Face Recognition Techniques - A Review

Bhaskar Gupta, MIEEE
Department of Computer and Electrical Engineering, Wollega University, Nekemte,
Federal Democratic Republic of Ethiopia (East Africa)
bhaskar.pics@gmail.com

Abstract **- With data and information accumulating in abundance, there is a crucial need for high security. Face biometrics, useful for a person's authentication is a simple and non-intrusive method that recognizes face in complex multidimensional visual model and develops a computational model for it. In this paper, first we present an overview of face recognition and discuss the methodology and its functioning. Thereafter we represent the most recent face recognition techniques, listing their advantages and disadvantages. Some techniques specified here also improve the efficiency of face recognition under various illumination and expression condition of face images.**

Keywords- Face recognition, Eigen faces, fisher faces, neural network, elastic bunch method, graph matching, feature matching and template matching.

I. INTRODUCTION

FACE RECOGNITION is one of the most biometrics authentication techniques. It is an interesting and successful application of Pattern recognition and Image analysis. Face recognition system has two main tasks: verification and identification. Face verification means a 1:1 match that compares a face images against a template face images whose identity is being claimed. Face identification means a 1: N problem that compares a query face image against all image templates in a face database. Machine recognition of faces is gradually becoming crucial due to its wide range of commercial and law enforcement applications, which include forensic identification, access control, border surveillance and human interactions and availability of low cost recording devices. Various biometric features can be used for the purpose of human recognition like fingerprint, palm print, hand geometry, iris, face, speech, gaits, signature etc. The problem with finger print, iris palm print, speech, gaits are they need active co-operation of the person while face recognition is a process that doesn't require active co-operation of a person, *i.e.* without instructing the person, recognition is possible. So face recognition is much more advantageous compared to the other biometrics. Face recognition has a high identification or recognition rate of over 90% for huge face databases with well-controlled pose and illumination conditions.

II. BASICS OF FACE RECOGNITION

Block diagram of a typical face recognition system is in Fig.1. Face detection and facial extractions are carried out simultaneously.

In Face recognition process, the input image is compared with the database. The input image is also called as probe and the database is called as gallery. Then it gives a match report and classification is done to identify the sub-population to which new observations belong [2].

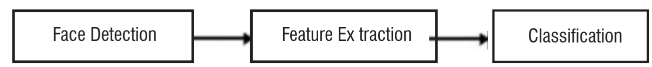

Figure 1. Block Diagram of a Face Recognition System [1].

There are basically three approaches for face recognition [1]:

Features-based approach: Here, local features like nose, and eyes are segmented and can be used as input data in face detection to facilitate the task of face recognition.

Holistic approach: In holistic approach, the whole face is taken as the input in the face detection system to perform face recognition.

Hybrid approach: Hybrid approach is combination of the above two approaches. Here, both local and whole face is used as the input to face detection system.

III. TECHNIQUES FOR FACE RECOGNITION

Eigenface:The Eigenface method is one of the generally used algorithms for face recognition. Karhunen-Loeve is based on 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. Mathematically, Eigenfaces are the principal components that 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 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, which is called as the "face space".

Principal Component Analysis is also used by Sirovich and Kirby [3] 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-picture.

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. Accuracy of eigenface depends on many things. Since it takes the pixel value as comparison for the projection, the accuracy would decrease with varying light intensity. Preprocessing of image is required to achieve satisfactory result. An advantage of this algorithm is that the eigenfaces were invented exactly for those purpose that makes the system very efficient [4].

A drawback is that it is sensitive for lightening conditions and the position of the head. Finding the eigenvectors and eigenvalues are time consuming on PPC. The size and location of each face image must remain similar: PCA (Eigenface) approach maps features to principle subspaces that contain most energy [4].

Neural Networks: Neural networks are used in many applications like pattern recognition problems, character recognition, object recognition, and autonomous robot driving. Main objective of neural networks in Face recognition is the feasibility of training a system to capture complex class of face patterns. To get the best performance by a neural network, it has to be extensively trained, number of layers, number of nodes, learning rates, etc. Neural networks are nonlinear and widely used for face recognition. The feature extraction step may be more efficient than the Principal Component Analysis. The authors achieved 96.2% accuracy in the face recognition process with 400 images of 40 individuals. The classification time is less than 0.5 second, but the training time is as long as 4 hours for features in a hierarchical set of layers that provide partial invariance to translation, rotation, scale, and deformation.

