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A Study on "A Soft Biometric Approach: Face Recognition"

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Abstract— Face recognition has long been a goal of computer vision, but only in recent years reliable automated face recognition has become a realistic target of biometrics research. Face recognition systems are increasingly being deployed in a wide range of practical applications. In this paper, an overview of some of the well-known methods in each of these categories is provided and some of the problems faced by the face recognition system are mentioned. This paper also mentions some of the algorithms developed for this purpose and attempts to give an idea of the state of the art of face recognition technology.

Keywords— Face Recognition, Person Identification, Biometrics, Eigen Faces, Surveillance systems.

I. INTRODUCTION

The human face plays an important role in our social interactions, conveying people's identity. Using the human face as a key to security, biometric face recognition technology has received significant attention in the past several years due to its potential for a wide variety of applications in both law enforcement and non-law enforcement. As compared with other biometrics systems such as retina scanning, finger print or palm print scan face recognition has distinct advantages because of its non-contact process. Face images can be captured from a distance without touching the person being identified and the identification does not require interaction with a person. In addition face recognition serves the crime deterrent purpose because face images that have been recorded and archived can later help to identify a person.

Although the concept of recognizing someone from facial features is intuitive, facial recognition, as a biometric, makes human recognition a more automated, computerized process. What sets apart facial recognition from other biometrics is that it can be used for surveillance purposes. For example, public safety authorities want to locate certain individuals such as wanted criminals, suspected terrorists, and missing children. Facial recognition may have the potential to help the authorities with this mission. Facial recognition offers several advantages. The system captures faces of people in public areas, which minimizes legal concerns for reasons explained below. Moreover, since faces can be captured from some distance away, facial recognition can be done without any physical contact. This feature also gives facial recognition a clandestine or covert capability. For any biometric system to operate, it must have records in its database against which it can search for matches. Facial recognition is able to leverage existing databases in many cases. For example, there are high quality mug shots of criminals readily available to law enforcement. Similarly, facial recognition is often able to leverage existing surveillance systems such as surveillance cameras or closed circuit television (CCTV).

II. APPLICATIONS

There are numerous application areas in which face recognition can be exploited for these two purposes, a few of which are outlined below.

- Security (access control to buildings, airports/seaports, ATM machines and border checkpoints; computer/ network security; email authentication on multimedia workstations).
- Surveillance (a large number of CCTVs can be monitored to look for known criminals, drug offenders, etc. and authorities can be notified when one is located.
- General identity recognition (electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, drivers' licenses, employee IDs).
- Criminal justice systems (mug-shot/booking systems, post-event analysis, forensics). Image database investigations (searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings).
- "Smart Card" applications (in lieu of maintaining a database of facial images, the face-print can be stored in a smart card, bar code or magnetic stripe, authentication of which is performed by matching the live image and the stored template).
- Multi-media environments with adaptive human computer interfaces (part of ubiquitous or context aware systems, behaviour monitoring at childcare or old people's centres, recognizing a customer and assessing his needs .
- Video indexing (labelling faces in video).
- Witnesses face reconstruction.

In addition to these applications, the underlying techniques in the current face recognition technology have also been modified and used for related applications such as gender classification, expression recognition and facial feature recognition and tracking ; each of these has its utility in various domains: for instance, expression recognition can be utilized in the field of medicine for intensive care monitoring while facial feature recognition and detection can be exploited for tracking a vehicle driver's eyes and thus monitoring his fatigue, as well as for stress detection .Face recognition is also being used in conjunction with other biometrics such as speech, iris, fingerprint, ear and gait recognition in order to enhance the recognition performance of these methods.

III. Challenges In Face Recognition

More efforts have been devoted to face recognition because of the availability of commodity cameras and deployment opportunities in many security scenarios. However, face recognition is susceptible to a variety of factors encountered in practice, such as pose and lighting variations, expression variations, age variations, and facial occlusions. Fig. 1 and Fig. 2 show examples of the pose and lighting variations and occlusion. Local feature based recognition has been proposed to overcome the global variations from pose and lighting changes. The use of multiple frames with temporal coherence in a video and 3D face models have also been proposed to improve the recognition rate.

