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**Review Article**

# Comparative Analysis of the Various Techniques Used for Face Recognition

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## Abstract

Face recognition presents a challenging problem in the field of image analysis and computer vision as such a large number of face recognition algorithms have been developed in last decade. In this paper firstly I present an overview of face recognition and discuss its application and technical challenges. Thereafter I represent the various face recognition techniques. This includes PCA, LDA, ICA, Gabor wavelet, soft computing tool like ANN for recognition and various hybrid combinations of these techniques. This review investigates face recognition and all these methods of face recognition with parameters that have challenges like illumination, pose variation and facial expressions.
**Keywords:** Principal Component Analysis (PCA), Independent Component Analysis **(**ICA), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN).
**General Terms:** Face recognition, Feature extraction, and Face detection.



## 1. INTRODUCTION

Over the last ten years, face recognition has become a specialized applications area within the larger field of computer vision and it becomes one of the most biometrics authentication techniques. Face recognition is an interesting and successful application of Pattern recognition and Image analysis. Face recognition is used for two primary tasks [1]:

1. **Verification (one-to-one matching):** When presented with a face image of an unknown individual along with a claim of identity, verify whether the individual is who he/she claims to be.
2. **Identification (one-to-many matching):** Given an image of an unknown individual, determining that person's identity by comparing (possibly after encoding) that image with a database of (possibly encoded) images of known individuals.

Face verification is a 1:1 match that compares a face images against a template face images, whose identity being claimed .On the contrary, face identification is a 1: N problem that compares a query face image against all image templates in a face database. Face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology: methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red imagery.

Therefore, a basic face recognition system contains the following sub-modules:

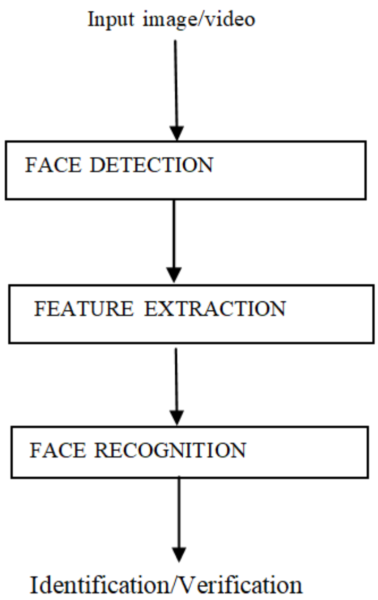


**Fig. 1: Generic face-recognition system**

## 2. HISTORICAL PERSPECTIVE

The earliest works on this subject were made in the 1950 in psychology. Then came attached to other issues like face expression, interpretation of emotion or perception of gestures. Engineering started to show interest in face recognition in the 1960. Historical perspective of this work started from Pioneers Automated Facial Recognition include: W. Bledsoe, H. C. Wolf, and C. Bisson. During 1964 and 1965, Bledsoe, along with Chan and Bisson, worked on using the computer to recognize human faces [2-4]. He was proud of this work, but because the funding was provided by a semi-automatic system unnamed intelligence agency that did not allow much publicity, so little of the work was published. He continued later his researches at Stanford Research Institute. Some face coordinates were selected by a human operator, and then computers used this information for recognition. He described most of the problems that even 50 years later Face Recognition still suffers - variations in illumination, head rotation, facial expression, and aging. Researches on this matter still continue, trying to measure subjective face features as ear size or between-eye distance. For instance, this approach was used in Bell Laboratories by A. Jay Goldstein, Leon D. Harmon and Ann B. Lesk.

They described a vector, containing 21 subjective features like ear protrusion, eyebrow weight or nose length, as the basis to recognize faces using pattern classification techniques.

