. If there are face(s) in the image then the detector outputs their position and size. The main necessities of the face detection block are that it functions at real-time while being highly accurate. The real-time speed is essential in order to minimize the waiting time of the user to be determined. High accuracy is required to minimize the problem caused to a user if the user's face is not located by the system. In this approach, the detector presented in [10] is utilized, which uses weak classifiers based on Haar-like features [11] with optimally weighted rectangles. When this detector is simulated over the MIT CMU dataset [12], attained a false acceptance rate of while correctly classifying higher percentage of the faces present in the database at speeds of real-time.

3.2 FACE SEGMENTATION USING ACTIVE APPEARANCE MODEL

The main aim of segmentation is to partition an image into regions and objects, in such a way that the segmented regions can be examined individually. Thus, a complex image is minimized into less complex segments that are much easier to interpret. Segmenting an object out of an image is determining and defining the boundary that encapsulates that object. In several scenarios, the shape of the boundary can give a lot of data about the object itself. Based on this, it is easy to observe that segmentation is valuable for isolating objects and shape.

Separation of a face from the background and accurate localization of facial features is essential as it is easy to extract facial features according to either shape or image intensities, considering region correspondences.

For the segmentation of the well-known facial features, this approach system utilizes Active Shape Models with Invariant Optimal Features (IOF-AAM) [10]. This approach integrates local image search with global shape constraints depending on a Point Distribution Model (IPDM) [13].

An Active Appearance Model (AAM) approach is proposed for matching a geometric model of object shape and look to a new image. They are constructed during a training phase. A group of images, along with coordinates of landmarks that appear in all of the images, is given to the training supervisor.

It is based on the Active Shape Model (ASM). But, the main drawback of ASM is that it only uses shape constraints and does not take benefit of all the available data - the texture across the target object. This can be modeled using an AAM.

3.3 FACE NORMALIZATION USING KERNEL DENSITY ESTIMATE/POINT DISTRIBUTION MODEL (KDE-PDM)

The face normalization process is to make easy identification by decreasing the intra class appearance discrepancy due to pose, expression and illumination. In this paper the normalization process is done by KDE-PDM. Finally, the texture acquired from a face is denoted in a shape of independent form.

This research work introduces a Kernel Density Estimate/Point Distribution Model (KDE-PDM) algorithm that is in accordance with PCA, and the KDE for providing a statistical shape model which can manage with high dimensional data sets, represent the correlated variation modes, and yield precise estimates of the shape distribution that lies beneath [14]. For the purpose of this paper, interest is shown in the creation of a statistical shape model of the manufactured stampings or assemblies which can be helpful in accurately representing the basic shape distribution. KDE renders very less assumptions regarding an underlying data set, apart from that it can be approximated by a Gaussian mixture. It can provide more accurate estimations of skewed and nonlinear data sets than by fitting a single multivariate Gaussian to the data. Combining the PDM and the KDE provides an approach that can capture correlated shape modes and estimate more complex shape distributions: this approach will be referred to as the KDE-PDM. For a sample consisting of n shapes, along with m measurement points, the KDE-PDM would be created as follows,

$$f(x) = \frac{1}{Nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{1}$$

where, K is some kernel (often the Gaussian), h is the bandwidth or smoothing parameter, and d is the dimension of the data. In the case of assembly process measurement data, each measurement point is seen as a dimension. Studies have shown that the selection of a kernel is not as important as the choice of the smoothing parameter [15]. For the purposes of this paper, maximum likelihood cross-validation is used: this method chooses a smoothing parameter h that maximizes the log likelihood,

$$\log L = \sum_{i=1}^{n} \log \hat{f}_{-i}(x_i) \tag{2}$$

where, the leave one out cross validation density estimator of the underlying distribution f is,

$$\hat{f}_{-i}(x_i) = \frac{1}{(n-1)h} \sum_{j \neq i}^{n} K\left(\frac{x_i - x_j}{h}\right). \tag{3}$$

In summary, the cross validation estimator involves removing one data point and using the remaining $n - 1$ points to construct a density estimator, and evaluating the estimate of the nth data point. This step is repeated n times for each data point, and the results averaged. Maximum likelihood cross-validation efficiently recognizes an h which reduces the Kullback-Liebler distance, I, which is a measure of the difference between two probability distributions [16]. In this case, h is selected to minimize the distance between the estimated distribution and the true underlying distribution.

$$I\left(f, \hat{f}\right) = \int f(x) \log\left(\frac{f(x)}{\hat{f}(x)}\right) dx . \tag{4}$$

Density estimation in this paper will be limited to the kernel density estimate along with a Gaussian kernel having a symmetrical covariance matrix.

