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An Assimilated Face Recognition System With effective Gender Recognition Rate

K. Akhil Sreenivasulu[1], Dr. G. Harinatha Reddy[2]

[1]*M. Tech. Scholar, NBKR Institute of Science and Technology, Andhra Pradesh, India*
[2]*Professor and HOD, Dept. of ECE, NBKR Institute of Science and Technology, Andhra Pradesh, India*

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Abstract - *This paper focuses on assimilating the existing Face Recognition techniques and also to perform Gender Recognition by calculating the Gender Recognition Rate (GRR), which is a metric of calculating the average efficiency of Gender Recognition. Numbers of experiments are conducted with the help of different databases. Few among these databases are GENDER-FERET database, Cambridge AT & T (ORL) database, and our own generated images. The GENDER-FERET database contains 946 images of 473 male and 473 female individuals with the size of 256 x 384 pixels. The Cambridge AT & T (ORL) database contains 400 images of 35 male and 5 female (40 people) in 10 poses with the size of 90 x 112 pixels. Our generated images database contains 20 images of 10 male and 10 female images with the size of 100 x 133 pixels. There is a wide range of applications for Face Recognition System. It still has prominent challenges of recognizing the faces in different facial conditions like illumination, occlusion (glasses), pose, expression, background, cluttering and RST (Rotation, Scaling, and Translation) variations. For the Face Recognition System, Eigenfaces (Principal Component Analysis - PCA) algorithm is applied on the databases mentioned above. For achieving effective Gender Recognition, a trainable COSFIRE (Combination of Shifted Filter Responses) filter with the help of fusion of Gabor filters is applied to obtain Face Descriptor. The face descriptors are further submitted for classifier namely Support Vector Machines (SVM) using chi-squared kernel for the purpose of gender classification and calculating the GRR. The main aim of this work is to explore the existing methods of Face Recognition System and Gender Recognition techniques and improve their effectiveness by optimizing the existing techniques.*

***Key Words*: Face Recognition, Gender Recognition Rate, SVM, COSFIRE Filter, Face Descriptor, GENDER-FERET dataset.**

1. INTRODUCTION

Gender Recognition (**GR**) in Face Recognition System (**FRS**) has predominant applications in the fields of demographic data collection, video surveillance, security, retail advertising, marketing and many places.

The contents in this paper are organized as follows. In section 2, the previous works are described. In section 3, the present work is thoroughly discussed. In section 4, mathematical relations are explained in detail. In section 5, experimental results are presented. In section 6, conclusions from the experimental results are extracted.

2. RELATED WORKS

P. Viola and M. J. Jones. [19], made a revolutionary change in finding the new Face Detection algorithmic approach, which became more popular within less span of time. There are many techniques for the purpose of FRS [23], out of them it can be broadly classified into Feature based methods **(FBM)**, Holistic based methods **(HBM)**, and Template Matching based methods **(TBM)** or Image-based Methods.

FBM algorithms extract the features, such as the distance between the eyes or the size of the eyes, and use these measures are fed to the structural classifier.

HBM algorithms consider the complete face region as input data into face catching system, and then perform mathematical operations to determine the query image with the trained images.

In **TBM** techniques, computer software can assess the overall texture of skin, shadows, and wrinkles to determine age, moles, and other features. It reads the shape of lips to determine the mood (expressions) and gender. It reads the eyebrow shape to determine the mood of the person. It reads the jewellery and the shadows cast by hair used to determine gender.

Examples of HBM techniques are Principal Component Analysis (**PCA** - Eigenfaces) [6], Linear Discriminant Analysis (**LDA** – Fisherfaces) [15], Independent Component Analysis (**ICA**) [5], Laplacianfaces, Evolutionary Pursuit (**EP**) [22], Kernel PCA, Kernel LDA, and Sparse Representation methods [24].

Examples of FBM techniques are Local Binary Patterns (**LBP)** [9], Local Ternary Pattern (**LTP**) [3] [8], Support Vector Machines (**SVM**) [20], Gabor and Elastic bunch Graph Matching (**EBGM**) [11], and other dynamic link architectures.

Examples of TBM techniques are Hidden Markov Model (**HMM**) [21], Active Appearance Model (**AAM**) [18], Scale Invariant Feature Transform (**SIFT**), Trace Transforms (**TT**) and component-based methods [24].

