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Study of Different Face Recognition Algorithms and Challenges

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***Abstract*— At present face recognition has wide area of applications such as security, law enforcement. Imaging conditions, Orientation, Pose and presence of occlusion are huge problems associated with face recognition. The performance of face recognition systems decreases due to these problems. Discriminant Analysis (LDA) or Principal Components Analysis (PCA) is used to get better recognition results. Human face contains relevant information that can extracted from face model developed by PCA technique. Principal Components Analysis method uses eigenface approach to describe face image variation. A face recognition technique that is robust to all situations is not available. Some techniques are better in case of illumination, some for pose problem and some for occlusion problem. This paper presents some algorithms for face recognition.**

***Index Terms*—** Eigenfaces, recognition, PCA, LDA.

I. INTRODUCTION

More passwords required for a person working in a huge organization and spend some time in a day to logging into systems. Face recognition system do not require user cooperation where as other system requires. The input image is discriminated into several classes by using face recognition system. The noise due to pose, lighting conditions is associated with input image, and patterns occur in input image. All signal contains such pattern, in case of face recognition they could be - the presence of some objects (eyes, nose, and mouth) in any face as well as relative distances between these objects [1]. Available face recognition techniques are the eigenfaces technique, the information theory technique, the multiresolutional technique, the neural network technique, and the statistical approach. Scan of face is an example of biometric indicator. Different biometric indicators are suited for different kinds of identification applications due to their variations in intrusiveness, accuracy, cost, and ease of sensing [2]. Features of face have highest compatibility then biometric indicator in [3]. Fig. 1 shows a machine readable travel documents (MRTD) system based on a number of evaluation factors [3].

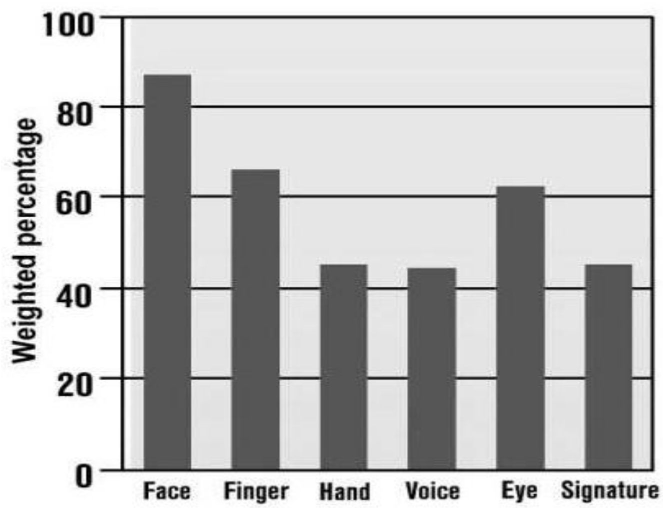

Figure 1: Facial features scored the highest compatibility [3].

II. PROBLEMS WITH FACE RECOGNITION METHODS

Though many face recognition techniques have been proposed and have demonstrated significant promise, the task of robust face recognition is still difficult [4]. Face recognition methods have several problems.

1. ***Orientation Problem:*** Rotation of image may be different with respect to optical axis of camera.

Figure 1.Orientation [FRAV database].

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2. ***Expression of face:*** Face expression can affect the appearance of face.

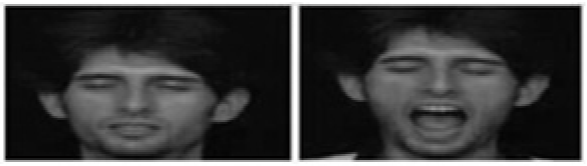

Figure 2.Expression of face [FRAV database].

3. ***Problem of pose:*** there may be side view or front view.

Figure 3.Pose problem [FERET dataset].

4. ***Occlusion:*** Due to presence of beards and glasses.

Figure 4.Presence or absence of structural components [6].

5. ***Illumination:*** Different lighting conditions can affect the recognition rate.

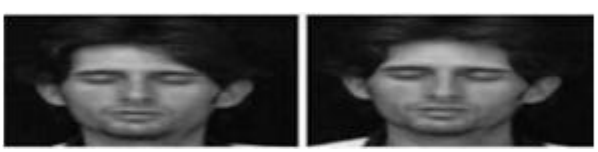

Figure 5.Imaging conditions [FRAV database].

III. FACE RECOGNITION METHODS

1. Model-based face recognition

A model developed by model-based approach can sense variations of face. Information related to face is required for model development. For example, feature-based matching is used to extract relative position and distance features. Automatic detection of features used to develop a face recognition algorithm by Kanade [7]. Frontal face image parameters such as eye corner distance, nostrils, etc. are compared with computed parameters. System of elastic bunch graph matching is developed by Wiskott et al. [8].

(A) Feature-based Matching

Bunch Graph - Every face has same topological structure. Wiskott et al. presents a method to classify members. Edges, contour points, eyes and nose tip are used to represent a face.