In face normalization process the text warping is one of the processes in that to eliminate the shape variation from the texture and build textures from two different faces similar. Given the images and the equivalent segmented facial shapes (top row), the texture is warped onto the mean shape in the middle.

Fig.3. Examples for Process of Face Normalization

The resulting images are shown on the bottom row in Fig.3.

Algorithm for Improved Point Distribution Model

Step 1: The shape of the object is describe for each training images.

Step 2: Label points are determined by extracting critical points.

$$L = [x_1(1), y_1(1), x_2(2), y_2(2), \ldots, x_i(N), y_i(N)]^T$$

where, N denotes the number of Training images, L denotes the mean shape, the covariance matrix is formed.

Step 3: For all training images, mean shape and a weighted sum is calculated from the covariance matrix.

$$L = L + Qb \tag{5}$$

where, Q = [|q₁|, |q₂|,….|qₜ|] represents the matrix of first eigen vectors and b = (b₁, b₂,….bₜ)ᵀ is weight vector.

Step 4: Curvature Vector Formation

Step 5: Send the final value to Gaussian density Model

Step 6: Edge is detected and the boundary is extracted

3.4 FEATURE EXTRACTION OF THE FACES USING LOCAL GABOR XOR PATTERNS

Feature extraction has a significant role to play in the area of face identification and verification. The aim of feature extraction is the reduction of the actual data set through the measurement of specific characteristics, or features, which differentiates one input pattern from another one. The texture of the tumor is extracted using method called Local Gabor XOR Patterns (LGXP) method [17]. This method initially forces the image to undergo a Gabor filtering, where the convolution of the image with the Gabor kernels is done to get the required output. After the Gabor filtering, the filter generates a complex number with real and imaginary parts at every image pixel. With the help of these two parameters magnitude and phase of the central pixel and every one of its neighbours. $LGXP^i_{\mu,w}(P = 1,2,\ldots,P)$ represents the pattern computed between $\varphi_{\mu,w}(l)$ and its neighbor z_c, which is calculated as below,

$$LGXP^i_{\mu,w} = q(\varphi_{\mu,w}(z_c))\, XOR\, q(\varphi_{\mu,w}(z_i)) \tag{6}$$

where, $\varphi_{\mu,w}(z_c)$ represents the phase and $q(\varphi_{\mu,w}(z_i))$ stands for the quantized value of the phase and where $\varphi_{\mu,w}(l)$ indicates the central pixel's position observed in the Gabor phase map with scale w and orientation μ,p refers to the size of neighborhood.

At last the resultant binary labels are then appended together to be the local pattern corresponding to the central pixel.

$$LGXP_{\mu,w}(z_c) = \left[LGXP^p_{\mu,w}, LGXP^{p-1}_{\mu,w}, \ldots, LGXP^1_{\mu,w}\right]_{binary} = \sum_{i=1}^{p} 2^{i-1}, LGXP^i_{\mu,w}. \tag{7}$$

After the process of LGXP, one equivalent value is got and then this value is substituted for the actual value and this process gets repeated for each block. After the process of feature extraction, the features are captured from the regions and then those features are provided to the Independent Component Analysis (ICA) classifier for the purpose of training.

3.4.1 Local Binary Pattern:

Local Binary Patterns yields a potential way of texture description [18]. LBP features are actually gray scale and rotation invariant texture operator. These features are extensively utilized for expression recognition. LBP features are also employed for face recognition task [18], [19]. LBP feature extraction is rapid in comparison with any of the feature extraction techniques and it renders better performance which makes this as one of the most explored features.

Suppose a 3×3 pixels having (X_c, Y_c) intensity value with G_c and local texture to be $T = t(G_0,G_1,G_2,G_3,G_4,G_5,G_6,G_7)$ in which $G_i(i = 0,1,2,3,4,5,6,7)$ is relative to the grey values of the 8 pixels in the surrounding. These surrounding pixels are threshold with the center value G_c to be $t(s(G_0 - G_c), \ldots s(G_7 - G_c))$ and the function $s(x)$ is defined below as,

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x \leq 0 \end{cases}. \tag{8}$$

The LBP pattern at the pixel given is defined to be a sorted set consisting of the binary comparisons and the resultant value can be got making use of the equation that follows. An instance of LBP operator is illustrated in Fig.4.

$$LBP(x_c, y_c) = \sum_{i=0}^{7} s(g_i - g_c)2^i. \tag{9}$$

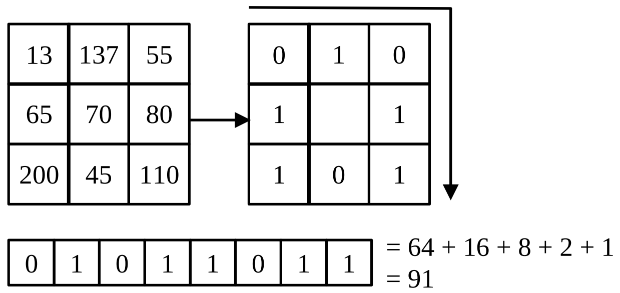

Fig.4. Feature Extraction Using LBP

3.4.2 Periocular Biometrics:

Eye lids, eye brow and the area surrounding the eye is known as the periocular region [20] that is observed to be have discrimination by nature. No database is available having images of periocular region. The only means of fetching this is making use of the face image that is available [21].

