Comparative Study of Face Recognition Techniques: A Review

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ABSTRACT
Many Algorithms for implementation of face recognition are popular in face recognition all having respective advantages and disadvantages. Some improves the efficiency of face recognition, under varying illumination and expression conditions for face images. Feature representation and classification are two key steps for face recognition. Authors have presented novel techniques for face recognition. In this paper, we presented an overview of face recognition techniques and its applications.

General Terms
Face recognition, feature extraction, face detection

Keywords
PCA, LDA , EigenFaces

1. INTRODUCTION
Human face recognition is currently a very active research area [1] in computer vision and pattern recognition with focus on ways to perform robust biometric identification. Many commercial applications of face recognition are also available such as criminal identification, security system, image and film processing. Accurate localization and tracking facial features are important in applications such as vision-based human machine interaction, face-based human identification, animation, entertainment, etc. However, automatic face recognition based on 2-D still images is a challenging task because of the problems such as variability in the appearance of a face image as it changes due to expression, occlusion, illumination, pose, aging etc. Research in this area has been conducted for more than 30 years; as a result, the current status of face recognition technology is well advanced. The reason for popularity of face recognition is that it can be applied in a wide range of fields, such as identity authentication, access control and so on [1].

Block diagram of a typical face recognition system is shown in Fig. 1. The face detection and face extraction are often performed simultaneously. The overall process is depicted in Fig 1.

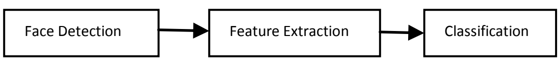

Figure 1. Block diagram of a typical face recognition system

In typical face recognition system, pre processing is used to reduce noise and reliance on precise registration. A first step of any face processing system is face detection: Given an arbitrary image, the goal of face detection is to determine whether or not there are any faces in the image and, if present, return the image location and extent of each face. The challenges associated with face detection can be attributed to the following factors:

- Pose.
- Presence or absence of structural components
- Facial expression
- Occlusion
- Image orientation
- Imaging conditions

facial feature detection is to detect the presence and location of features, such as eyes, nose, nostrils, eyebrow, mouth, lips, ears, etc., with the assumption that there is only one face in an image [2], [3]. Face recognition or face identification compares an input image (probe) against a database (gallery) and reports a match, if any and classification is the performed for identifying the sub-population to which new observations belong. First present a brief background on differential geometry and topology basics, which is followed by the feature extraction technique developed.

Generally speaking, there are two categories of methods in face recognition [4]. One approach is based on facial feature and the other approach takes a holistic view of the recognition problem.

1.1 Nor Holistic approach
It extracts the statistical characterization by the statistical method directly out of the entire training sample images instead of extracting the feature of the nose, mouth, or the eyes separately. Examples of holistic methods are eigenfaces (most widely used method for face recognition), probabilistic eigenfaces, fisherfaces, support vector machines, nearest feature lines (NFL) and independent-component analysis approaches.

1.2 Feature based approach
In feature-based approaches, local features on face such as nose, and then eyes are segmented and then used as input data for structural classifier. Pure geometry, dynamic link architecture, and hidden Markov model methods belong to this category. Neurophysiologic Research and studies have determined that eyes, mouth, and nose are amongst the most important features for recognition [5].

1.3 Hybrid approach
The idea of this method comes from how human vision system perceives both local feature and whole face. There are modular eigenfaces, hybrid local feature, shape normalized, and component based methods in hybrid approach. Human facial features play a significant role in perceiving faces. Thus, when a human face is represented as an image, it is very natural for

these features to depict distinguishing characteristics not present in other facial components such as forehead, cheeks and chin. The eyes, the mouth, and the nostrils are the local minima of a facial image, whereas, the tip of the nose is a local maximum.

2. FACE RECOGNITION TECHNIQUES

This section gives an overview on the major human face recognition techniques that apply mostly to frontal faces, advantages and disadvantages of each method are also given. The methods considered are eigenfaces (eigenfeatures), neural networks, dynamic link architecture, hidden Markov model, geometrical feature matching, and template matching. The approaches are analyzed in terms of the facial representations they used.

2.1 Eignfaces

The eigenface technique using the Principal Components Analysis (PCA) method known as Karhunen-Loeve method is successfully used in order to perform dimensionality reduction. In mathematical terms, eigenfaces are the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. Turk and Pentland applied principal component analysis to face recognition and detection [6]. PCA finds the eigen-vectors, called "EigenFaces", of the covariance matrix corresponding to the generic training images. The eigenvectors are ordered to represent different amounts of the variation, respectively, among the faces. Each face can be represented exactly by a linear combination of the eigenfaces. It can also be approximated using only the "best" eigenvectors with the largest eigenvalues. The best M eigenfaces construct an M dimensional space, the "face space". L. Sirovich and M. Kirby [7, 8] used principal component analysis to efficiently represent pictures of faces. They argued that any face images could be approximately reconstructed by a small collection of weights for each face and a standard face picture (eigenpicture). The weights describing each face are obtained by projecting the face image onto the eigenpicture.

