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Comparative Analysis of Eigen face and Sparsity Based Face Recognition Schemes

[I]Dr. Renuka Devi S.M , [II]E. Bhargavi
[I]Dept. of Electronics and Communication Engineering, GNITS, Telangana, India.
[II]PG Scholar, Dept. Of Electronics and Communication Engineering, GNITS, Telangana, India.

Abstract
Face Recognition has been one of the predominant research areas in the field of Biometric Analysis where there is a strong need for user friendly systems that can safeguard ones critical assets and privacy. Lately there were many algorithms that implemented face recognition systems but the theory of Compressed Sensing has gained popularity in recent times which enabled representation of data using Sparse Computations from Convex Optimization techniques. In this paper the comparative study between Nearest Neighbor Classifier method using Eigen faces and Sparse Classifier method is considered using a well-known face database which provides better Recognition rates even in various noise conditions.

Keywords
Face Recognition, Compressed Sensing, Sparse Computations, Convex Optimization, Recognition rate.

I. Introduction

With the advancement in the digital technology there is a strong need to safeguard the privacy of the user and the face recognition is one such application which helps us in preserving our assets. With its gaining popularity there has been a huge research in this area but primarily in Biometrics applications, Generally any face recognition system carries out three major tasks like face detection, feature extraction and face recognition (or) face classification [2]. In this paper we focus on face recognition section for static frontal face images, With a variant of face recognition methods implemented the top level categorization has divided them into three subcategories they are holistic matching methods which use the whole face region as the raw input to a recognition system like the Eigen face approach also known as Principle Component Analysis. The other two categories are Feature Based and Hybrid methods, where in local features like eyes, nose and mouth are locally extracted and by using statistical methods the classification is performed. The Hybrid methods make use of both local features as well as the whole face region to perform classification [2].

Within each of these categories, further classification is possible. Using principal-component analysis (PCA), many face recognition techniques have been developed, EigenFaces which use a nearest-neighbour classifier; feature-line-based methods, which replace the point-to-point distance with the distance between a point and the feature line linking two stored sample points. Fisher-faces which use Linear/Fisher discriminant analysis (FLD/LDA) Bayesian methods, which use a probabilistic distance metric; and SVM methods, which use a support vector machine as the classifier [2].

Many types of systems have been successfully applied to the task of face recognition, but they all have some advantages and disadvantages. Appropriate schemes should be chosen based on the specific requirements of a given task. Most of the systems here focus on the sub-task of recognition, but others also include automatic face detection and feature extraction, making them fully automatic systems [2].

In recent times there has been a huge research towards a topic known as Compressed Sensing also called as Compressed Sampling or Sparse sampling ,is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem [12].

In this Paper a Comparative Study between Face Classification methods like the Eigen-face dependent nearest neighbour approach also known as Principle Component Analysis as well as Sparse Coding based Classification methods are considered.

II. Related Work

A. Eigen-Face Approach

Much of the previous work on automated face recognition has ignored the facts of just what aspects of the face stimulus are important for identification, information content of face images were studied using information theory concepts emphasizing local and global features. In the language of information theory we want to extract the relevant information in a face image, encode it as effectively as possible and compare face encoding with a database of models encoded similarly [1].

Eigen-face approach is a simple method for extracting the information contained in a collection of face images, independent of any judgement of features and uses this information to encode and compare individual face images [1].

Mathematically, we wish to find the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images, creating an image as a point (or vector) in a very high dimensional space, the eigen vectors are ordered each one accounting for a different amount of variation among face images these eigen vectors can be thought of as a set of features that together characterize the variation between face images [1].

The main idea for Eigen faces arises from the problem of performing recognition in a high dimensional space which can be addressed by mapping the image to a lower dimensional space and then by computing Eigen vectors.