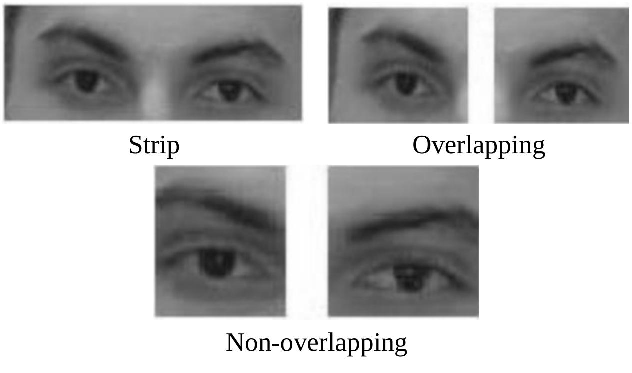

Fig.5. Different Types of periocular Regions

Periocular biometric is a procedure where the feature of the periocular region could be utilized for classifying. Periocular biometrics [21] is carried out in three kind of means which are overlapping, Non-overlapping and Strip [19]. All these three different kinds of periocular regions are got by making use of four important points present in the eye region and lips and are illustrated in Fig.5. LBP is employed for the cause of feature extraction. After feature extraction process, the features are extracted from the regions and those features are given to the Independent Component Analysis (ICA) classifier for training.

3.5 CLASSIFICATION USING FAST-INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent Component Analysis (ICA) is a geometric technique for decaying a sophisticated dataset into autonomous sub-portions. It evolves from blind source separation and attempts to modify a considered multidimensional vector into constituents which are independent statistically from one another to the maximum. There are at the least three diverse generally utilized definitions for the case of linear ICA.

Definition 1: ICA of the random vector X comprises of getting a linear transform S = WX such that the constituents S_i are independent to the maximum, in the view of maximization of some function $F(S_1,\ldots,S_m)$ which provides the measurement of the independence.

Definition 2: ICA of a random vector X comprises of the estimation of the generative model for the data, X = AS + *n*, where, X refers to the vector of signals observed and *n* indicates a random noise vector. The matrix A refers to the mixing matrix that has to be estimated, and S indicates the mutually independent constituents.

Definition 3: The Noise-free ICA model is expressed as below,

$$X = AS \tag{10}$$

where, matrix A and S are similar as given in Definition 2. In this research work, focus wills beover this definition.

Fast ICA algorithm that was suggested by Hyvarinen [12] is more efficient, it is actually a fixed-point algorithm that is in accordance with an optimized entropy function known as the negative entropy. Dissimilar to PCA, ICA can be considered to be a tool on the basis of higher order statistics, and it does the decorrelation of the input signals along with making the outcome independent to the maximum. Fast-ICA algorithm is in accordance with the negative entropy of the input signal for the purpose of measuring its non-Gaussian. The algorithm executes with a quick speed for the case of objective function optimization, and offers better stability. The Fig.6 illustrates the Fast-ICA model.

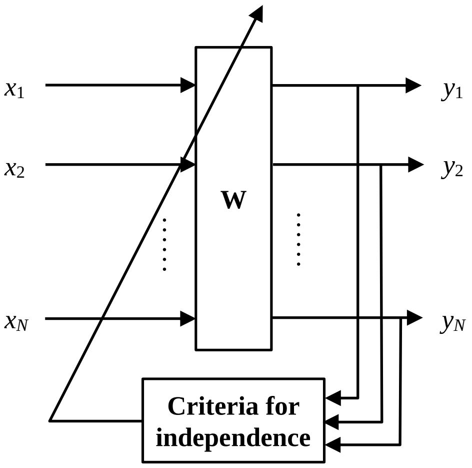

Fig.6. Fast-ICA Model

Based on the approximate computation of negative entropy the following is the generally employed objection function,

$$J_G(W_i) = \left[E\left\{G\left(W_i^T X\right)\right\} - E\left\{G(v)\right\}\right]^2 \tag{11}$$

where, $y_i = W_i^T X$ and *w* refers to an m-dimensional vector restrained in such a way that $E\{W^T X)^2\} = 1$, *v* refers to a Gaussian random variable having zero mean and unit variance. $G(y_i)$ stands for a non-quadratic function. For the purpose of achieving the signal separation, only the under restrictive criteria are needed such that

$$E\left\{\left(W_k^T X\right)\left(W_j^T X\right)\right\} = \delta_{jk} \quad \text{for maximizing} \quad \sum_{i=1}^{N} J_G(W_i).$$