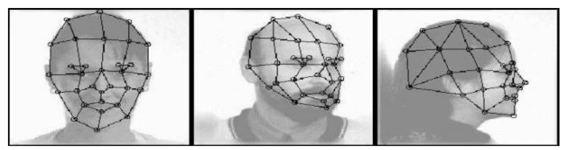

Figure 6: Multiview faces overlaid with labeled graphs [8].

Every node contains a set of 40 complex Gabor wavelet coefficients. Wavelet coefficients are extracted by Gabor kernels with 8 orientations and 5 different spatial frequencies. Recognition of face is performed by labeled graph. Labeled graph is a edges connected nodes set; nodes and edges are labeled with jets and distances respectively. Thus nodes (jets) are used to encode distribution of gray value while edges are used to encode object geometry.

Faces of individual human can be represented by simple labeled graph; detection of every variation in face requires more comprehensive representation. Face bunch graph is formed by combining sample face graph.

Elastic Graph Matching - A new face image can identify by positioning a face graph on the face image in elastic bunch graph matching. Elastic graph matching is used to find fiducial points of input face image. This process may be automatic, if face bunch graph (FBG) is initialized appropriately. a collection of individual face model graphs consisted by a face bunch graph (FBG) combined into a stack-like [8]. Each node is leveled by using a bunch of six jets. According to situation one jet from each bunch has selected.

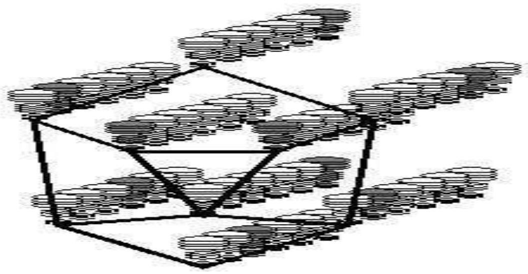

Figure 7: A sketch of a face bunch graph [8].

(B) AAM - 2D Morphable Model

Active Appearance Model (AAM) is a combination of appearance and shape variation model. A statistical shape model and object's gray-level appearance are contained in an AAM. A model and image difference can be minimized by model parameters. Matching is used to find these model parameters. A large number of parameters make this a huge problem.

AAM Construction **-** The AAM is constructed by using labeled images training set. Features can be extracted by marking landmark points at key position on face. A vector consisted of landmark points is used to represent face shape,

$s = (x_1, y_1, ..., x_n, y_n)^T$,
Where, (x_j, y_j) denotes the image coordinate.

All input face shape vectors are normalized into a common coordinate system. 400 face images are used to build the model and 122 landmark points are used [9]. A shape model, a shape-normalized texture model and a combined appearance model with 23 parameters, 113 parameters and 80 parameters respectively are generated.

Recognition of Face by AAM **-** All training images use model parameter vectors as the feature vectors. Linear discrimination analysis (LDA) is used to build the discriminant subspace for recognition of face image. AAM fitting extracts the feature vector of input face image. Recognition is performed by matching input face image vectors with the stored prototype feature vectors. Vector projection is done by using discriminant subspace.

2. Appearance-based face recognition

Many methods use vector space structure to represent images. Appearance-based approaches are used to represent an object in terms of several raw intensity images. Statistical techniques are used by many appearance-based methods to analyze the input image vectors distribution in vector space and effective feature space is derived according to need. Feature space is used to project similarity between test view and stored prototypes [10]. Image is represented by using vectors.

(A) Principal Component Analysis (PCA)

Dimensionality reduction is done by using Principal Component Analysis to find vectors; these vectors are used for the distribution of face images within the entire image space [11]. A set of eigenfaces is extracted from original face images of the training set. Set W is used for storage of weight of each image. Vector W_x is used for storage of weights of input image. Then compare the weights of image and weights W_x. Euclidean distance is used for comparision [10].

(B) Independent Component Analysis (ICA)

Components distribution is non-Gaussian in Independent Component Analysis (ICA) [12].

Figure 8: Images derived from the ORL face database [13].

For face recognition Bartlett et al. [15] presents two architectures based on ICA. The ICA separates second-order and high-order moments of the input.

(C) Kernel Principal Component Analysis (PCA)

A nonlinear mapping is done by kernel PCA [16] and denoted by $\Psi(x)$. Mapping is applied from input space R^M to the feature space R^L, where M is less than L. Kernel function is given by
$k(x_i, x_j) = \Psi(x_i) \cdot \Psi(x_j)$

TABLE I

COMPARISON OF RESULTS

Parameter	PCA	ICA	KPCA
Accuracy	77%	77%	87%
Computation (floating-point operations)	10^8	10^9	10^9
Uniqueness	Yes	No	Yes
Projections	Linear	Linear	Nonlinear

IV. Conclusion

Face recognition is useful in many different fields such as computer vision, neural networks, image processing and pattern recognition. There are many challenges in face recognition process. Face recognition is done by two types of algorithms – appearance-based and model-based. Occlusion, pose variation and illumination problems are still challenging. Appearance-based approaches used to develop illumination-invariant face recognition system by Georghiades et al. [21]. Future work can be done to get better results in case of partial occlusion and pose variation.

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