Computation of the EigenFaces starts with obtaining face images $I_1, I_2 \ldots I_M$ (training faces).It is very important to note that the face images must be centered and of the same size [1]. Next is to represent every image I_i as a vector Γ_i. Then we need to compute the average face vector Ψ by using the equation (1)

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma i \quad (1)$$

Then we compute the normalised images by subtracting the image vectors from the average face vector Ψ, using the normalised faces we then compute the covariance matrix using the equation (2)

$$C = \frac{1}{M} * \sum_{n=1}^{M} \Phi n \, \Phi n^{T} \quad (2)$$

$= AA^T$

Where $A = [\Phi_1, \Phi_2 \ldots \Phi_M]$ (N^2xM matrix), we then compute the eigenvectors u_i of AA^T. The matrix AA^T is very large so it is not practical to calculate it [5]. Then we consider the matrix $A^T A$ (M x M matrix) and compute the eigenvectors v_i of $A^T A$ using (3)

$A^TAv_i = \mu_i v_i$, (3)

The relationship between u_i and v_i is given by (4)

$u_i = Av_i$ (4)

Thus, AA^T and A^TA have the same eigenvalues and their eigenvectors are related as follows $u_i = Av_i$. Important points to note are that AA^T can have up to N^2 eigenvalues and eigenvectors and A^TA can have up to M eigenvalues and eigenvectors and The M eigenvalues of A^TA (along with their corresponding eigenvectors) correspond to the M largest eigenvalues of AA^T (along with their corresponding eigenvectors) [1].We need to compute the M best eigenvectors of AA^T as $u_i = Av_i$ and it is important to normalize u_i such that $||u_i|| = 1$.Then finally we keep only K eigenvectors (corresponding to the K largest eigenvalues), Representing faces onto this basis is done by subtracting each face with the mean Φ_i in the training set can be represented as a linear combination of the best K eigenvectors using (5)

$$\widehat{\Phi i} - \text{mean} = \sum_{i=1}^{K} wjuj \quad (5)$$

Where $w_j = u_j^T\Phi_i$ and here we call the u_j's EigenFaces. Each normalized training face Φ_i is represented in this basis by a face vector Ω_i as (6)

$$\Omega i = \begin{bmatrix} w1^i \\ \ldots \\ wk^i \end{bmatrix} \text{(where i=1,2,M)} \quad (6)$$

Then face recognition of an test image is done by computing the projection of that image by finding the Eigen face of the image using $w_i = u_i\Phi$ then we compute the corresponding face vector, finally the Euclidian distance between the face vectors of test and training images is computed and least distance value is used to classify the image [1].

III. Methodology

A. Sparse Coding based Classifier method

In this method Face Recognition is performed using the Sparse Classifier in order to get optimized results with excellent accuracy. Sparse Representation helps us to study the Distinctive nature between the training samples to perform classification between them.

According to the Theory of Compressive sensing the test samples are represented using the Over complete dictionary form by training samples used as base elements [12]. The test samples are represented as a linear combination of the training samples in order to study the sparse structure of test sample [4].

In this method we also study that, even in the presence of various noise conditions applied to test samples the theory of sparse coding and classification helps us to achieve better results.

Initially a database of face images is considered, where part of database is used as training set and other as test set. With the training samples available, if a class of training set is considered then the test sample selected from the same class is represented as a linear combination of those training samples as equation (7) below [4]

$y = \alpha_{i,1} v_{i,1} + \alpha_{i,2} v_{i,2} + \ldots + \alpha_{i,ni} v_{i,ni}$ (7)

where $[v_{i,1}, v_{i,2 \ldots} v_{i,ni}] = A_i$ □ R^{mxn} and $\alpha_{i,j}$ □ R are some scalars, $j=1,2\ldots n_i$. As the membership of the test sample is not known so in a more general sense the above equation (7) is written as (8)

$y = A x_0$ □ R^m (8)

Where $A=[A_1 A_2 \ldots A_k] = [v_{1,1} v_{1,2} \ldots\ldots v_{k,nk}]$ is an Over-Complete Dictionary and x_0 is the sparse vector whose coefficients are associated with only a single class represented as non-zero elements [4].

The Sparse vector x_0 is in linear form so it can be computed using linear programming methods involving convex optimizations according to the sparse coding theory. The sparsiest solution can be obtained using a optimization method known as l_0-minimization but it is computationally non solvable in polynomial time and hence is called as a NP-hard problem, alternatively l_1-minimization is employed to find the sparse vector, mathematically it is represented as equation (9) below [8]

$x_1 = min_x \parallel x \parallel_1$ subject to $Ax = y$ (9)

The above equation is for noiseless condition, In noisy conditions the equation (10) is as follows

$x_1 = min_x \parallel x \parallel_1$ subject to $\parallel Ax - y \parallel_2 \leq$ □ (□ ≥ 0) 10)

The solution for l_1 norm equation is found using linear programming methods involving convex computations; l_1 norm condition is also called as Basis pursuit problem [8]. Basis Pursuit finds the best representation of an image or a signal by minimizing the l_1- norm of the components of x that is the coefficients in the representation [7]. The components of x would be zero or as close to zero as possible. To better exploit the linear structure, we classify y based on how good the coefficients are associated with all training samples of each class in order to reproduce y.