Disadvantage of this approach is when the number of classes increases [5], [6].

Multi-Layer Perceptron (MLP) with a feed forward learning algorithms was chosen for the proposed system for simplicity and capability in supervised pattern matching. It has been successfully applied to many pattern classification problems [7]. A new approach to face detection with Gabor wavelets and 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. Experimental results showed that proposed method achieves better results compared to other successful algorithms like the graph matching and eigenfaces methods. A new class of convolutional neural network (CNN) was proposed, where the processing cells are shunting inhibitory neurons. Previously shunting inhibitory neurons have been used in conventional feed-forward architecture for classification and nonlinear regression and were shown to be more powerful than MLPs *i.e.* they can approximate complex decision surfaces much more readily than MLPs.

A hybrid neural network was presented which is combination of local image sampling, a self-organizing map (SOM) neural network, and a CNN. 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. 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 [8].

A new face detection method is proposed using polynomial neural network (PNN) [9]. The PCA technique is 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 in proposed method [10]. When the sample vectors are nonlinear, 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. [11]

Fisherfaces:
Fisherfaces is one the most successfully widely used method for face recognition. It is based on appearance method. In 1930 R.A Fisher developed linear/fisher discriminant analysis for face recognition [12]. It shows successful result in the face recognition process.

LDA method is demonstrated in (Belhumeur *et al*., 1997; Zhao *et al*., 1999; Chen *et al.*, 2000; Yu and Yang, 2001; Liu and Wechsler., 2002; Lu *et al*., 2003a, b; Ye and Li., 2004) [13]. All used LDA to find set of basis images which maximize the ratio of between-class scatter to within-class scatter. Disadvantage of LDA is that within the class the scatter matrix is always single, since the number of pixels in images is larger than the number of images so it can increase detection of error rate if there is a variation in pose and lighting condition within same images. To overcome this problem, many algorithms were proposed. Because the fisherfaces technique uses advantage of within-class information, it minimizes the variation within class, so the problem with variations in the same images such as lighting variations can be overcome [2].

The fisherface method for face recognition described by Belhumeur *et al*. [14] uses both principal component analysis and linear discriminant analysis to produce a subspace projection matrix, similar as used in the eigenface method. However, the fisherface method is able to take advantage of within-class information, minimising variation within each class, still maximising class separation. Like the eigenface construction process, the first step of the fisherface tecnique is to take each (N x M) image array and reshape into a ((N*M) x 1) vector.

Fisherface is similar to Eigenface but with enhancement of better classification of different classes image. With FLD, one can classify the training set to deal with different people and different facial expression. We have better accuracy in facial expression than Eigen face approach. Besides, Fisherface removes the first three principal components which are responsible for light intensity changes; it is more invariant to light intensity [4].

Disadvantages of Fisherface are that it is more complex than Eigenface in finding the projection of face space. Calculation of ratio of between-class scatter to within-class scatter requires a lot of processing time. Besides, due to the need of better classification, the dimension of projection in face space is not as compact as Eigenface, resulting in larger storage of the face and more processing time in recognition [4].

Elastic bunch Graph matching:
Face recognition using elastic bunch graph matching is based on recognizing faces by estimating a set of features using a data structure called a bunch graph [15]. Same as for each query image, the landmarks are estimated and located using bunch graph. Then the features are extracted by taking the number of instances of Gabor filters which is called “face graph”. The matching percentage (*MSEBGM*) is calculated on the basis of similarity between face graphs of database and query image.

In 1999, Elastic Bunch Graph Matching was suggested by LaurenzWiskott, Jean-Marc Fellous, Norbert Kruger and Christoph von der Malsburg of University of Southern California. This approach is totally different to Eigenface and Fisherface. It uses elastic bunch graph to automatically locate the fudicial points of the face such as eyes, nose, mouth, etc and recognize the face according to these face features. Elastic Bunch Graph Matching (EBGM) uses the structure information of a face which reflects the fact that the images of the same subject tend to translate, scale, rotate, and deform in the image plane. It uses the labeled graph, where edges are labeled the distance information and nodes are labeled with wavelet coefficients in jets. After that, this model graph can be used to generate image graph. The model graph can be rotated, scaled, translated and deformed during the matching process.

Gabor wavelet transformation is used to produce local features of the face images. Gabor wavelets are biologically motivated convolution kernels in the shape of plane waves restricted by a Gaussian envelop function, the set of convolution coefficients for kernels of different orientations and frequencies at one image pixel is called a jet [4].