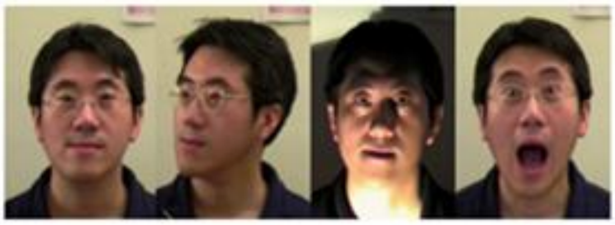

Figure 1: Example of images showing pose, lighting and expression variation.

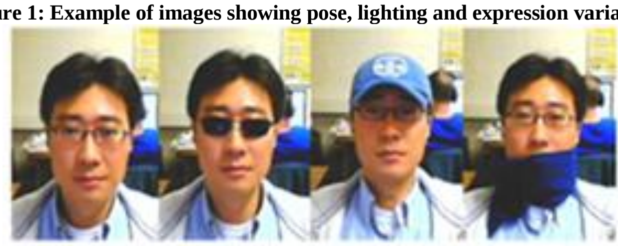

Figure 2: Example of images showing occlusion.

3.1 Pose Variation

Pose variation is one of the major sources of performance degradation in face recognition . The face is a 3D object that appears different depending on which direction the face is imaged. Thus, it is possible that images taken at two different viewpoints of the same subject (intra-user variation) may appear more different than two images taken from the same view point for two different subjects (inter-user variation).

3.2 Lighting Variation

It has been shown that the difference in face images of the same person due to severe lighting variation can be more significant than the difference in face images of different persons . Since the face is a 3D object, different lighting sources can generate various illumination conditions and shadings. There have been studies to develop invariant facial features that are robust against lighting variations, and to learn and compensate for the lighting variations using prior knowledge of lighting sources based on training data . These methods provide visually enhanced face images after lighting normalization and show improved recognition accuracy of up to 100%.

3.3 Occlusion

Face images often appear occluded by other objects or by the face itself (i.e., self-occlusion), especially in surveillance videos. Most of the commercial face recognition engines reject an input image when the eyes cannot be detected. Local feature based methods are proposed to overcome the occlusion problem.

3.4 Expression

Facial expression is an internal variation that causes large intra-class variation. There are some local feature based approaches and 3D model based approaches designed to handle the expression problem. On the other hand, the recognition of facial expressions is an active research area in human computer interaction and communications.

3,5 Age Variation

The effect of aging on face recognition performance has not been substantially studied. There are a number of reasons that explain the lack of studies on aging effects:

i. Pose and lighting variations are more critical factors degrading face recognition performance.
ii. Template update1 can be used as an easy work-around for aging variation.
iii. There has been no public domain database for studying aging until recently.

Aging related changes on the face appear in a number of different ways:

i. Wrinkles and speckles,
ii. weight loss and gain, and
iii. change in shape of face primitives

(e.g., sagged eyes, cheeks, or mouth). All these aging related variations degrade face recognition performance. These variations could be learned and artificially introduced or removed in a face image to improve face recognition performance. Even though it is possible to update the template images as the subject ages, template updating is not always possible in cases of:

i. missing child,
ii. screening, and
iii. multiple enrollment

problems where subjects are either not available or purposely trying to hide their identity. Therefore, facial aging has become an important research problem in face recognition.

IV. Face **Recognition Technologies**

The task of recognizing faces has attracted much attention both from neuroscientists and from computer vision scientists. This chapter gives a literature survey on state of the art of 2D based face recognition algorithms.

Various approaches for 2D face recognition have been proposed in the literature, which can be classified into three categories: analytic (feature based), holistic (global) and hybrid methods. While analytic approaches compare the salient facial features or components detected from the face, holistic approaches make use of the information derived from the whole face pattern. By combining both local and global features, hybrid methods attempt to produce a more complete representation of facial images.

4.1 ANALYTIC APPROACH:

For analytic approaches, distances and angles between feature points on the face, shapes of facial features, or local features, e.g. intensity values extracted from facial features or components are usually applied for face recognition. The main advantage of analytic approaches is to allow a flexible deformation at the key feature points so that pose changes can be compensated. In [4], both template and geometrical feature based analytic methods are implemented and compared. For template based method, facial regions are matched with templates of eyes, nose and mouth respectively and the similarity scores of each facial feature are simply added into a global score for face recognition. For geometrical feature based methods, eyes, mouth and nose facial features are firstly detected. The nose width and length, mouth position and chin shape features are then input to a Bayes classifier for identification. Figure 3 shows how these geometry features are measured, e.g. the chin shape is represented by the distance between the edge of the chin and the centre of the mouth. However, the experimental results favour the template matching approach.