2.2 Fisherfaces

R. A. Fisher developed Linear/Fisher Discriminant Analysis (LDA) in 1930 [11]. The Fisherface method, One of the appearance-based FR methods, those utilizing linear/fisher discriminant analysis (LDA) techniques have shown promising results as it 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) [12][9], applies linear discriminant analysis (LDA) to find a set of basis images that maximizes the ratio of between-class scatter to that of within-class scatter. In face recognition application, one problem for LDA is that the within-class scatter matrix is almost always singular since the number of image pixels in image is usually much larger than the number of images which can increase detection error rate if there is a significant variation in pose or lighting condition within same face images. In order to overcome the complication of a singular matrix, many algorithms have been proposed [4-10]. Since, the fisherfaces approach takes advantage of within-class information; minimizing variation within each class, yet maximizing class separation, the problem with variations in the same images such as different lighting conditions can be overcome.

2.3 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 representing the position and size of the main facial features, such as eyes and eyebrows, nose, mouth, and the shape of face outline. Every type of geographical element (such as river, road, contour line and so on) has innate geometric features represented by the geometric data (coordinates). These data processed should demonstrate their geometric features. By comparing the geometric features of the data with the innate ones, we know which links are the best ones. So the geometric features of elements may be regarded as credible data in the process.

2.4 Neural network

Neural networks have been applied successfully in many pattern recognition problems, such as optical character recognition, object recognition, and autonomous robot driving. The advantage of using neural networks for face detection is the feasibility of training a system to capture the complex class conditional density of face patterns.

However, one drawback is that the network architecture has to be extensively tuned (number of layers, number of nodes, learning rates, etc.) to get exceptional performance [13]. The attractiveness of using neural networks could be due to its non linearity in the network. Hence, the feature extraction step may be more efficient than the linear Karhunen-Loève methods which choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples [14]. The authors reported 96.2% correct recognition on ORL database of 400 images of 40 individuals. The classification time is less than 0.5 second, but the training time is as long as 4 hours features in a hierarchical set of layers and provides partial invariance to translation, rotation, scale, and deformation. However, when the number of persons increases, the computing expense will become more demanding. In general, neural network approaches encounter problems when the number of classes (i.e., individuals) increases. Moreover, they are not suitable for a single model image recognition test because multiple model images per person are necessary in order for training the systems to "optimal" parameter setting.

2.5 Graph matching

Graph matching has applications in a variety of fields, from computer vision to computational biology. In graph matching, patterns are modeled as graphs and pattern recognition amounts to finding a correspondence between the nodes of different graphs [15]. The Graph Matching formulation for Pattern Recognition reduces to essentially that of finding the best match between representative model (class) graphs and given data graphs. In general, graphs may be matched by comparing vertices and edges according to their contribution to a relational distance metric [16]. M. Lades et al [17] presented a dynamic link structure for distortion invariant object recognition, which employed elastic graph matching to find the closest stored graph. Dynamic link architecture is an extension to classical artificial neural networks. The matching process is computationally expensive, taking about 25 seconds to compare with 87 stored objects on a parallel machine with 23 transporters. L. Wiskott et al [18] extended the technique and matched human faces against a gallery of 112 neutral frontal view faces. In general, dynamic link architecture is superior to other face recognition techniques in terms of rotation invariance; however, the matching process is computationally expensive.

3. FACIAL FEATURE EXTRACTION

The importance of facial features for face recognition cannot be overstated. It is well known that even holistic matching methods, for example, eigenfaces proposed by Turk and Pentland [19] and Fisherfaces, which proposed by Belhumeur et al [20], need accurate locations of key facial features such as eyes, nose, and mouth to normalize the detected face. Facial features can be of different types: region [21, 22], key point (landmark) [23, 24], and contour [25, 26]. A challenging situation for feature extraction is feature "restoration," which tries to recover features that are invisible due to large variations in head pose. The best solution here might be to hallucinate the missing features either by using the bilateral symmetry of the face or using learned information. It performs two tasks: transforming input parameter vector into a feature vector and/or reducing its dimensionality. A well-defined feature extraction algorithm makes the classification process more effective and efficient. Feature extraction can be conducted independently or jointly with either parameter extraction or classification. LDA and PCA are the two popular independent feature extraction Methods and PCA is unsupervised linear feature extraction method.

4. TECHNIQUES FOR FACIAL FEATURE EXTRACTION

4.1 Appearance-based approaches

The concept of "feature" in these approaches differs from simple facial features such as eyes and mouth. Any extracted characteristic from the image is referred to a feature. Methods such as principal component analysis (PCA), independent component analysis, and Gabor-wavelets [27] are used to extract the feature vector. In contrast to template matching, the models (or templates) are learned from a set of training images which should capture the representative variability of facial appearance. These learned models are then used for detection. These methods are designed mainly for face detection.

4.2 Template-based

Several standard patterns of a face are stored to describe the face as a whole or the facial features separately. The correlations between an input image and the stored patterns are computed for detection. These methods have been used for both face localization and detection. This technique, match facial components to previously designed templates using appropriate energy functional. The best match of a template in the facial image proposed by Yuille et al [28] will yield the minimum energy, where these algorithms require a priori template modelling, in addition to their computational costs, which clearly affect their performance. Genetic algorithms have been proposed for more efficient searching times in template matching.

4.3 Colour segmentation techniques

Colour segmentation technique makes use of skin colour to isolate the face. Any non-skin colour region within the face is viewed as a candidate for eyes and/or mouth. The performance of such techniques on facial image databases is rather limited, due to the diversity of ethnical backgrounds [29].

4.4 Geometry-based

The features are extracted using geometric information such as relative positions and sizes of the face components. This technique is proposed by Kanade [30] the eyes, the mouth and the nose base are localized using the vertical edge map. These techniques require threshold, which, given the prevailing sensitivity, may adversely affect the achieved performance.

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