3.5.1 *Fast-ICA based Damaged Face Classification:*

Supposing that the composition of every mixed pixel is actually a random variable (i.e. a signal source that is random), and the spectral response curves corresponding the ground types are independent from one another. Every spectral response curve comprises a source signal, and the multi-spectral image can be treated to be a mixed-signal obtained of these source signals. Therefore the classification with respect to the multi-spectral image becomes anissue of mixed-signal's blind source separation, and this merely satisfies the mathematical model of the ICA.

The steps formaking use of the Fast-ICA algorithm for the purpose of multi-spectral image classification are as below,

1. Centering of the input image bands, which is, the observation signal *x*;
2. Whitening of the centered signal *x*;
3. Initialization of weight vector *w*, and setting of convergence error ε;
4. Updating the weight vector *w*. The iterative formula that follows is used for adding the step-size μ in order to enhance the stability.

$$W_i^+ = W_i - \mu\left[E\left\{xg\left(W_i^T x\right)\right\} - \beta W_i\right] \Big/ \left[E\left\{g'\left(W_i^T x\right)\right\} - \beta\right] \tag{12}$$

   where, $\beta = E\left\{W_i^T xg\left(W_i^T x\right)\right\}$. The step size μ is changed adaptively;
5. Normalization of the weight vector *w*;
6. If $|W_{k+1} - W_k| > \varepsilon$, algorithm has not reached convergence, then repeat steps (4) and (5);
7. If the algorithm has not converged and the iteration exceeds more than the pre-fixed largest number (for instance 100), half the step-size and go back to step (4) and step (5) till $|W_{k+1} - W_k| < \varepsilon$;
8. Obtain the separation matrix w and ICA transform actual image, and extract the thematic information from the ICA constituents.

3.5.2 *Selection Method for Automatic Updates:*

The selection method is based on the following four confidence measures:

Temporal Confidence

Here an image is suitable to denote a user if it is not more than 1,825 days (~5 years) old, behind which it is considered unsuitable to characterize the user's appearance.

To quantify C_t, used a linear function in Eq.(2). A linear function was selected because the accuracy of FRSs has been exposed to reduce linearly with the time beyond between enrollments and testing. The quantity t_e indicate time elapsed in days among the time of attainment of the data and the present time.

$$C_t = \max(0,1) - \frac{t_e}{1825} \tag{13}$$

Confidence of the Face Detector C_d

Two observations are made if a frontal face detector is worn to detect faces. The first one is a several detections are found over a face if it is frontal. Faces among the in-plane and out-of-plane rotations obtain smaller amount detection. Next, the possibility of a face is high for a frontal face. Both these measures are used to calculate the confidence of face detection as mentioned in Eq.(14),

$$C_d = \sqrt[n]{\bar{l}} \tag{14}$$

where,

$\bar{l}$ is the mean of likelihood values.

l is work out for all detection windows that are combined to form a single detection region and its value is between 0 and 1.

The certain amount denotes the number of detections in the region of a face. When n increases, C_d also increases. Suppose if the face which is non-frontal or not sufficiently illuminated, usually have fewer detection windows, therefore, be liable to have lower confidence of detection.

Confidence of the Segmentation Algorithm C_s

In [22] explained about the reliability score, calculated by means of the texture information removed by the segmentation algorithm in process matching. The reliability score point out that if the fitting of the statistical face model to a test face can be measured to be correct or not [22] is illustrated in Fig 7.

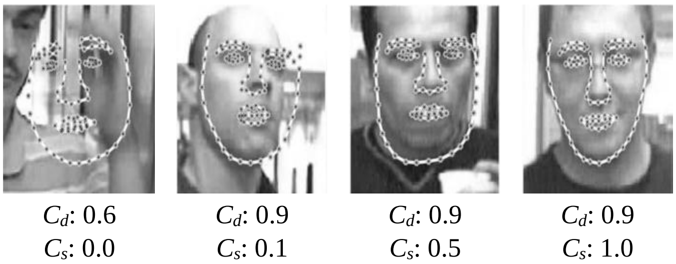

Fig.7. Confidence of Segmentation, C_s, Computed on Several Test Images [23]

Confidence of the Classification Algorithm C_c

The confidence of OSTCM-NN classifier is used in [24]. The values are calculated in two steps, initially strangeness ($\propto$) of a test exemplar with a label y is figured out by the Eq.(15),

$$\propto_i^y = \left(\sum_{j=1}^{k} d_{iy}^y\right)\left(\sum_{j=1}^{k} d_{iy}^y\right)^{-1}. \tag{15}$$

The quantity, $\sum_{j=1}^{k} d_{iy}^y$ represents to the sum of all distances of the test exemplar to the adjacent exemplars in the training set that fit in to a class with a label.

