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Comparison of Various Algorithms for Face Matching and Retrieval in Forensic Applications

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Abstract*— This paper highlights the challenges in applying face recognition technology in forensic applications. It addresses two specific research problems 1) face retrieval using various pose and expressions 2) matching forensic sketches to face photograph databases. Solutions to these problems are necessary to accurately remove the duplicates in various government databases, including passport, driver license photos; to apprehend the criminals when no photos of suspect is available (sketch to photo matching).This can be done by using several algorithms. For pose, expression and sketches Wavelet Transform, Cosine Transform, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Scale Invariant Feature Transform (SIFT) algorithms are used.

***Index Terms*— DCT, DWT, Forensic pose and expressions, Forensic sketches, LDA, PCA, SIFT.**

I. INTRODUCTION

Law enforcement has successfully used the forensic clues such as fingerprint drop of blood on the floor to catch the criminals for decades. But consider a face image captured by a surveillance camera that needs to be matched against millions of mug shots across the country. With the rapid increase in the number of surveillance cameras and mobile devices with built-in cameras, the forensics world is changing, and the progress in face recognition is helping to lead the way.

II. FACE RECOGNITION OVERVIEW

This paper discusses about the scenario in which man and machine plays a major role for successful face recognition. Face identification becomes difficult with various pose, expression in conventional ways. Various algorithms have been developed to avoid these problems. This shows in Fig.1.

Major computational stages of face recognition

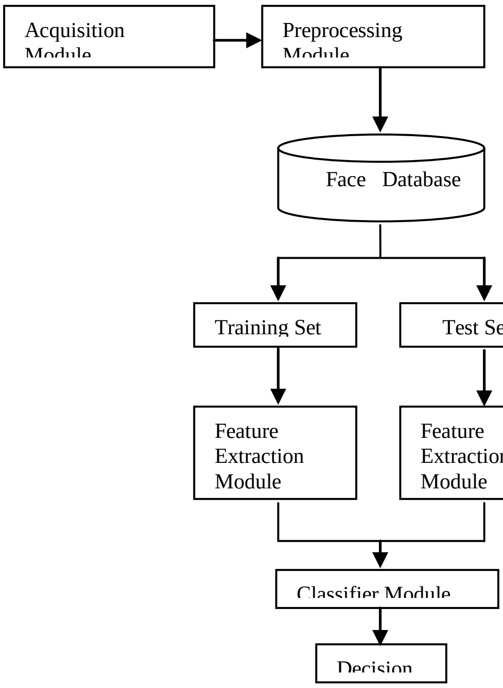

Fig.1. General steps in face recognition

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The system starts with the acquisition module where images are captured with a digital or surveillance camera or any image capturing devices. In the second phase, captured images are sent through the Preprocessing module to meet the standards required by the given recognition system. The preprocessing module performs task like color to gray scale conversion, resizing and illumination and background removal in order to normalize the input image. Then the normalized images are added to the face database. Some of the databases are taken as training database and one of the face databases is taken as test database.

The Feature Extraction module takes the normalized image as input and outputs only the important features of input image, thereby reducing its dimensionality [3]. Finally the classifier module performs the comparison between the test image and training image and further it decides the closest match and retrieves it.

III. METHODOLOGY

In this paper [4], our goal is to develop a system that can recognize faces whose appearance changes according to different factors such as pose, expression, sketches where the treatment of face may fail to produce correct recognition. One of the images is taken as test image and consider rest as training image. The important features of face are extracted and similarity measure between training image and test image is taken. Finally, the person who receives minimum distance is chosen as the best match.

To provide a perspective on the angle of our region-division approach that uses majority voting, compare the recognition performance of three techniques, namely the Discrete Wavelet Transform (DWT) Principle component analysis (PCA) and Linear Discriminant Analysis (LDA) are compared. To provide the perfect match for forensic sketches Scale Invariant Feature Transform (SIFT) can also be used.