In the Elastic graph matching, the basic process is to compare graphs with images and to generate new graphs. In its simplest version, a single labeled graph is matched onto an image. A labeled graph has a set of jets arranged in a particular spatial order. A relative set of jets can be selected from the Gabor-wavelet transform of the image.

The image jets initially have the same relative spatial arrangement as the graph jets, and each image jet relatives to one graph jet. The similarity of the graph with the image then is simply the average jet similarity between image and graph jets. For increased similarity it allows some translation, rotation and distortion up to some extent.

In contrast to eigenfaces, the elastic bunch graph matching technique treats one vector per feature of faces. The advantage is that change or missing any one feature does not mean that the person will not be recognized. The stored data can be easily extended to a database for storage. When a new face image is added, no additional effort is need to modify templates, as it is already stored in the database. It is possible to recognize person up to rotation of 22 degrees. Disadvantage of this algorithm is that it is very sensitive to lighting conditions and a lot of graphs have to be placed manually on the face. When the changes in lighting are large, the result will have a significant decrease in the recognition rate [4].

Template matching: In template matching, we can exploit other face templates from different prospects to characterize single face. Primarily, grey levels that match the face image can also be processed in proper format (Bichsel 1991). In Bruneli and Poggio (1993) the Pop and Bruneli is available for all aspects of developing automatic four template features *i.e*., eyes, nose, mouth, face and selecting the entire set. The system is evaluated by comparing results from geometrical based algorithms on 188 images of 47 subjects. The pattern matching algorithm is a very practical approach, very simple to use and approximately achieves 100% recognition rate.

The Principal Component Analysis using Eigenface provides the linear arrangement of templates. The main advantage of this approach is that it is easy to implement and is less expensive than any other feature classifier.

Comparatively, template based algorithms are more expensive and cannot be easily processed. However, the recognition process is easily handled between the given template and input image. The complexity arises only during the extraction of template. Generally, template based techniques outperform as compared to feature based methods. Karungaru *et al*. (2004) use template based genetic algorithm that exposes different results on target image by adjusting the size of the template as preprocessing.

The edge detection and YIQ color templates are exploited. Results are taken around the distance measure face recognition approach and comparison is performed with existing methods. Anlong *et al*. (2005) works on the grid to construct reliable and proper infrastructure. This method is highly effective for larger databases that solve the problem of face recognition under reasonable computational cost. In Sao and Yegnanarayana (2007) an algorithm is proposed for person verification using template based face recognition method. Primarily, the edginess based face representation is calculated to process one dimensional images. The system is somehow associated with Neural Networks to test the images under varying pose and illumination conditions.

Similarly in Wang and Yang (2008), a face detection algorithm is proposed rather than face recognition algorithm as preprocessing steps. Now the advantage is taken from template based algorithm for face detection by constructing a general frame work for hierarchical face detection. The features are extracted using PCA from 2D images. At the end, it concludes that it is good to use template algorithms for face detection because it gives highest recognition rate.

Similarly in Leva da *et al*. (2008), Dynamic Time Warping (DTW) and Long Short Term Memory (LSTM) are investigated under the Neural Network classification in which a single feature template is large enough for feature extraction. It actually implements the gradient based learning algorithm by handling associated gradient problems. The experimental result reveals that both methods perform well for face recognition while the learning strategy gives robust recognition rate. The working of this approach is summed up by saying that further improvements are still required in order to solve the recognition problem that seems to be very common in real world [16].

A simple version of template matching is that a test image represented as a two-dimensional array of intensity values is compared using a suitable metric, such as the Euclidean distance, with a single template representing the whole face.

There are several other more sophisticated versions of template matching on face recognition. One can use more than one face template from different viewpoints to represent an individual's face. A face from a single viewpoint can also be represented by a set of multiple distinctive smaller templates. The face image of gray levels may also be properly processed before matching. Bruneli and Poggio [17] automatically selected a set of four features templates, *i.e.*, the eyes, nose, mouth, and the whole face, for all of the available faces. They compared the performance of their geometrical matching algorithm and template matching algorithm on the same database of faces which contains 188 images of 47 individuals. The template matching was superior in recognition (100 percent recognition rate) to geometrical matching (90 percent recognition rate) and was also simpler.