For a particular class i, we compute a characteristic function which selects the coefficients associated with the i^{th} class. The sparse vector x and the Characteristic function being the new vector consists of only the nonzero entries of the sparse vector associated with class i [4]. Using only the coefficients associated with the i^{th} class, we can approximate the given test sample y as $\hat{y}i = A\,\delta_i(x_1)$. We then classify y based on these approximations by assigning it to the class that minimizes the residual between y and $\hat{y}i$, The residual function is given as equation (11)

$$\min r_i(y) = \parallel y - \hat{y}i \parallel_2 \min r_i(y) = \parallel y - \hat{y}i \parallel_2 \quad (11)$$

Using the Sparse Coding theory we can compute robust results in both noiseless and noisy conditions the identity and validity of a the test sample is also determined with high accuracy.

The Face recognition process using Sparse Coding in a sequence is given in the form of flow chart as figure below

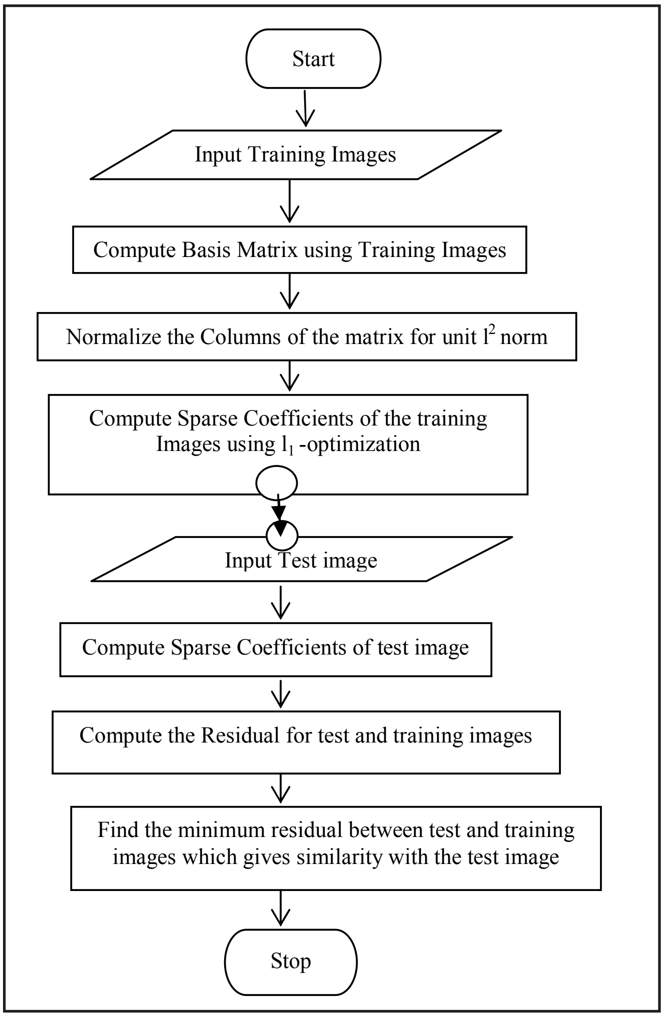

Fig.1: Flow Chart Depicting the Process for Face Recognition using Sparse Coding

IV. Experimental Results

The Performance of any Classification system is studied based on the computations from Confusion matrix, which indicates the preciseness of the model in classifying the instances. A Confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. Many objective metrics are derived from confusion matrix in order to predict the behavior of the model like the True Positives, True negatives, False Positives and False Negatives [11] .The confusion matrix for a binary class problem is as shown in Table (1)

The General Definitions for these metrics based on a ground truth about images from a database are defined as, If the instance is positive and it is classified as positive, it is counted as a true positive. If the instance is positive and if it is classified as negative, it is counted as a false negative. If the instance is negative and it is classified as negative, it is counted as a true negative. If the instance is negative and if it is classified as positive, it is counted as a false positive [11].