A. Discrete Wavelet Transform

A signal is decomposed into a set of basis functions called "wavelets" in DWT [3]. Here decomposition means resolution of signal. In DWT multi resolution analysis performed with localization in both frequency and time domains. Mathematically DWT can be expressed as:

$$DWT_{x(n)} = d_{j,k} = \sum x(n) h_j^*(n - 2^j k) \qquad (1a)$$

$$DWT_{x(n)} = a_{j,k} = \sum x(n) g_j^*(n - 2^j k) \qquad (1b)$$

The coefficients $d_{j,k}$, are called detail components of signal x(n) and coefficients $a_{j,k}$, are called approximation components .the functions g(n) and h(n) refer to the coefficients of low pass and high pass filters with parameters j and k as wavelet scale and translation factors. In case of 2D images ,DWT is done as a set of filter banks (combination of low pass and high pass filters).Finally image is decomposed into four nonoverlapping ,multi-resolution sub bands:LL,LH,HL,HH where, LL corresponds to approximation details(coarse scale) and LH,HL,HH corresponds to horizontal, vertical and diagonal details(fine scale) respectively. Size of each band is quarter to the original image size .The next level of DWT is obtained by further decomposition of LL sub band. DWT can be repeated for multiple times for multiple level of resolution as shown in Fig.2.

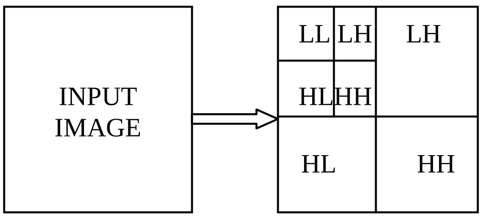

Fig.2. Decomposition levels of DWT

Size of each band in 1st level =1/4th of original. Size of each band in 2nd level=1/4th of LL1 (approximation).
The same level of decomposition is done for test image and similarity measure is taken for both train and test image. It is obtained by means of Euclidean distance.

$$\text{Euclidean distance} = \sum_{i=1}^{n} \left\| x_i - y_i \right\|^2 \qquad (2)$$

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A. Principal Component Analysis

Principal Component Analysis (PCA) is a dimensionality reduction technique that is used for image recognition and compression [4],[5],[6]. Eigenvectors of the covariance should be found in order to reach the solution. The eigenvectors correspond to the directions of the principle components of the original data, and their statistical significance is given by their corresponding eigen values.

1. *Calculating Eigen faces*

Consider NxN image face image $\Gamma(x, y)$ as a vector of dimension $N^{2,}$ so the image can be thought as a point in N^2 dimensional space. A database of M images can therefore be mapped to a collection of points in this high dimensional "face space" as $\Gamma_1, \Gamma_2, \Gamma_3 \ldots\ldots \Gamma_M$.

To compute Eigen faces [8], first an average of all training images needs to be computed.

The average image Ψ is computed using Equation 3:

$$\Psi = \frac{1}{M}\sum_{i=1}^{n}\Gamma_n \qquad (3)$$

Each image Γ_i differs from the average image Ψ by the vector $\Phi_i = \Gamma_i - \psi$, where i=1, 2, 3….M. The covariance matrix C of the data is defined by the Equation 4:

$$C = \frac{1}{M} = \sum_{n=1}^{M}\Phi\Phi_n \qquad (4)$$

where the matrix $A=[\Phi_1,\Phi_2,\Phi_3,\ldots..\Phi_M]$.The matrix C has the dimension of N^2xN^2 eigenvectors and eigenvalues, and, for typical image sizes, this size would be a very high value. Therefore, a method which is computationally feasible is required to determine these eigenvectors.

If the number of data points in the image space is less than the dimension of space $M<N^2$, there will be only (M-1) meaningful eigenvectors, and the rest of the eigenvectors will have eigenvalues of zeros. Consider the eigenvectors v_i of A^TA such that

$$A^TAv_i = \mu_i v_i \qquad (5)$$

Multiplying both sides by A, we have

$$AA^TAv_i = \mu_i Av_i \qquad (6)$$

From Equation 6, we can see that Av_i are the eigenvectors of $C=AA^T$. Then we can construct a MxM matrix:

$$L=A^TA \qquad (7)$$

Then the M eigenvectors v_i of L can be found. These vectors determine linear combinations of the M training set face images to form eigenfaces u_i.

$$u_j = \sum_{k=1}^{M} v_{ik}\Phi_k \qquad (8)$$

Eigenvectors u_i are in fact images, and they are called eigenfaces, and the eigenvectors with the highest eigenvalues are more useful. Therefore those $M^I < M$ eigenfaces that are most significant are used for constructing the "face subspace" for projections that are used in identifying and classifying images.

$$\omega_k = u_k^T(\Gamma - \Psi),\ k= 1,2\ldots\ldots M^I \qquad (9)$$

where ω_k is the k-th coordinate of the Φ in the new "face space."

$$\Omega^T = [\omega 1, \omega_2, \omega_{3\ldots}\omega_M] \qquad (10)$$

$$\varepsilon_k = \| \Omega - \Omega_k \|^2 \qquad (11)$$

where Ω_k describes k-th face class, which is the average of the Eigen faces representation of the face images for each individual in the training set. A face will be classified as belonging to some class if the minimum ε_k is below some specified threshold. Otherwise, that image will be classified as unknown face.