Image Selection Using Confidence Measures

The selection is done through a test face, with a label is added to the training set of the user, if the confidence values calculated on it (C_d, C_s and C_c) are greater than current thresholds.

The threshold for C_c be changed in the experiments. The thresholds intended for C_d and C_s has been set based on the outlier detection method introduced by Frigge et al. [25].

1. For every image present in the training set corresponding to a user, C_d and C_s values were calculated resulting in the vectors $C_d = \{C_d\}$ and $C_s = \{C_s\}$.
2. The first, second and third quartiles (Q_1, Q_2 and Q_3) of C_d and C_s were computed.
3. The thresholds were set at $Q_1 - 3 \times (Q_3 - Q_1)$

In the next experiments, it was tacit that when and values calculated from a test image are better than the individual thresholds set for a user, after that, the test image's classification label is deemed valid. Or else, the face in the test image is deemed an impostor.

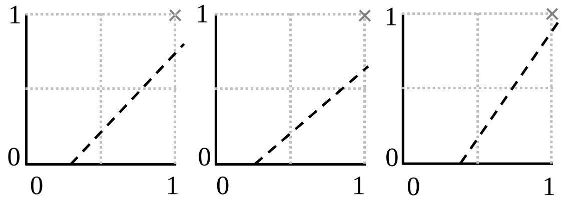

Fig.8. Illustration of the Optimal Line of Projection

The Fig.8 illustrates the optimal lime of projection (represented as a dotted line), whose Slope is defined by the Texture and Shape Fusion Weights, whose interpretation is in the form of a projection on a line. The markers represent values obtained for genuine user labels and the rest of the users, in that order.

Note that, as a result of the proposed normalization, the dynamic range of both vertical and horizontal axes of the plots is between 0 and 1. Here, p-values recorded for the genuine users labels overlap and take the maximum value (1, 1). Because the plots were created on yourself enrolled with training database where there was no sleaze. C_t, is to eradicate the total number of images per person. When of an image in the training set becomes zero, and then it is deleted.

4. EXPERIMENTAL RESULTS

The experiments are carried out making use of database consisting of surgery and non-surgery face. The images that exist in the face database are gathered from various sources of internet. Deploying these images, the database of plastic surgery face is generated. This work presents a new image database containing 14,279 images of 35 users and 74 impostors acquired on a day-to-day basis over five months. The database, called Gradual Evolution of Facial Appearance database (GEFA), can be obtained free of cost from http://cilab2.upf.edu/gefa/. To detect faces accurately in real-time, our system employs Viola and Jones face detection procedure. The detector works at a speed of 15 frames per second at 12 resolution levels, while achieving low false acceptance rates.

The training set was collected by choosing 472 images from the 3,498 images captured in the first month. This testing set includes a total of 2000 images captured at the period of fifth month.

This database comprises of one preand post-surgery face image along with frontal pose, various lighting conditions, and different expressions. In addition, the resolution of the face image is low. This might adversely impact the performance and accuracy corresponding to the face recognition system. Pre-surgery images are employed for the purposes of training and post surgery images in the form of test set. The necessary software for this experiment accounts to MATLAB. The proposed Improved Self Updating Face Recognition Authentication System (SUFRAS) is compared with the Self Updating FRS approach (SUFRS).

In the proposed experiments, the quantity was varied from 0 to 6. The higher the values, the higher the impostor threshold. The input images taken for experimentation are shown in Fig.9.

4.1 IMAGE RESULTS

Fig.9. Input Images

Fig.10. Face Detection Result

The Fig.10 show the face detection results, whether there are face(s) in an image.

The Fig.11 show the Face Segmentation results. The main aim of segmentation is to partition an image into regions and objects, in such a way that the segmented regions can be examined individually.

The Fig.12 shows the global features extracted from the image. The proposed approach shows efficient separation of a face from the background and accurate localization of facial features to extract facial features according to either shape or image intensities.

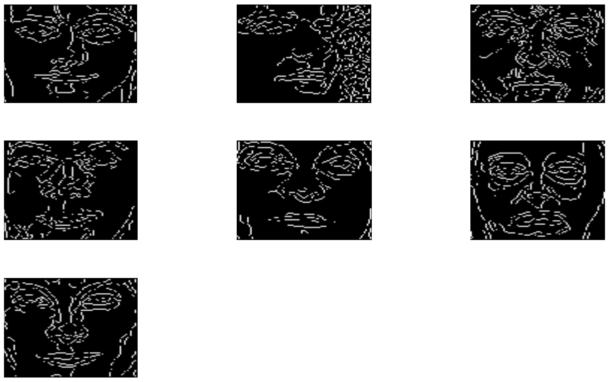

Fig.11. Face Segmentation

Fig.12. Global Feature

4.2 IMPLEMENTATION RESULTS

Fig.13. Input Test Image

The input image is considered for experimentation is as shown in the Fig.13.