The Important metrics computed using these metrics are Sensitivity, Specificity and Accuracy given by equations (12), (13) and (14)

$$\text{Sensitivity} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (12)$$

$$\text{Specificity} = \frac{True\ Negative}{False\ Positive + True\ Negative} \quad (13)$$

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (14)$$

Table 1: Binary Class Representation of Confusion Matrix

Actual vs. Predicted	Predicted Class 1	Predicted Class 2
Actual Class1	True Positive	False Negative
Actual Class 2	False Positive	True Negative

In this paper the concept of sparse representation of the images is studied by which we notice better recognition rates than the traditional methods where Euclidian Distance based classifier is used for classifying the instances.

The Face recognition by nearest neighbour using Eigen Face based Classifier and Sparse coding based Classifier has been performed in Matlab using the ORL database comprising of 400 images with 40 classes where each class has10 images.[14]

The database has images with varying illumination and expressions which also proves that these classifiers perform well in these conditions. Apart from these the classifier's performance based on sparse coding gives excellent results in case of noises like Gaussian and Salt & Pepper Noise with varying values. The accuracy of the classifiers is also evaluated by treating the images to occlusion also.

Table 2: Performance of the Classifier's based on Noiseless Condition

Method (Noiseless)	True positive Rate	False Positive Rate	Accuracy
Sparse Classifier	0.8650	0.0035	99.32 %
Eigen face Classifier	0.0250	0.0240	95.12 %

Table 3: Performance of the Classifier's based on Gaussian Noise

Method (Gaussian noise) σ^2=0.05,μ =0.09	**True positive Rate**	**False positive Rate**	**Accuracy**
Sparse Classifier	0.7900	0.0054	98.94 %
Eigen face Classifier	0.0245	0.0240	95.12 %

Table 4: Performance of the Classifier's based on Salt & Pepper Noise

Method (Salt & Pepper noise) Noise density (D)=0.05	**True positive Rate**	**False positive Rate**	**Accuracy**
Sparse Classifier	0.8600	0.0036	99.30 %
Eigen face Classifier	0.0240	0.0232	95.10%

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Table 5: Performance of the Classifier's based on Block Occlusion

Method (Block Occlusion) (50 %)	True positive Rate	False positive Rate	Accuracy
Sparse Classifier	0.5450	0.0117	97.72 %
Eigen face Classifier	0.0230	0.0214	95.05 %

The Experimental Results in matlab using Eigen face approach with face images from ORL database [14] in noiseless and various noisy conditions is as follows

Fig.2: Nearest neighbor based Classification using Eigen face in noiseless condition

Fig.3: Nearest neighbor based Classification using Eigen face for Gaussian noise with variance 0.01

Fig. 4: Nearest neighbor based Classification using Eigen face for Salt & Pepper noise with noise density 0.01

Fig.5: Nearest neighbor based Classification using Eigen face in case of Block Occlusion

The Experimental Results using Sparse Classifier for various noisy and noiseless conditions is as follows

Fig.6: Sparse Classification in Noiseless case

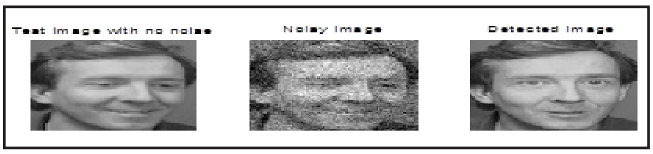

Fig.7: Sparse Classification in Gaussian Noise with Variance 0.01

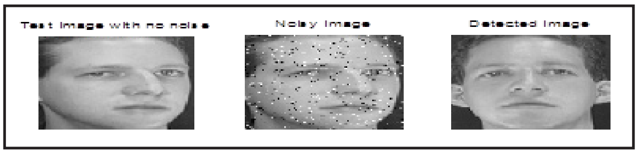

Fig.8: Sparse Classification in Salt & Pepper Noise with noise density 0.01

Fig.9: Sparse Classification in Block occlusion

V. Conclusion And Future Scope

In this paper the two Classification methods one based on Eigen face and other Sparse Classifier methods have been studied and implemented using Matlab for ORL database and it is observed from the results that even in noiseless and various noisy conditions the Performance of the Sparse Classifier is robust compared to one based on Eigen face Classifier and has high recognition rates measured in terms of Accuracy computed from Confusion matrices. This Sparse classifier can be used in biometric applications for finding the identity of users in various security conditions.

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