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# Face Recognition Using Principle Component Analysis Techniques

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***Abstract- This paper presents an effective and naval approach for face detection using Principle component analysis techniques. The system commences feature extraction through Principle component analysis method, in which the needed features of faces are extracted out in the form of feature vectors. The feature vectors based upon principle component analysis techniques are used as the input of the classifier, which is a feed forward neural network on reduced feature subspace learned by principle component approach for recognition of faces. The effectiveness of the system has been justified over a face database with face images captured in different illumination and orientation conditions of face.***

***Keywords: PCA, Principle Gabor Filter, eigen images, eigen face.***

## 1. Introduction

Human face detection and recognition is an active area of research spanning several disciplines such as image processing, pattern recognition and computer vision. Face detection and recognition are preliminary steps to a wide range of applications such as personal identity verification, video-surveillance, lip tracking, facial expression extraction, gender classification, advanced human and computer interaction. Most methods are based on neural network Up to now, there have been many successful algorithms for face recognition. But there are still some outliers which will impact the performance of face recognition algorithms. These outliers are facial expression, illumination, pose, masking, occlusion etc. So how to make current algorithms robust to these outliers or how to develop some powerful classifiers is the main task for face recognition. Principal Component Analysis (PCA) [1], Fisher's Linear Discriminate (FLD) [2] and Independent Component Analysis (ICA) [3] are three basic algorithms for subspace analysis in face recognition.

Henery et al. [6] proposed a neural network based upright frontal face detection system. This paper has demonstrated the effectiveness of detecting face rotated in the image plane by using a router network in combination with an upright face detector.

Lamiaa et al [4] proposes a system combines two algorithms for face detection to achieve better detection rates. The two algorithms are skin detection and neural networks. Guoqiang et al [5] summarizes the some of the most important developments in neural network classification research. Specifically, the issues of posterior probability estimation, the link between neural and conventional classifiers, learning and generalization trade of in classification, the feature variable selection, as well as the effect of misclassification cost are examined. This paper has presented a focused review of several important issues and recent development of neural network for classification problems.

Apart from this Eigen face approach provides recognition using class Specific linear projection and other benefits as explained in [7-9]. Elastic facing is another added advancement in the field of face recognition [10-11] are the well known papers in this era. Alongwith this Neural Techniques implementation through its various algorithms as explained in[12].Since the main hurdle in the face detection and recognition is the intensity variation and pose variation, which creates practical implication in any face recognition system as discussed in[13-13] are also the benchmarks for any practical system design.

Principal Component Analysis(PCA), and the method proposed in thesis is based on row or column deletion, as the later one consumes less time as compare to PCA when image data is too large.

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## 2. Methodology of Principal Component Analysis

The Principle Behind Principal Component Analysis also called the "Hotteling Transform" or the "Karhunen-Loeve Method" for an orthogonal coordinate system so that the correlation between different axis is minimized. PCA involves the calculation of the Eigen value decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings. PCA is the simplest of the true eigenvector based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data

The mathematical steps used to determine the principal components of a training set of face images are outlined in this paragraph .A set of training images $N$ are represented as vectors of length $L \times L$, where $L$ is the number of pixels in the x (y) direction. The average image $m$ of the $N$ training set images is given by the following formula:

 

$$m = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where $x_i$ is the $L \times L$ dimension vector corresponding to the $i$th image in the training set. An $N \times N$ matrix $O$ is formed, whose elements $O_{ij}$ are given by the inner product of image vectors $(x_i - m)$ and $(x_i - m)$. Let $\nu_n$ and $\lambda_n$ be the eigenvectors and the eigen values of $O$, respectively; then, there will be $N - 1$ eigenvectors of length $N$.

These eigenvectors determine linear combinations of the $N$ training set images to form the basis set of images, $w_i$, that best describe the variations in the training set images:

$$w_i = \sum_{r=1}^{N} v_{ir}(\bar{u}_r - m) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

for $i = 1, 2, \ldots N$.