A graph structure, called Dynamic Link Architecture (DLA), is proposed by Lades et al. [10] to represent face images. In this system, an elastic graph matching process is used to learn the representing graph of face images. Once faces are represented by appropriate graphs, Gabor features extracted from graph nodes, named Gabor jets, are then used for face recognition. Figure 4 shows two example face images overlaid with the representative graph [10]. Later on, Wiskott et al [19] extended DLA to Elastic Bunch Graph Matching (EBGM), where graph nodes are located at a number of selected facial landmarks. The EBGM has shown very competitive performance and been ranked as the top method in the FERET evaluation [13].

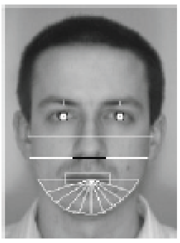

Figure 3: Geometric Feature for Face Recognition.

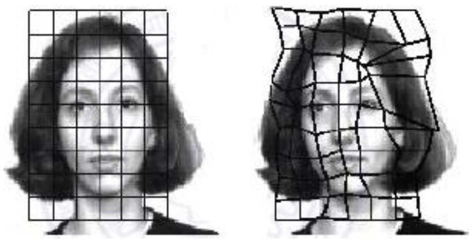

Figure 4: face Images represented by Graph.

The Hidden Markov Model (HMM), widely used to learn the state and transitional probabilities between a number of hidden states, has also been applied to face recognition. HMMs are normally trained from examples that are represented by a sequence of observations. The parameters of the HMM are firstly initialized and then adjusted to maximize the probability of the observation of the given training samples. The observation of test samples can then be input to the trained HMMs for classification according to the output probabilities given different HMMs. Samaria and Young [27] first proposed a HMM architecture for face recognition. A face pattern is divided into several regions such as forehead, eyes, nose, mouth and chin. These regions occur in the natural order from top to bottom and they are used to form the hidden states of ID or pseudo 2D HMMs. To train a HMM, each face image is represented by a sequence of observation vectors, which are constructed from the pixels of a sub window. Nehan and Hayes [25] proposed the embedded 2D HMM, which consists of a set of super states with each super state being associated with a set of embedded states. Super states represent primary facial regions whilst embedded states within each super state describe in more detail the facial regions. As shown in Figure 5, transitions between embedded states in different super states are not allowed. Instead of using pixel intensities directly, the Discrete Cosine Transform (DCT) coefficients are used to form the observation vectors. Compared to 1D and pseudo 2D HMM, the system can perform more efficiently. Based on this work, Bai and Shen replaced DCT with the Discrete Wavelet Transform (DWT) for observation vector extraction [16], the results show the improved performance. However, HMM based systems require lots of images for training, and are only capable of operating on small databases. The performance drops dramatically as the size of database is scaled up. As observed in experiments, the accuracy of Nefian and Haye's method drops from 97.5% to 32.5% when the number of subjects rises from 40 to 200.

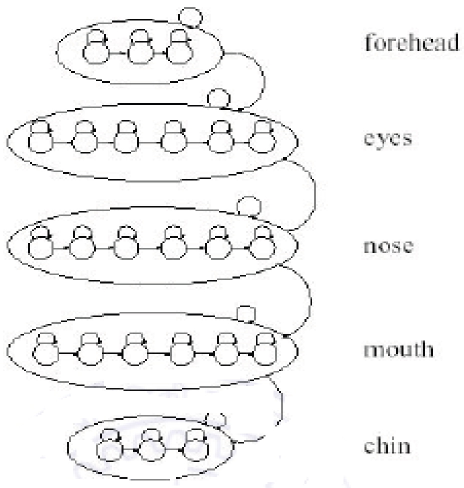

Figure 5: Embedded HMM Structure.