Fig.14. Face detection of Test Image

The input image given is considered for further processing. The given input image is checked, where it consists of a face or not a face is shown in the Fig.14.

Fig.15. Face Segmentation of Test Image

The Fig.15 show the result of segmentation of the test image. From this the segmented features are used by Active Shape Models with Invariant Optimal Features for matching a statistical model of object shape and appearance to a new image.

Fig.16. Global Feature extraction of Test Image

The Fig.16 show the global feature extraction of the test image for identification and verification.

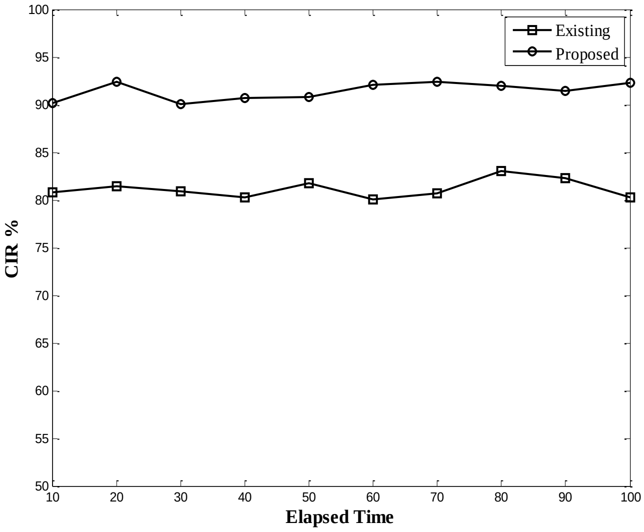

Fig.17. CIR Comparison

The Fig.17 and Fig.18 show the plots of Correct Identification Rate (CIR) and the Classifier confidence as a function of time for GIT and UIT, respectively. CIR was computed as the ratio of the number of correctly classified images (i.e., a test image belonging to user '*j*' has been identified as '*j*') to the total number of images that are tested.

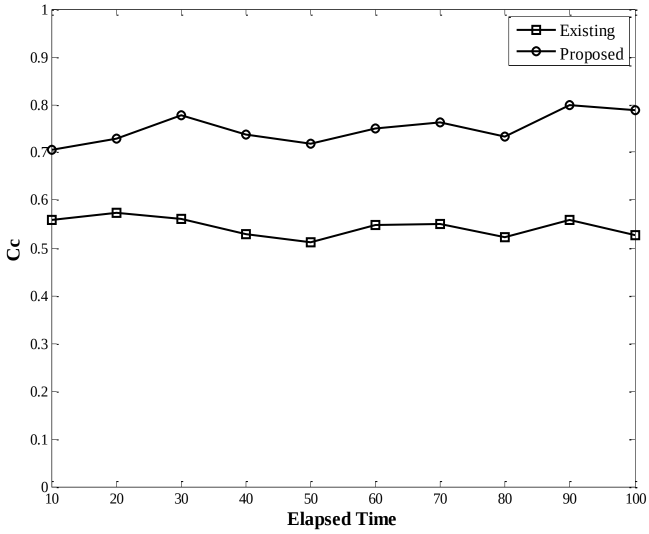

Fig.18. Classifier Confidence Comparison

5. PERFORMANCE COMPARISON

The proposed face recognition system is simulated using MATLAB for different database images. It is observed that this proposed method provides much more effective in identifying a specific face as compared to other edge detection algorithms like Principal Component Analysis (PCA) and Local Binary Patterns (LBP). The performance metrics used for analyzing the proposed method are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR).

5.1 PEAK SIGNAL TO NOISE RATIO (PSNR)

The PSNR is represented by the ratio between the maximum possible powers to the power of corrupting noise. It is also referred as the logarithmic function of peak value of image and mean square error and hence represented as,

$$PSNR = 10\log_{10}\left(MAX_i^2 / MSE\right). \tag{16}$$

5.2 MEAN SQUARE ERROR (MSE)

Mean Square Error (MSE) of an estimator is to quantify the difference between an estimator and the true value of the quantity being estimated.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2 . \tag{17}$$

Table.1. Performance Comparison

Methodology	MSE	PSNR
PCA	0.3259	34.258
PCA-LBP	0.2369	37.259
Proposed Fast ICA- LGXP	0.2145	40.256