George Azzopardi et al. [1] introduced concept of COSFIRE Filter for calculating the Gender Recognition Rate (**GRR**) using filter operators.

Xipeng Yang et al. [2] proposed a new CEDA approach for GR technique by combining two methods namely Cauchy Estimation and Discriminant Analysis (**CEDA**).

C. B. Ng et al. [4] presented a review on facial gender recognition based on the various applications on pattern analysis.

J. Bekios-Calfa et al. [7] used facial attribute dependencies to obtain the robust Gender Recognition.

J. E. Tapia and C. A. Perez [9] applied fusion of various spatial scale features to obtain GR from the face images.

C. Shan. [13] utilized **LBP** technique on real world images to obtain the Gender Recognition.

Z. Xu et al. [17] introduced a hybrid approach for the Gender Classification using Template Matching technique termed as Histogram of Gradients (**HOGs**).

Many comprehensive reviews on FRS [10] and GR for 2D faces [12] and for 3D faces [14] came later onwards [16].

Face Recognition process includes these steps: Detection, Alignment, Measurement, Representation, Matching, Verification or Identification.

Detection meant for the capturing of a face, whereas *Alignment* stands for determining the location, size, and angle of the face. *Measurement* symbolize that assigning values to each curve of the face to make a template with the specific focus on the outside of the eye, the inside of the eye and angle of the nose, whereas, *Representation* converts the template into a code (a numerical representation of the face).

Matching compares the received data with the faces in the existing database. *Identification* is to identify a person based on the image of the face, whereas, *Verification* validates a claimed identity based on the image of a face, by either accepting or rejecting the identity claim.

3. PRESENT WORKS

Two experiments are performed in this paper with the same dataset of assimilated face databases namely GENDER-FERET Database, Cambridge AT & T (ORL) Database, and our own generated images.

One of the two experiments is FRS by Eigenfaces system or PCA, while the other experiment is Gender Recognition using COSFIRE filter responses and Support Vector Machines (**SVM**) classification process.

While performing face recognition, it is recommended to go for preprocessing of the face images from the query image, so that it will reduce the size of the image as well as increases the speed of operation. This preprocessing is also termed as *Face Detection*. Once the Face image is detected, the facial features will be extracted and then classifier will classify the query image with the trained images.

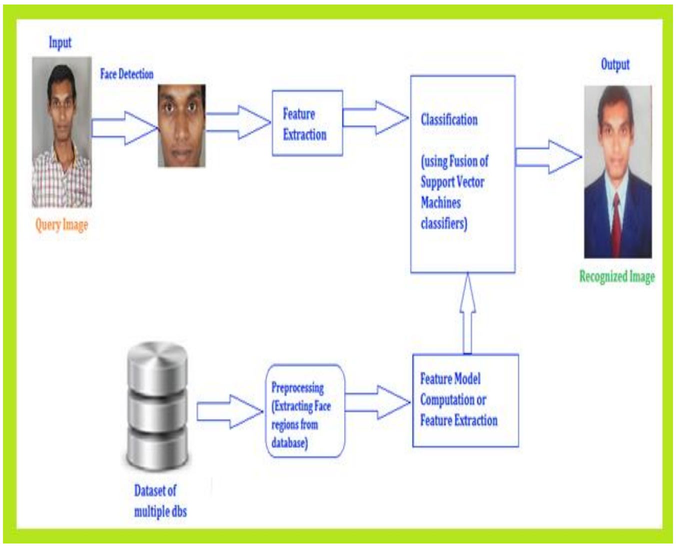

Fig -1: Face Recognition Procedure

In Figure 1, the workflow of Face Recognition (First Experiment) was given in which we have two phases. In phase 1 (training phase) trained dataset and Feature model is obtained, whereas, in phase 2 (testing phase), Query Image has been submitted for recognition procedure.

4. MATHEMATICAL APPROACH

4.1 Experiment of FRS

Step 1: Transform the image & compute the mean image

Initially we transform the m x n image into a vector of size 1 x N image where N= mn with the help of concatenation (of rows/columns).