## 3. APPLICATION AREAS

There are numerous application areas in which face recognition can be exploited, a few of which are outlined below [1]:

**Table 1: Applications of face recognition**

| **Areas** | **Application** |
|---|---|
| Biometrics | Person identification (national IDs, Passports, voter registrations, driver licenses), Automated identity verification |
| Information Security | Access security (OS, data bases), Data privacy, User authentication (trading, on line banking) |
| Investigation of reports | Missing person identification, criminal identification |
| Access management | Secure access authentication, Permission based systems, Access log or audit trails |
| Law Enforcement | Video surveillance, Suspect identification, Suspect tracking ,Simulated aging, Forensic Reconstruction of faces |
| Personal security | Home video surveillance systems, Expression interpretation (driver monitoring system) |

## 4. TECHNICAL CHALLENGES

There are some key factors that can significantly affect system face recognition performances:

1. **Illumination:** The variations due to skin reflectance properties and due to the internal camera control. Several 2D methods do well in recognition tasks only under moderate illumination variation, while performances noticeably drop when both illumination and pose changes occur.
2. **Pose:** Changes affect the authentication process, because they introduce projective deformations and self-occlusion. Even if methods dealing with up to 32 Degree head rotation exist, they do not solve the problem considering that security cameras can create viewing angles that are outside of this range when positioned.
3. **Expression:** On the contrary, with exception of extreme expressions such as scream, the Algorithms are relatively robust.
4. **Time Delay**: This happen because the face changes over time, in a nonlinear way over long periods. In General this problem is harder to solve with respect to the others and not much has been done especially for age variations.
5. **Occlusions:** Occlusion can dramatically affect face recognition performances, in particular if they located on the upper-side of the face.
6. **Image Orientation:** Face images directly vary for different rotations about the camera's optical axis.
7. **Imaging Conditions:** When the image is formed, factors such as lighting (source distribution and intensity) and camera characteristics (sensor response, lenses) affect the appearance of a face.
8. **Presence or Absence of structural components:** Facial features such as beards, must aches, and glasses may or may not be present and there is a great deal of variability among these components including shape, color, and size.

## 5. TECHNIQUES FOR FACE RECOGNITION

### 5.1 Principal Component Analysis (PCA)

The PCA method is one of the generally used algorithms for face recognition. Karhunen-Loeve is the eigenfaces technique in which the Principal Component Analysis (PCA) is used. This method is successfully used to perform dimensionality reduction. Principal Component Analysis is used by face recognition and detection [5]. Mathematically, Eigenfaces are the principal components divide the face into feature vectors. The feature vector information can be obtained from covariance matrix. These Eigenvectors are used to quantify the variation between multiple faces. The faces are characterized by the linear combination of highest Eigenvalues. Each face can be considered as a linear combination of the eigenfaces. The face can be approximated by using the eigenvectors having the largest eigenvalues. The best M eigenfaces define an M dimensional space, called "face space". Principal Component Analysis is also used by L. Sirovich and M.

Kirby to efficiently represent pictures of faces. They defined that a face images could be approximately reconstructed using a small collection of weights for each face and a standard face picture. The weights describing each face are obtained by projecting the face image onto the Eigen Pictures. Eigenface is a practical approach for face recognition. Because of the simplicity of its algorithm, implementation of an eigenface recognition system becomes easy. It is efficient in processing time and storage. PCA reduces the dimension size of an image in a short period of time. There is a high correlation between the training data and the recognition data. The accuracy of eigenface depends on many things. As it takes the pixel value as comparison for the projection, the accuracy would decrease with varying light intensity. Pre-processing of image is required to achieve satisfactory result. An advantage of this algorithm is that the eigenfaces were invented exactly for those purpose what makes the system very efficient. A drawback of this is that it is sensitive for lightening conditions and also finding the eigenvectors and eigenvalues are time consuming on PPC. This limitation is overcome by Linear Discriminant Analysis (LDA). LDA is the most dominant algorithms for feature selection in appearance based methods [6]. But many LDA based face recognition system first used PCA to reduce dimensions and then LDA is used to maximize the discriminating power of feature selection. Due to this Modified PCA algorithm for face recognition were proposed in [7], this method was based on the idea of reducing the influence of eigenvectors associated with the large Eigen values by normalizing the feature vector element by its corresponding standard deviation. The simulation results show that the proposed method results in a better performance than conventional PCA and LDA approaches and the computational cost remains the same as that of PCA and much less than that of LDA.

