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Face Detection with Skin Color Segmentation & Recognition using Genetic Algorithm

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Abstract: Face recognition in video has gained wide attention as a covert method for surveillance to enhance security in variety of application domains (e.g., airports, traffic, Terrorist attack).A video contains temporal information as well as multiple instances of a face, so it is expected to lead to better face recognition performance compared to still face images. However, faces appearing in a video have substantial variations in pose and lighting. We propose a face recognition system that identifies faces in video. The system utilizes the rich information in video. The description of the proposed method and preliminary results are provided.

Keyword- Face detection, Image Enhancement, Skin Color detection, Feature Extraction, Pattern Recognization, *Luminance, Color transforms*

I. INTRODUCTION

Humans make use of face as an important clue for identifying people. This makes automatic face recognition very crucial from the point of view of a wide range of commercial and law enforcement applications. Although significant work has been done the current systems are still not close to the human perceptual system [3]. Traditionally, face recognition research has been limited to recognizing faces from still images. Most of these approaches discount the inherent 3-D structure of the face and therefore are very susceptible to pose changes [5]. One way to overcome this is to generate 3-D models using multiple still images or video and then use them while testing any probe image. Even if the resolution of the images/video is high (which is usually not the case), the face model generated by the known techniques is usually far from perfect which makes this approach often not practical for face recognition. Recently, methods based on multiple images/video sequences that do not involve creating an explicit 3-D model have been suggested. Such an approach is supported by many psychophysics works like, where authors argue that a 3-D object is represented as a set of 2-D images in our brains. Leaving out the algorithms based on simple voting, most of these methods make use of either the natural variability in a face or the information present in the temporal variation of face. In, book all recognize a face from a sequence of rotating head images by computing the Euclidean distances between trajectories formed by face sequences in PCA feature space. The Mutual Sub-space Method (MSM) considers the angle between input and reference subspaces formed by the principal components of the image sequences as the measure of similarity [12]. This approach discounts the inherent temporal coherence present in a face sequence that might be crucial for recognition. Face recognition is cast as a statistical hypothesis testing problem, where a set of images is classified using the Kullback-Leibler divergence between the estimated density of the probe set and that of gallery sets [14]. This method is based on the underlying assumption that face recognition can be performed by matching distributions. However, two such distributions for the same subject might look very different depending on the range of poses and expressions covered by the two sets. Moreover, this approach is sensitive to illumination changes.

II. LITERATURE REVIEW

Liu learn temporal statistics of a face from a video using adaptive Hidden Markov Models to perform video-based face recognition [20]. Kernel principal angles, applied on the original image space and a feature space, are used as the measure of similarity between two video sequences. Zhou proposes a tracking-and-recognition approach by resolving uncertainties in tracking and recognition simultaneously in a probabilistic framework. Lee in their recent work, represent each person by a low-dimensional appearance manifold, approximated by piece-wise linear subspaces. They present a maximum a posteriori formulation for recognizing faces in test video sequences by integrating the likelihood that the input image comes from a particular pose manifold and the transition probability to this manifold from the previous frame [19]. Among the methods mentioned, Lee method seems to be the one most capable of handling large 2-D and 3-D rotations.

Eigen face-based Recognition

2D face recognition using eigenfaces is one of the oldest types of face recognition. Turk and Pentland published the groundbreaking "Face Recognition Using Eigenfaces" in 1991. The method works by analyzing face images and computing eigenfaces which are faces composed of eigenvectors. The comparison of eigenfaces is used to identify the presence of a face and its identity.

There is a five step process involved with the system developed by Turk and Pentland. First, the system needs to be initialized by feeding it a set of training images of faces. This is used these to define the face space which is set of images that are face like. Next, when a face is encountered it calculates an eigenface for it. By comparing it with known faces and using some statistical analysis it can be determined whether the image presented is a face at all. Then, if an image is determined to be a face the system will determine whether it knows the identity of it or not. The optional final step is that if an unknown face is seen repeatedly, the system can learn to recognize it.

The eigenface technique is simple, efficient, and yields generally good results in controlled circumstances [1]. The system was even tested to

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track faces on film. There are also some limitations of eigenfaces. There is limited robustness to changes in lighting, angle, and distance [6]. 2D recognition systems do not capture the actual size of the face, which is a fundamental problem [4]. These limits affect the technique's application with security cameras because frontal shots and consistent lighting cannot be relied upon.

3D Face Recognition

3D face recognition is expected to be robust to the types of issues that plague 2D systems [4]. 3D systems generate 3D models of faces and compare them. These systems are more accurate because they capture the actual shape of faces. Skin texture analysis can be used in conjunction with face recognition to improve accuracy by 20 to 25 percent [3]. The acquisition of 3D data is one of the main problems for 3D systems.