As a hyper plane classifier, Support Vector Machines (SVM) have also been successfully applied to face recognition. A set of SVM classifiers is applied to extract different facial components and the grey values of each component are then combined into a single feature vector [7]. The component based method has been compared with a SVM classification based global method and the results show its robustness against variance of pose and illumination. However, the database consists of images from 5 subjects only and a large number of images are required to train those SVMs. In [18], a 3D morphable model has been used to generate synthesized images with different illumination and pose for training. As a result, only 3 training images of each person are required. However, the results are based on a database from 6 persons only. Thus, how the performance scales with the number of subjects in the database remains unknown.

4.2 HOLISTIC METHOD:

Based on principal components analysis (PCA), Kirby and Sirovich [23] first developed the well known Eigenface method for both face representation and recognition. In this method, the whole face pattern is transformed to a feature vector and a set of training samples are used to compute Eigenfaces [17]. PCA can achieve the optimal representation in the sense of maximizing the overall data variance. However, the difference between faces from the same person due to illumination and pose (within-class scatter) seems to be larger than that due to facial identity (between-class scatter). Based on this observation, Linear discriminant analysis (LDA) is applied for Fisher face methods [3]. LDA defines a projection that makes the within-class scatter small and the between class scatter large. This projection has shown to be able to improve classification performance over PCA. However, it requires a large training sample set for good generalization, which is usually not available for face recognition applications. To address such Small Sample Size (SSS) problems, Zhao et al [28] perform PCA to reduce feature dimension before LDA projection. Figure 6 shows the different bases of LDA, PCA + LDA, and PCA projection. By using higher order statistical analysis, Independent Component Analysis (ICA) was first adopted by Bartlett, Movellan, & Sejnowski [1] for face recognition. The work showed that ICA outperformed PCA. However, in [5], Bartlett et al observed that when the right distance metric is used, PCA significantly outperforms ICA on the FERET database. Recently, kernel methods have been successfully applied to solve pattern recognition problems because of their capacity to handle nonlinear data. By mapping sample data to a higher dimensional feature space, effectively a nonlinear problem defined in the original image space is turned into a linear problem in the feature space [14], PCA or LDA can subsequently be performed in the feature space and are thus called Kernel Principal Component Analysis (KPCA) and Generalized Discriminant Analysis (GDA) [2]. Experiments show that KPCA and GDA are able to extract nonlinear features and thus provide better recognition rates in applications such as face recognition [15, 20].

Neural networks[21, 11] have also been used to classify global facial features. When face images are treated as 1D signals and wavelet analysis was used for feature extraction [11], the Radial Basis Function (RBF) network was applied to the projection of face images to Fisherfaces for classification [8]. The diagram for the method is plotted in Figure 7. While PCA + LDA were first used to decrease the feature dimension of face patterns, sample information was adopted to determine the structure and initial parameters of the RBF network.

Since SVM is a binary classifier, Phillips [26] turned the face recognition problem into a two class problem by introducing the difference space. Two classes, the dissimilarities between faces of the same person and dissimilarities between faces of different people, are designed in the difference space. A single SVM is trained to classify the intra-person and inter-person difference classes. The results on a difficult image set from the FERET database showed that SVMs outperformed the Eigenface method significantly. A binary tree system was adopted in [6] to use SVMs for the multi-class face recognition problem. The results on the ORL database and a larger face collection from several databases showed that SVMs achieve higher accuracy than Eigenface approach. In [9], each person is associated with a SVM that was trained to discriminate the face images from the same people and those from others. Both PCA and LDA were used for feature extraction and tested on a recognition application. By applying different illumination normalization techniques, the results show that SVMs are robust and relatively insensitive to the feature space and pre-processing methods. However, when the representation feature already captures and emphasizes the discriminatory information, e.g., features extracted using LDA or SVMs lose their superiority in comparison with the simplest Euclidean distance plus nearest neighbour classifier.

Global techniques work well for frontal view face images, but they are sensitive to translation, rotation and pose changes [22]. Usually normalization is an important and inevitable process for these methods. A small number of prominent points in the face such as eyes, nostrils or centre of the mouth are required to resize and rotate the input face image. After normalization, the input face image can be aligned with the model face and recognition can be performed thereafter.