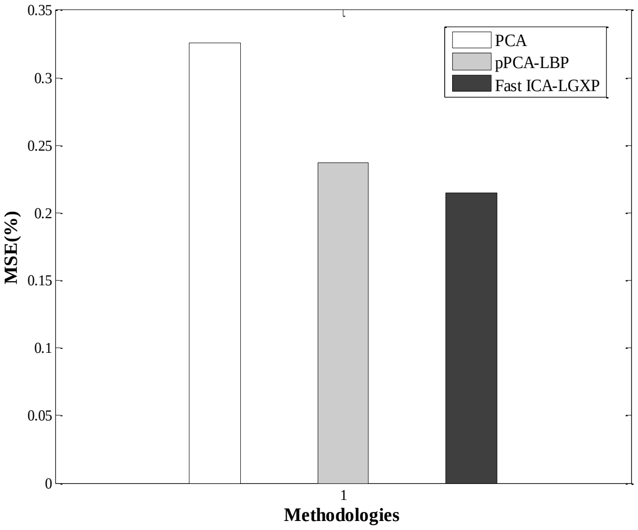

Fig.19. Comparison of MSE of Various Edge Detection Methods with Fast ICA- LGXP

The graphical representation of the comparison made of MSE and PSNR of the newly introduced technique with the existing techniques such as cluster algorithms, SVM and WSVM has been represented graphically in Fig.19 and Fig.20. Hence, the performance of the proposed methodology using Fast ICA- LGXP is found to be far better than the existing edge detection algorithms such as PCA and PCA-LBP.

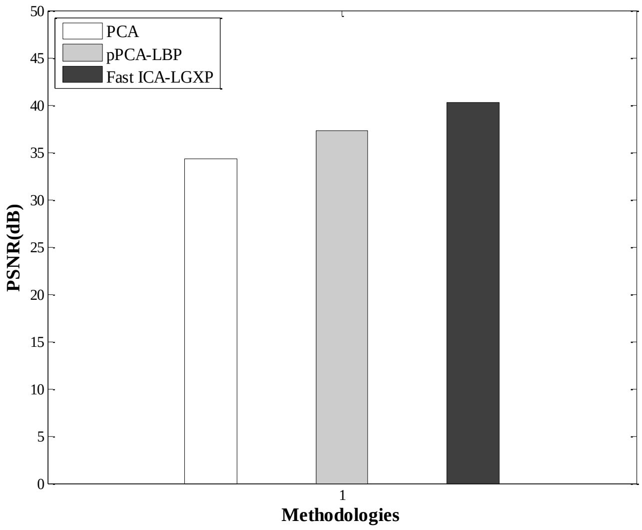

Fig.20. Comparison of PSNR of Various Edge Detection Methods with Fast ICA- LGXP

From these measures the following measures were used to measure the result of the edge detection methods,

$$\text{Sensitivity}=\frac{TP}{TP+FN} \tag{18}$$

$$\text{Specificity}=\frac{TN}{TN+FP} \tag{19}$$

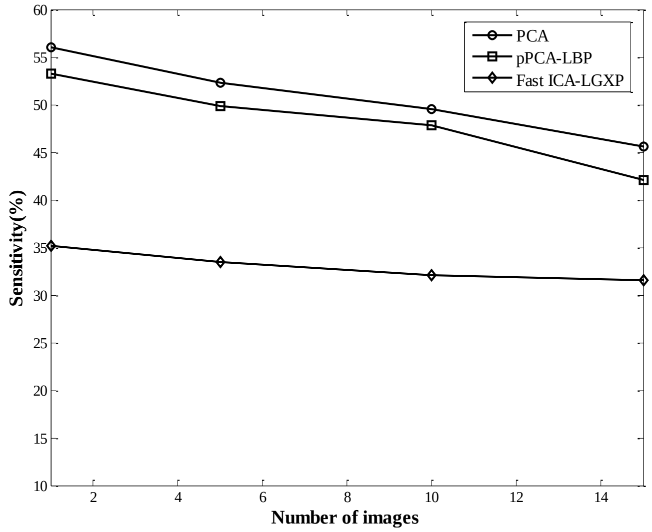

Fig.21. Sensitivity Results Comparison for Various Methods

The sensitivity results of the proposed Fast ICA-LGXP have also been compared with the other methods such as PCA and PCA-LBP. The graphical representation of comparison of sensitivity results is shown in Fig.21. The results showed that the proposed Fast ICA-LGXP is less sensitive than the existing edge detection methods such as PCA and PCA-LBP.