Let M such vectors (Γ) of length N form a matrix S of learning images.

$$S = \{ \boldsymbol{\Gamma_1}, \boldsymbol{\Gamma_2}, \boldsymbol{\Gamma_3}, \boldsymbol{\Gamma_4}, \dots, \boldsymbol{\Gamma_M} \}$$

Mean value of each image is determined as below:

$$\psi = \frac{\sum_{n=1}^{M} \Gamma_n}{M} \quad (1)$$

Step 2: Calculate the covariance matrix

Compute the difference between input image and the mean image

$$\phi_i = \boldsymbol{\Gamma_i} - \boldsymbol{\psi} \quad (2)$$

A new training matrix of size N x M is obtained with the help of these differences $A = \{\boldsymbol{\phi_1}, \boldsymbol{\phi_2}, \boldsymbol{\phi_3}, \dots, \boldsymbol{\phi_n}\}$.

Obtain the covariance matrix with the help of the differences calculated in the above step

$$C = \frac{\sum_{n=1}^{M} \phi_n \phi_n^T}{M} = \boldsymbol{AA^T} \text{ or } \boldsymbol{A^T A} \quad (3)$$

Now, calculate the eigenvalues λ_i and eigenvectors ϑ_i of the covariance matrix using

$$C\vartheta_i = \lambda_i\vartheta_i \quad (4)$$

Covariance matrix C has dimensions N x N. From that we get N eigenvalues and eigenvectors. Most of these vectors are not required.

As per a theorem in the linear algebra, the eigenvalues and eigenvectors can be obtained by finding covariance matrix $C=A^TA$ which has the size of M x M.

$$A^T A\, v_i = \mu\, v_i \quad (5)$$

$$AA^T(A\, v_i) = A\mu_i\, v_i$$

$$C(Av_i) = \mu_i\,(Av_i) \quad (6)$$

Comparing equations (4) and (6), $\vartheta_i = A\, v_i,\ \lambda_i = \mu_i$

Eigen vector associated with the highest Eigen value reflects the highest variance, and the one associated with the lowest Eigen value reflects the lowest variance.

Step 3: Project the query image vector matrix onto the trained Eigen vector matrix

Eigen values decrease exponentially so that about 90% of the total variance is contained in the first 5% to 10% Eigen vectors. These vectors are then sorted in descending order and normalized.

New matrix E is obtained so that each vector ϑ_i is a column vector with the size of N x D, D represents the desired Eigen vectors. It is used for projection of data matrix A and calculation of y_i vectors of matrix $Y = (y_1, \dots, y_M)$.

$$Y = E^T A \quad (7)$$

Project a matrix of Eigen vectors *E* on to the query image which is transformed into a vector *P.*

Each value would represent a weight and would be saved on a vector (say omega).

$$\omega = E^T(P - \psi) \quad (8)$$

Step 4: Recognize the face

Now we determine which face class provides the best description for the input image.

Manhattan Distance: $d(A,B) = \sum_{i=1}^{D}|a_i - b_i| \quad (9)$

Euclidean Distance:

$$d(A,B) = \sqrt{\sum_{i=1}^{D}(a_i - b_i)^2} = \|A - B\| \quad (10)$$

It is done by minimizing the Euclidean distance.

The input face is considered to a class, if Euclidean distance is below than established threshold, and then face is considered to be a known face if difference is above than given threshold, the image can be considered as unknown face.

If input image is below than two thresholds, the image is determined not to be a face.

4.2 Experiment of GRR

For calculation of Gender Recognition Rate, trainable COSFIRE Filter is applied with the number of operators to obtain the face descriptor and then classify the Gender with the help of SVM Classifier with Chi- Squared Kernel.

Step 1: Configure the COSFIRE Filter

Consider scale and orientation of Gabor filter of i^{th} tuple as $\boldsymbol{\lambda_i}, \boldsymbol{\theta_i}$ and $(\boldsymbol{\rho_i}, \boldsymbol{\phi_i})$ be the parameters of the filter response in the polar coordinates, then the configuration of the COSFIRE filter is given by:

$$S_f = \{(\boldsymbol{\lambda_i}, \boldsymbol{\theta_i}, \boldsymbol{\rho_i}, \boldsymbol{\phi_i}) \mid i = 1, 2, \dots \mathrm{n}\} \quad \text{(a)}$$

Here f is the given prototype pattern, and n represents the number of local maximum points.

Step 2: Compute the Filter Response

Computing the filter response combining the blurred and shifted responses by geometric mean:

$$r_{S_f} = \left(\prod_{i=1}^{n} \mathbf{S}_{\lambda_i,\theta_i,\rho_i,\phi_i}(\mathbf{x}, \mathbf{y})\right)^{\frac{1}{n}} \quad \text{(b)}$$

Step 3: Formulate the face descriptor

Form a face descriptor using maximum responses of a collection of COSFIRE filters that are selective for the different parts of face such as eyes, nose, and mouth.