## 5.2 Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant methods, that used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or more commonly for dimensionality reduction before later classification. Linear discriminant analysis (LDA) is a powerful method for face recognition. It yields an effective representation that linearly transforms the original data space into a low-dimensional feature space where the data is well separated. However, the within-class scatter matrix becomes singular in face recognition and the classical LDA cannot be solved which is the under sampled problem of LDA (also known as small sample size problem). A subspace analysis method for face recognition called kernel discriminant locality preserving projections was proposed in [8] based on the analysis of LDA, LPP and kernel functions. The nonlinear subspace which can not only preserves the local facial manifold structure but also emphasizes discriminant information, Combined with maximum margin criterion (MMC) and a new method called maximizing margin and discriminant locality preserving projections (MMDLPP) was proposed to find the subspace that best discriminates different face change and preserving the intrinsic relations of the local neighbor hood in the same face class according to prior class label information. But this method has variation problem, for that Illumination adaptive linear discriminant analysis (IALDA) was proposed to solve illumination variation problems in face recognition. The recognition accuracy of the suggested method (IALDA), far higher than that of PCA method and LDA method. The recognition accuracy of the suggested method was lower than that the nearby in the output space, thereby providing Logarithmic Total Variation (LTV**)** algorithm. However, The LTV algorithm has high time complexity. Therefore, the LTV method is not practically applicable. At the same time, this also indicates that the proposed IALDA method is robust for illumination variations. David Monzo *et al.*, [9] compared several approaches to extract facial landmarks and studied their influence on face recognition problems. In order to obtain fair comparisons, they used the same number of facial landmarks and the same type of descriptors for each approach. The comparative results were obtained using FERET and FRGC [1] datasets and shown that better recognition rates were obtained when landmarks are located at real facial fiducial points. In this work, comparison was done using Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Orthogonal Linear Discriminant Analysis (OLDA). OLDA is one of the many variations of LDA which aims to tackle the problem of under sampling. The key idea of OLDA, the discriminant vectors are orthogonal to each other. Ye provide an efficient way of computing OLDA, Logarithmic Total Variation (LTV**)** algorithm. However, The LTV algorithm has high time complexity. Therefore, the LTV method is not practically applicable. Implementing LDA directly resulted in poor extraction of discriminating features. For this in some methods Gabor filter is used to filter frontal face images and PCA is used to reduce the dimension of filtered feature vectors and then LDA is used for feature extraction. LDA is better than PCA if we need a method which has better computational time but due to its small sample space its usability is limited.

## 5.3 Independent Component Analysis (ICA)

ICA is a widely used subspace projection technique that projects data from a high-dimensional space to a lower dimensional space. This technique is a Generalization of PCA that de-correlates the high-order statistics in addition to the second-order moments. ICA provided a more powerful data representation than PCA as its goal was that of providing independent rather than uncorrelated image decomposition and representation.

A fast incremental principal non-Gaussian directions analysis algorithm called IPCA_ICA was proposed in [10]. This algorithm computes the principal components of a sequence of image vectors incrementally without estimating the covariance matrix and at the same time transforms these principal components to the independent directions that maximize the non-Guassianity of the source. PCA_ICA achieves higher average success rate than Eigenface, the Fisherface and FastICA methods.