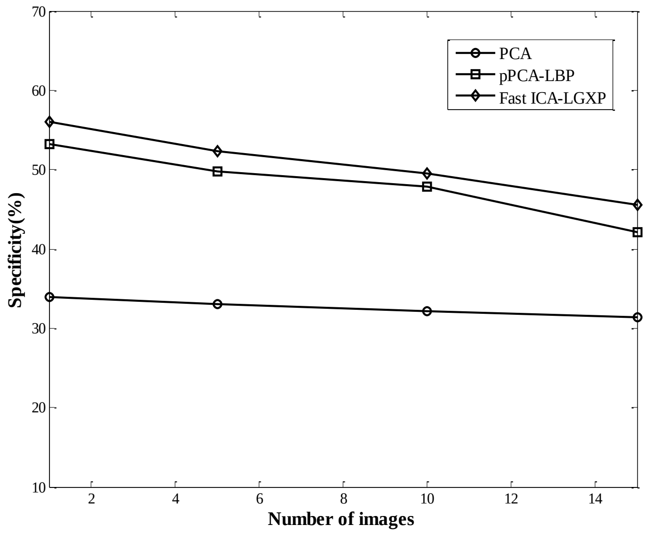

Fig.22. Specificity Results Comparison for Various Methods

The specificity results of the Proposed Fast ICA-LGXP are higher than the existing methods such as PCA and PCA-LBP. The Fig.22 shows the graphical representation of comparison of specificity results with other methods such as PCA and PCA-LBP.

Precision

Precision is defined as the proportion of the true positives against both true positives and false positives results for fake and real fingerprint images. Its definition follows,

$$\text{Precision}=\frac{TP}{TP+FP} \tag{20}$$

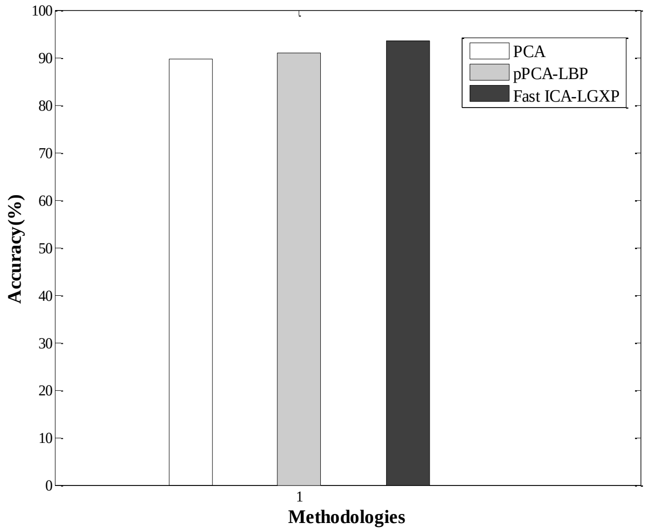

Fig.23. Performance comparison for Classification Accuracy

The Accuracy results of the Proposed Fast ICA-LGXP are higher than the existing methods such as PCA and PCA-LBP. The Fig.23 shows the graphical representation of comparison of specificity results with other methods such as PCA and PCA-LBP.

6. CONCLUSION

In the area of recognizing faces, many techniques have been introduced with the purpose of addressing the issues of illumination, pose, expression, aging and camouflage. However plastic surgery based face recognition is still a lesser explored area. These types of surgeries changes the facial features to such large extent that often human beings find it tedious to recognize a person face once the surgery is performed. This paper introduces a novel Multimodal Biometric approach making use of a novel approaches for improving the rate of recognition and security. The proposed method consists of various processes like Face segmentation, Face Normalization, Feature extraction and Classification. In the first step for Segmenting an object out of an image is determining and defining the boundary that encapsulates that object. In several scenarios, the shape of the boundary can give a lot of data about the object itself. For the segmentation of the well-known facial features, this approach system utilizes Active Shape Models with Invariant Optimal Features (IOF-AAM). This approach integrates local image search with global shape constraints depending on a Point Distribution Model (IPDM). Then the second step introduces a Kernel Density Estimate/Point Distribution Model (KDE-PDM) algorithm that is in accordance with PCA, and the Kernel Density Estimation for providing a statistical shape model which can manage with high dimensional data sets, represent the correlated variation modes. In the third stage, feature extraction is performed to the reduction of the actual data set through the measurement of specific characteristics, or features from one to another one. The texture of the tumor is extracted using method called Local Gabor XOR Patterns (LGXP) initially forces the image to undergo a Gabor filtering, where the convolution of the image with the Gabor kernels is done to get the required output. Finally classification is done by Independent Component Analysis (ICA) for decaying a sophisticated dataset into autonomous sub-portions. It evolves from blind source separation and attempts to modify a considered multidimensional vector into constituents which are independent statistically from one another to the maximum. Also to evaluate the proposed approaches, The FRSs were updated using two large and significant facial image databases: GEFA and YT databases with 14,279 and 31,951 images, correspondingly. The above said methods have given significant results when compared with existing techniques.

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