Since the principal components (also known as eigenfaces or eigenfeatures) are linear combinations of the templates in the data basis, the technique cannot achieve better results than correlation, but it may be less computationally expensive. One drawback of template matching is its computational complexity. Another problem lies in the description of these templates. Since the recognition system has to be tolerant to certain discrepancies between the template and the test image, this tolerance might average out the differences that make individual faces unique.

In general, template-based approaches compared to feature matching are a more logical approach. In summary, no existing technique is free from limitations. Further efforts are required to improve the performances of face recognition techniques, especially in the wide range of environments encountered in real world [17], [18].

Geometrical feature matching: Geometrical feature matching techniques are based on the computation of a set of geometrical features from the picture of a face. The overall configuration can be described by a vector which represents the position and size of the main facial features like eyes and eyebrows, nose, mouth and an outline of face.

The primary works on automated face recognition by using geometrical features was done in 1973. The system achieved 75% recognition rate on a database of 20 people using two images per person, one as the model and the other as the test image. In 1993, R. Bruneli and T. Poggio, automatically extracted a set of geometrical features from the picture of a face, such as nose width and length, mouth position and chin shape. There were 35 features extracted form a 35 dimensional vector. The recognition was then performed with a Bayes classifier. They achieved recognition rate 90% on a database of 47 people [17].

I.J. Cox *et al*. introduced a mixture-distance technique which achieved 95% recognition rate on a query database of 685 individuals. Each face was represented by 30 manually extracted distances [20].

Reference [21] used Gabor wavelet decomposition to detect feature points for each face image which reduced the storage requirement for the database. Typically, 35-45 feature points per face were generated. Two cost values, the topological cost, and similarity cost, were evaluated. The recognition accuracy of the right person was 86% and 94% of the correct person's faces were in the top three candidate matches. In summary, geometrical feature matching based on precisely measured distances between features may be useful for finding matches in a large database. However, it will be dependent on the accuracy of the feature location algorithms.

Disadvantage of current automated face feature location algorithms are that they don't provide a high degree of accuracy and require considerable computational time.

In 2006 Basavaraj and Nagaraj proposed a geometrical model for facial feature extraction. The basic process includes improvement of frontal face images including ears and chin and also of potential features because it enhances the development of methods in face recognition process. The face model proposed by the ability to identify is divided into four steps. The starting step is pre-processing. The main aim of this step is to reduce the noise and the input image is converted into a binary one. The second step contains labeling of facial features and then finding the origin of these labeled features. Finally, it calculates the estimated distance used for matching purpose. In Khalid *et al*. (2008) the author tries to reduce the search space by minimizing the facial features information.

The information is limited by extracting 60 fiducially control points (nose, mouth, eyes etc) of face with different light and expression images. The functional classification of these features is large-scale point of distance and angle measurement. This process achieve 86% recognition rate.

In Huiyu and Sadka (2011) the diffusion distance over the calculation of face images is produced. These images describe the shape of Gabor filters which includes the size and extent. Gabor filter results for the discriminatory image are used to distinguish between face representations in the database.

Zhen *et al*. (2011) presented a recognition approach based on facial geometry. In this approach, first the face image is segmented into multiple facial geometrical domains such as image space and image orientation at different scale. In second step LBP is calculated. The presented approach provides good face representation by exploring facial information from different domains which gives efficient face recognition systems.

Similarly Pavan *et al*. (2011) presented a geometry based face recognition method which makes use of subspace based models. These models provide geometrical properties of the face space which can assist efficient recognition system for number of image applications [19].

IV. CONCLUSION

Face recognition is a challenging problem in the field of image processing and computer vision. Because of lots of application in different fields, the face recognition has received great attention. In this paper, different face recognition algorithms are mentioned with their advantages and disadvantages. One can use any of them as per your requirement and application. One can also work over to improve the efficiency of the discussed algorithms and improve the performance.

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Bhaskar Gupta is currently working as an Associate Professor in Computer Science and Electrical Engineering division in Wollega University, Federal Democratic Republic of Ethiopia under UNDP scheme.

Served as Director in Shivdan Singh Institute of Technology and Management Aligarh and Principal, Brahmanand Institute of Reserach, Technology and Management, Khurja.

He was also associated with Ministry of Higher education, Sultanate of Oman, Islamic Republic of Afghanistan through World Bank project.

Published over 40 research papers and has a vast teaching experience. He is Member of IEEE, IETE and IE(I).