The higher number in filter operators gives the effective results in terms of accuracy.

Step 4: Classify with SVM (chi-squared kernel)

Classify the face descriptors that are formed in the above step using SVM Classification model with the following chi-squared kernel:

$$K(x_i, y_j) = \frac{(x_i - y_j)^2}{\frac{1}{2}(x_i + y_j) + \epsilon} \quad \text{(c)}$$

Where x_i, y_j are the descriptors of the training images i and j, and the parameter $\in$ represents a very small value to avoid division by zero errors.

5. EXPERIMENTAL RESULTS

Face Recognition experiment and Gender Recognition experiment are performed and those results are presented here.

Fig -2.a: Training Dataset (10 images from ORL database)

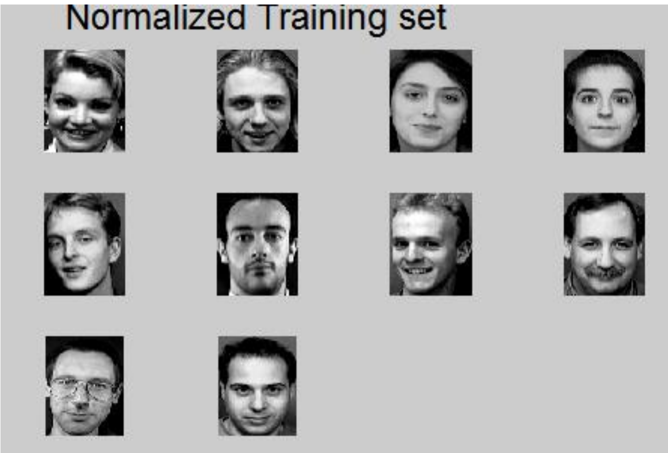

Fig -2.b: Normalized Training set images with improved illumination

Fig -2.c: Average (Mean) Image of all normalized images

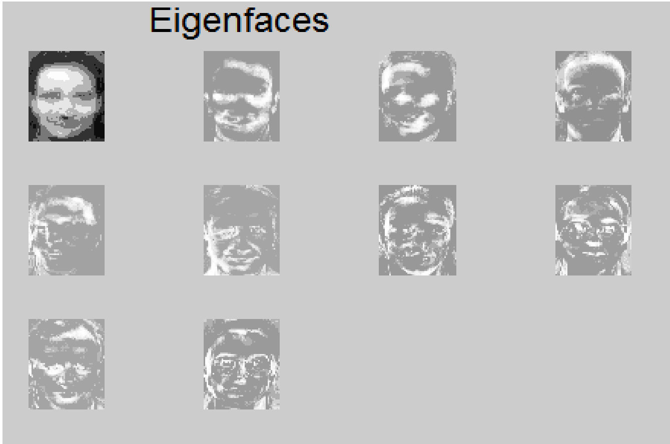

Fig -2.d: Eigen faces of Mean Images (Principal components)

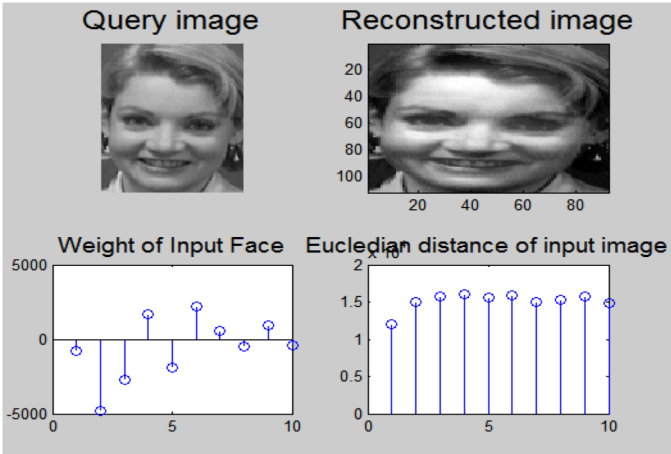

Fig -2.e: Successful Recognized image (trained image)