B. Linear Discriminant Analysis

The LDA approach or Fisher discriminants group images of the same class and separates images of different classes. Images are projected from N-dimensional space (where N is the number of pixels in the image) to C-1

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dimensional space (where C is the number of classes of images) [7].For example, consider two sets points in 2-dimensional space that are projected onto a single line. Depending on the direction of the line, the points can either be mixed together (Fig.3 (a)) or separated (Fig.3 (b)).

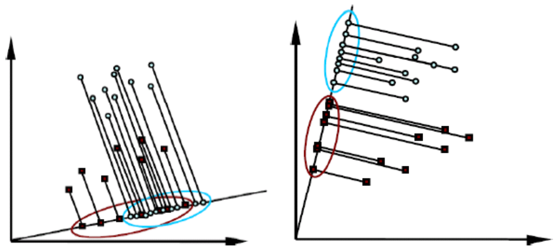

Fig.3(a). Points are mixed when projected onto line. **Fig.3(b). Points are grouped when projected onto line.**

Fisher discriminants [8] find the line that best separates the points. To identify a test image, the projected test image is compared to each projected training image, and the test image is identified as the closest training image.
As with eigenspace projection, training images are projected into a subspace. The test images are projected into the same subspace and identified using a similarity measure. What differs is how the subspace is calculated. Following are the steps to follow to find the Fisher discriminants for a set of images.

1. Calculating Fisher faces

The steps followed in the evaluation of the Fisher faces are as follows:

• Read images (faces) in the database and divide them into two sets, one for training and the other for testing.

• Images for training
• Create the training set and find the average of each class and find the average for each person's training images, μ_j .
• Find average of the training images in the database, μ.
• Apply the Linear Discriminant Analysis to find the within-scatter matrix and between scatter matrix:

a) Within class matrix

$$S_w = \sum_{j=1}^{C}\sum_{i=1}^{N}(X_i^j - \mu_j)(X_i^j - \mu_j)^T \qquad (12)$$

b) Between-scatter matrix

$$S_b = \sum_{j=1}^{C}(\mu_j - \mu)(\mu_j - \mu)^T \qquad (13)$$

• Find the associated eigenvectors using the between scatter matrix and within scatter matrix: $S_w^{-1}S_b$.
• Transform the test images and all the faces in the database into the face space created in the previous step.
• Using Euclidean distance method, find the identity of the test image:

$$\varepsilon_k = \| \Omega - \Omega_k \|^2 \qquad (14)$$

• Compute the system accuracy rate.

C. SCALE-INVARIANT FEATURE TRANSFORM

Scale-invariant feature transform (or SIFT) [10] is an algorithm in computer vision to detect and describe local features in images. Key locations are defined as maxima and minima of the result of difference of Gaussians function applied in scale-space to a series of smoothed and resampled images. SIFT descriptors robust to local

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affine distortion are then obtained by considering pixels around a radius of the key location, blurring and resampling of local image orientation planes. The steps involved are as follows.

Constructing scale space

The scale space is constructed by finding laplacian of Gaussian which is given by

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x,y) \qquad (15)$$

Where G(x, y, σ) is given by

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \qquad (16)$$

***Laplacian of Gaussian approximation* (LoG)**

It takes second order derivative of G which provides edges and corners on image. Difference of Gaussian D(x, y, σ) is given by

$$D(x, y, \sigma) = L(x, y, k_i\sigma) - L(x, y, k_j\sigma) \qquad (17)$$

Finding Key points

Maxima and minima is located in DoG images and sub pixel maxima\minima is found by Taylor expansion,

$$D(x) = D + \frac{\partial D^T}{\partial x} + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \qquad (18)$$

Eliminate low contrast regions

The key points with low contrast are eliminate by computing second order value for D(x) and discard if it is less than certain value.(say 0.03)

Eliminate edge points

The edge points are eliminated by Hessian matrix,

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{yx} & D_{yy} \end{bmatrix} \qquad (19)$$

Assigning Key point Orientation

The key point orientation is assigned by computing magnitude and direction and by creating histogram and peak point is assigned as orientation key point.