### 5.4 Gabor Wavelet

Gabor wavelets have proven to be good at local and discriminate image feature extraction as they have similar characteristics to those of the human visual system. Gabor wavelet transform [12–13] allows description of spatial frequency structure in the image while preserving information about spatial relations which is known to be robust to some variations, e.g., pose and facial expression changes. Although Gabor wavelet is effective in many domains, it nevertheless suffers from a limitation. The dimension of the feature vectors extracted by applying the Gabor wavelet to the whole image through a convolution process is very high. To solve this dimension problem, subspace projection is usually used to transform the high dimensional Gabor feature vector into a low dimension one. For enhancing face recognition high intensity feature vectors extracted from Gabor wavelet transformation of frontal face images combined together with ICA in [14]. Gabor features have been recognized as one of the best representations for face recognition. In recent years, Gabor wavelets have been widely used for face representation by face recognition researchers, because the kernels of the Gabor wavelets are similar to the 2D receptive field profiles of the mammal cortical simple cells, which exhibit desirable characteristics of spatial locality and orientation selectivity. Previous works on Gabor features have also demonstrated impressive results for face recognition. Typical methods include the dynamic link architecture (DLA) [15], elastic bunch graph matching (EBGM) [16], Gabor Fisher classifier (GFC) [17] and AdaBoosted GFC (AGFC) [18]. The Gabor phases are sensitive to local variations, they can discriminate between patterns with similar magnitudes, and i.e. they provide more detailed information about the local image features. Therefore, the Gabor phases can work comparably well with the magnitudes, as long as its sensitivity to misalignment and local variations can be compensated carefully. P. Latha use Gabor wavelet to present face, and applied neural network to classify views of faces. The dimensionality was reduced by the principal component analysis. A technique to extract the feature vector of the whole face in image database by using Gabor filters, known to be invariant to illumination and facial expression. This network achieved higher recognition rate and better classification efficiency when feature vectors had low dimensions.

### 5.5 Artificial Neural Networks (ANN)

The neural networks are used in many applications like pattern recognition problems, character recognition, object recognition, and autonomous robot driving. The main objective of the neural network in the face recognition is the feasibility of training a system to capture the complex class of face patterns. To get the best performance by the neural network, it has to be extensively tuned number of layers, number of nodes, learning rates, etc. The neural networks are nonlinear in the network so it is widely used technique for face recognition. So, the feature extraction step may be more efficient than the Principal Component Analysis. The authors achieved 96.2% accuracy in the face recognition process when 400 images of 40 individuals are analyzed. The disadvantage of the neural network approach is that when the number of classes increases its ability is decreased. Due to this, Multi-Layer Perceptron (MLP) with a feed forward learning algorithm was chosen for the proposed system for its simplicity and its capability in supervised pattern matching. It has been successfully applied to many pattern classification problems. A new approach to face detection with Gabor wavelets & feed forward neural network was presented. The method used Gabor wavelet transform and feed forward neural network for both finding feature points and extracting feature vectors. The experimental results have shown that proposed method achieves better results compared to other successful algorithm like the graph matching and eigenfaces methods. Ahybrid neural network was presented which is combination of local image sampling, a self- organizing map neural network, and a convolutional neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, therefore providing dimensionality reduction and invariance to minor changes in the image sample. The convolutional neural network (CNN) provides for partial invariance to translation, rotation, scale, and deformation. PCA+CNN and SOM+CNN methods are both superior to eigenfaces technique even when there is only one training image per person. SOM +CNN method consistently performs better than the PCA+CNN method. After that a new face detection method is proposed using polynomial neural network (PNN).The PCA technique used to reduce the dimensionality of image patterns and extract features for the PNN. Using a single network the author had achieved fairly high detection rate and low false positive rate on images with complex backgrounds. In comparison with a multilayer perceptron, the performance of PNN is superior. To best reflect the geometry of the 3D face manifold and improve recognition, Spectral Regression Kernel Discriminate Analysis (SRKDA) based on regression and spectral graph analysis introduced, when the sample vectors are non-linear SRKDA can efficiently give exact solutions than ordinary subspace learning approaches. It not only solves high dimensional and small sample size problems, but also enhances feature extraction from a face local non-linear structure. SRKDA only needs to solve a set of regularized regression problems and no eigenvector computation involved, which is a huge saving in computational cost. This ANN yield better performance in face recognition rate and accuracy.

## 6. SUMMARY

This paper has attempted to review a significant number of papers to cover the recent development in the field of face recognition. Present study reveals that for enhanced face detection, new algorithm has to evolve using hybrid methods of soft computing tools such as ANN and Gabor filter (Feature Extractor) that yield better performance in terms of face detection rate and accuracy.

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