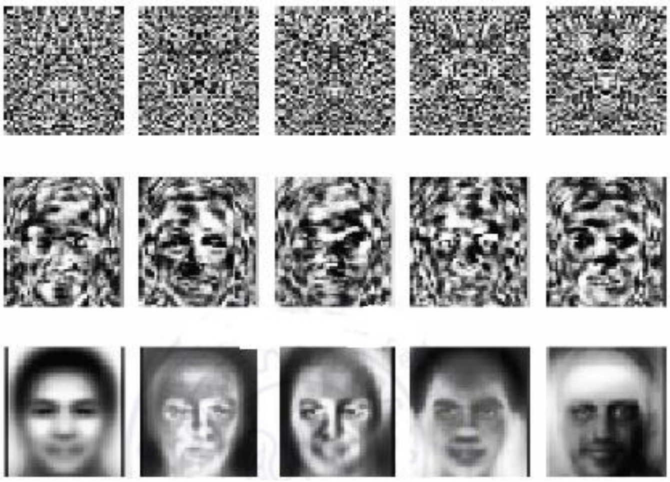

Figure 6: Different bases of linear projection: LDA, PCA+LDA and PCA.

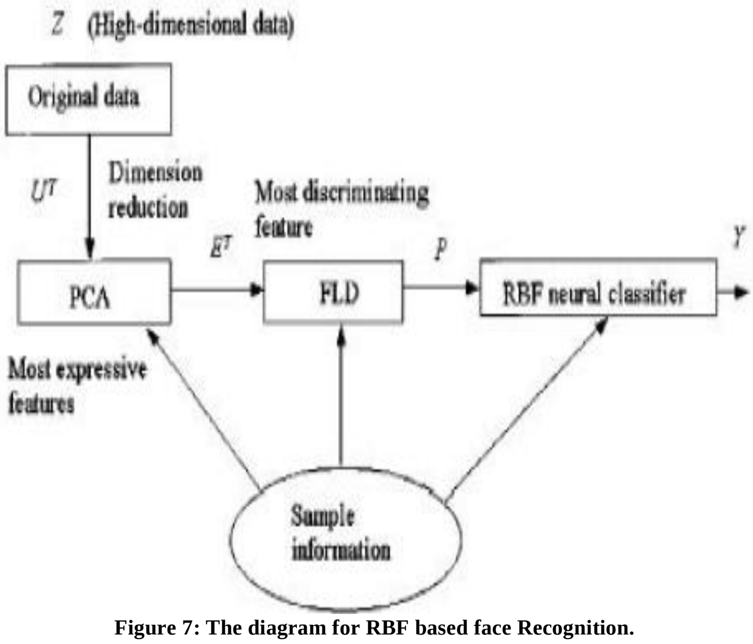

Figure 7: The diagram for RBF based face Recognition.

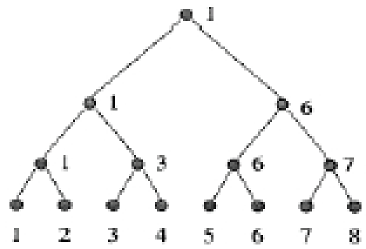

Figure 8: Binary SVM Tree

4.3 HYBRID METHOD:

Hybrid methods utilize both local and global features for recognition. One of the early works is Pentland's modular Eigenfaces [12]. In this work, the eigenface technique is extended to the description and encoding of facial features, yielding eigenfeatures such as eigeneyes, eigennoses and eigenmouths. The experimental results show that the eigenfeatures outperform the eigenface method; the performance was further improved by using the combined representation of eigenfeatures and eigenfaces.

Another famous work is the Active Shape Model (ASM) and Active Appearance Model (AAM) . In this work, ASM and AAM are used to model the variance of shape and appearance respectively. Both ASM and AAM are learned from a large number of training images, which are then used to model test images. To recognize a face image, both ASM and AAM are adjusted to fit the new image, which generates a number of shape and texture parameters. Those parameters, together with the local profiles at model points, are used for face recognition.

IV. Conclusion

Face recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted vigorously in this area for the past four decades or so, and though huge progress has been made ,encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life. The ultimate goal of researchers in this area is to enable computers to emulate the human vision system and, as has been aptly pointed out by Torres [24], "Strong and coordinated effort between the computer vision, signal processing, and psychophysics and neurosciences communities is needed" to attain this objective.

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