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \qquad (20)$$

$$\theta(x,y) = a\tan 2(L(x,y+1) - L(x,y-1) - L(x+1,y) - L(x-1,y)) \qquad (21)$$

Generate SIFT features

The SIFT features are generated by computing descriptor vector for each key point such that descriptor must be highly distinctive and partially invariant to illuminations.

D. Discrete Cosine Transform

Face Recognition using Discrete Cosine Transform [11] (DCT) for Local and Global Features involves recognizing the corresponding face image from the database. The face image obtained from the user is cropped such that only the frontal face image is extracted, eliminating the background. The image is restricted to a size of 128 × 128 pixels. All images in the database are gray level images. DCT is applied to the entire image. This gives DCT coefficients, which are global features. Local features such as eyes, nose and mouth are also extracted and DCT is applied to these features. Depending upon the recognition rate obtained for each feature, they are given weightage and then combined. Both local and global features are used for comparison. By comparing the ranks for global and local features, the false acceptance rate for DCT can be minimized.

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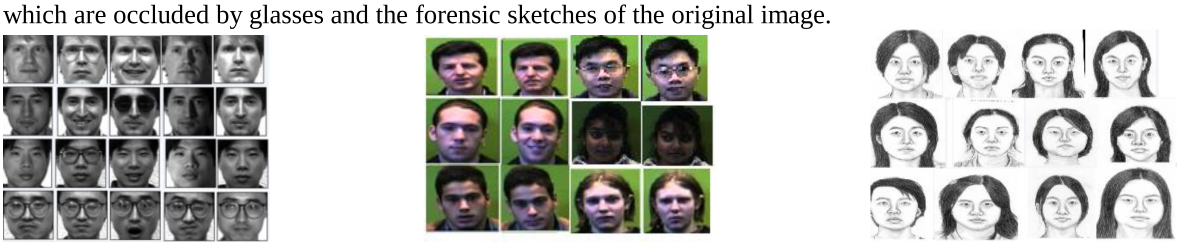
Volume 3, Issue 4, July 2014

IV. RESULTS

A. Database

The database collected for expression and pose are FERET and ORL database. The database included the images which are occluded by glasses and the forensic sketches of the original image.



(a) (b) (c)

Fig .4.Database (a) Expression (b) Pose (c) sketches

Fig.4 shows the database for different expressions and poses of different persons. First of all the images are read. These images undergo pre-processing steps, feature extraction and matching process. The final comparison results can be seen in the Table 1 and Fig 5.

(a) (b) (c)

Fig.5. (a) Number of Training images vs. recognition time (b) Number of training images vs. Efficiency (c) Recognition time vs. Efficiency

As shown in the Fig.6. When the number of training images increases the efficiency also increases. It is applicable for all the three algorithms as mentioned in this paper. It is also noted that the recognition time increases proportionally when the database increases.

TABLE I. Comparison of Efficiency for Various Algorithms

Method/ No of training images	EFFICEINCY %				
	20	40	60	65	75
DWT	70	75	78.3	81.25	86.6
DCT	70	75	80	84.61	88
PCA	80	85	90	93.75	95
LDA	85	90	93.3	95	97.5
SIFT	90	95	96.66	98.4	98.67

TABLE II. Comparison of recognition time for various algorithms

Method/No of training images	Time(s)				
	20	40	60	65	75
DWT	1.00475	1.52235	1.7982	2.4005	2.58235
DCT	0.9874	0.9883	0.9996	1.0857	1.09586

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PCA	0.7325	0.7531	0.8231	0.8543	0.9712
LDA	0.545	0.6425	0.7221	0.8142	0.8721
SIFT	0.003414	0.003565	0.00385	0.00416	0.00428

It is to be concluded that SIFT outperforms better when compared to PCA, LDA and DWT since it directly deals with the elimination of noises and low contrast regions. The recognition time of SIFT is also reduced to fraction of seconds with better efficiency when compared to DWT, LDA and PCA.

V.CONCLUSION AND FUTURE WORK

This paper presents an independent, comparative study of five most popular appearance based face recognition algorithms (DWT, DCT, PCA, LDA and SIFT) for pose expression and sketches. Face recognition in forensic departments can make their work ease in finding the criminals rather than using conventional methods. Our future work is to further improve the accuracy of face recognition in forensic approach by utilizing the demographic information and forensic sketches.

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