These basis set images are called *eigen images*. The eigen images associated with the largest eigen values capture most of the information in the training set images. Each image in the set can then be approximated with a linear combination of these eigen images:

$$x_p \approx \sum_p w_p u_p \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The coefficients $w_p$ are the feature description for the image $x_r$, each of which is assigned to a different class $r$. A new query image, $q_i$, is projected similarly onto the eigen space and the coefficients $w_q$ are computed. The class that best describes the query image is determined by a similarity measure defined in terms of the euclidean distance of the coefficients $w_q$ and $w_p$ (where $p = 1, 2 \ldots k$ for $k$ classes in the training set). The training set image whose coefficients are closest (in the euclidean sense) to those of the query image is selected as the match image. If the minimum euclidean distance exceeds a preset threshold, the query image is assigned to a new class. Pictorial representation of PCA tech can be shown as

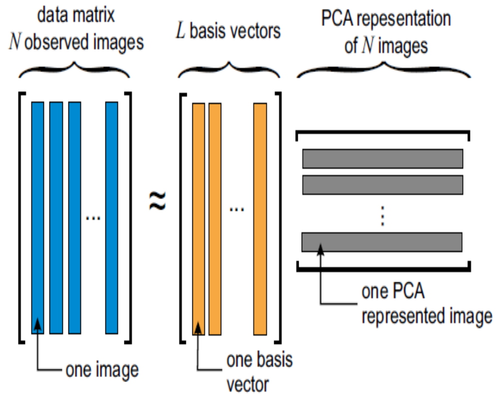


Fig 1.Pictorial Representation of PCA

## 3. Results

By using methodology of principle component analysis for face recognition we first construct a data bank of image samples The face image is convolved with a set of Gabor wavelets and the resulting images are further processed for recognition purpose. Whenever an unknown image (not stored in the training data set) but having the same class get compared with trained images sets and evolves the look alike image for same class.

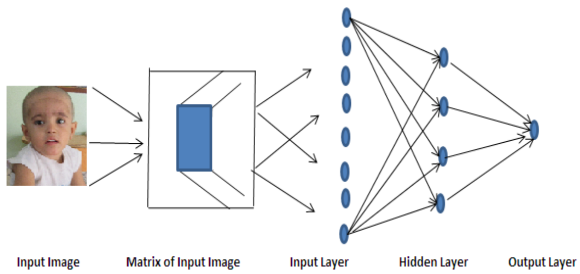


Fig 2. Implementation of MLP algorithm.

 

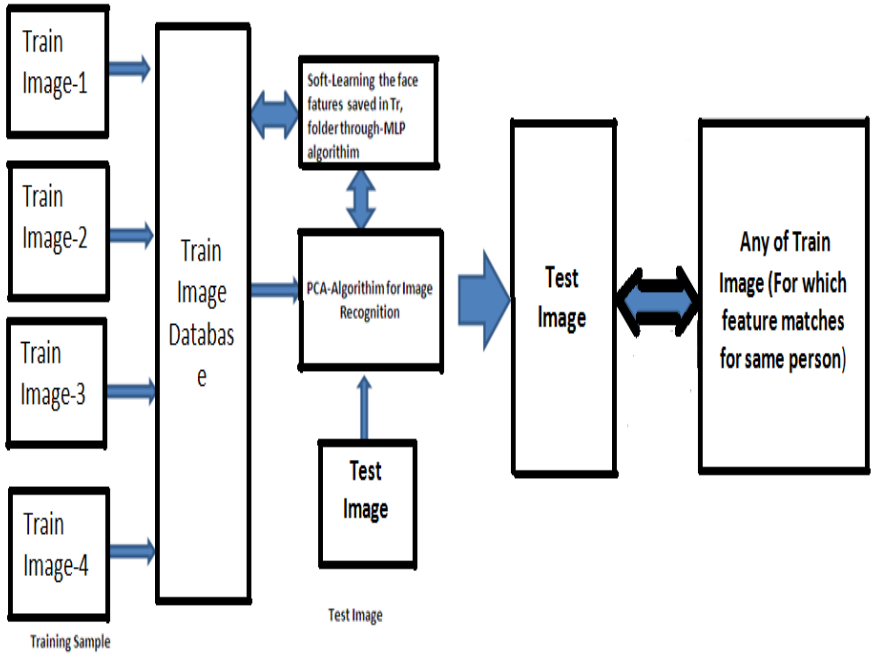


Fig 3 Display of image recognition methodology

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