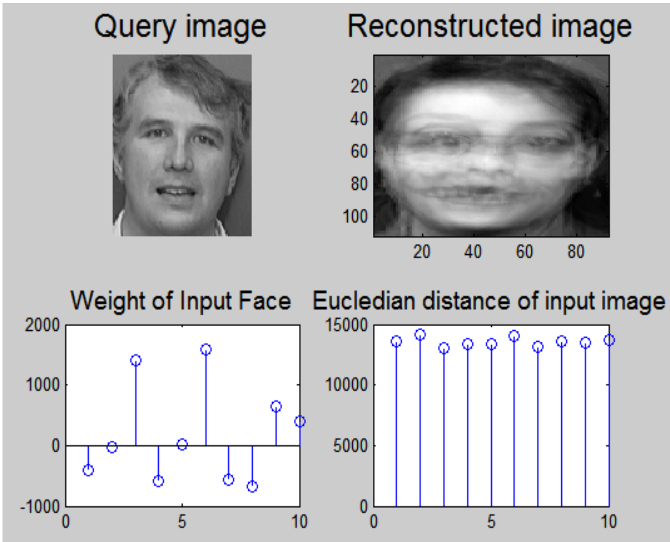

Fig -2.f: Unsuccessful Recognized image (which is excluded in ORL training set).

In Figure 2, the experimental results of FRS using ORL database are given. As per the mathematical approach mentioned above, these outputs are attained using Euclidean Distance method.

Fig -3.a: Successful Recognized Images (Male)

Fig -3.b: Successful Recognized Images (Female)

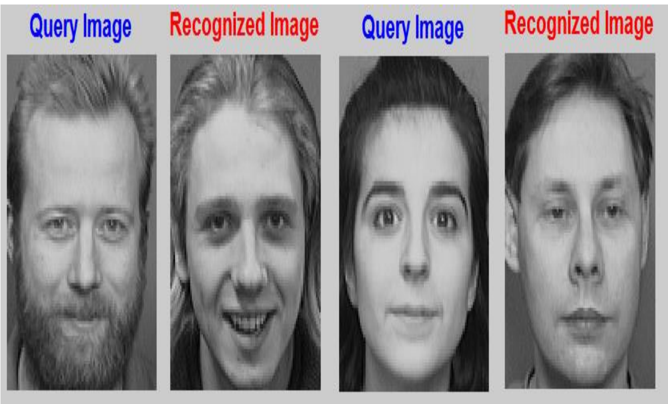

Fig -3.c: Unsuccessful Recognized Images (Male as Female, Female as Male)

In Figure 3, the experimental results of FRS are given in three categories. The first two categories are successful recognitions of male and female respectively, whereas, the other category corresponds to unsuccessful recognized images.

Table-1: Accuracy of various experiments

S. No.	Trained Dataset	Raw Linear	LBP	HOG	COSFIRE (Chi-Squared Kernels)	Accuracy of GRR (%)
1	FERET	C	-	-	-	89.3
2	FERET	-	C	-	-	84.2
3	FERET	-	-	C	-	89.0
4	FERET	C	C	-	-	90.3
5	FERET	C	-	C	-	91.9
6	FERET	-	C	C	-	91.6
7	FERET	C	C	C	-	92.3
8	FERET	-	-	-	C	93.7
9	Assimilated	-	-	-	C	91.6

C- Cumulatively applied

In Table 1, we presented the results of Gender Recognition Rate using various classifier techniques at different conditions.

6. CONCLUSIONS

The PCA model is widely used for the Face Recognition. And the experiment in which trainable COSFIRE filters and combined with an SVM classifier of a chi-squared kernel applied is highly effective for gender recognition from face images.

This Gender Recognition experiment outperforms an ensemble of three classifiers that rely on the HOG and LBP handcrafted features along with the raw pixel values.

The approaches of two experiments are suitable for various image classification tasks. Improvements are going on for making the recognition more robust and more effective.

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9. BIOGRAPHIES

K. Akhil Sreenivasulu is currently pursuing M. Tech. (DECS) from NBKRIST, Andhra Pradesh. He completed his B. Tech. (ECE) from Brilliant Inst. Of Engg. & Tech, Telangana. His areas of interest are Digital Image Processing especially Computer Vision and Machine Learning.

Dr. G. Harinatha Reddy, Ph. D., is a Professor & HOD (ECE). He has done Ph. D. (ECE) from JNTU, Hyderabad. He has many research papers in International Journals and Conferences. His areas of interest are Digital Signal Processing and Digital Image Processing.