Holistic Approach

In holistic approach, the whole face region is taken into account as input data into face detection system. 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

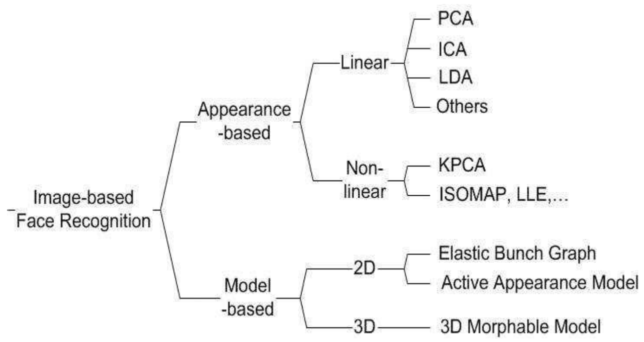
Analysis approaches. They are all based on principal component analysis(PCA) techniques that can be used to simplify a dataset intolower dimension while retaining the characteristics of dataset.

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.

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, component based methods in hybrid approach.

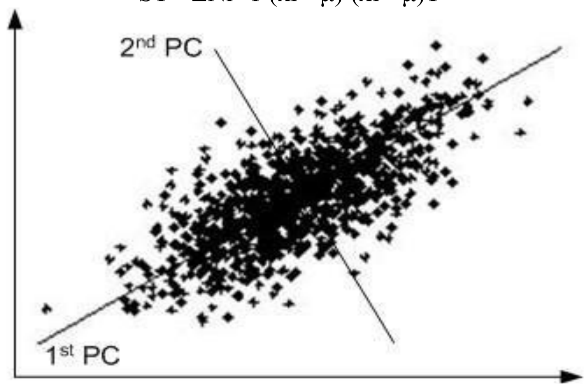


2.1Some Face recognition methods

Principal Component Analysis (PCA)

Derived from KarhunenLoeve'stransformation. Given a dimensional vector representation of each face in a training set of images, Principal Component Analysis (PCA) tends to find a dimensional subspace whose basis vectors correspond to the maximum variance direction in the original imagespace. This new subspace is normally lower dimensional (t<<s). If the image elements are considered as random variables, the PCA basis vectors are defined as eigenvectors of the scatter matrix. The Eigenface algorithm uses PCA for dimensionality reduction to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of face images and the subspace is called face space. All faces in the training set are projected onto the face space to find a set of weights that describes the contribution of each vector in the face space. To identify a test image, it requires the projection of the test image onto the face space to obtain the corresponding set of weights. By comparing the weights of the test image with the set of weights of the faces in the training set, the face in the test image can be identified. The key procedure in PCA is based on KarhumenLoeve transformation. If the image elements are considered to be random variables, the image may be seen as a sample of astochastic process. The PCA basis vectors are defined as the eigenvectors of thescatter matrix *ST*,

$$ST = \Sigma Ni=1\ (xi - \mu)\ (xi - \mu)T$$



2.2 Principal Components (PC) of a twodimensionalset of points.Thefirstprincipal component provides an optimal linear dimension reduction from 2D to1D, in the sense of the mean square error.

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is similar to PCA except that the distributions of the components are designed to be nonGaussian.ICA minimizes both second order and higher order dependencies in the input data and attempts to find the basis along which the data (when projected onto them) are statistically independent. Bartlett et al. provided two architectures of ICA for face recognition task:

- Architecture I statistically independent basis images,
- Architecture II factorial code representation.

Linear Discriminates Analysis (LDA)

Both PCA and ICA construct the face space without using the face class(Category) information. The whole face training data is taken as a whole. In LDA the goal is to find an efficient or interesting way to represent the face vector space. But exploiting the class information can be helpful to the identification tasks; Linear Discriminates Analysis (LDA) finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between class scatter matrix SB and the within class scatter matrix SW are defined. The goal is to maximize SB while minimizing SW, in other words, maximize the ratio **det|SB|/det|SW|.** This ratio is maximized when the column vectors of the projection matrix are the eigenvectors of (SW^1× SB).

Evolutionary Pursuit (EP)

An Eigenspace based adaptive approach that searches for the best set of projection axes in order to maximize a fitness function, measuring at the same time the classification accuracy and generalization ability of the system. Because the dimension of the solution space of this problem is too big, it is solved using a specific kind of genetic algorithm called Evolutionary Pursuit (EP).

Kernel Methods

The face manifold in subspace need not be linear. Kernel methods are a generalization of linear methods. Direct nonlinear manifold schemes are explored to learn this nonlinear manifold.

Trace Transform

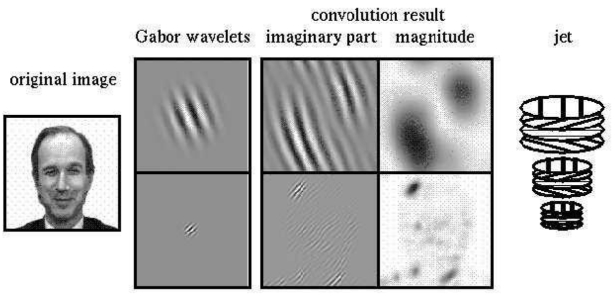
The Trace transform, a generalization of the Radon transform, is a new tool for image processing which can be used for recognizing objects under transformations, e.g. rotation, translation and scaling. To produce the Trace transform one computes a functional along tracing lines of an image. Different Trace transforms can be produced from an image using different trace functional.

Support Vector Machine (SVM)

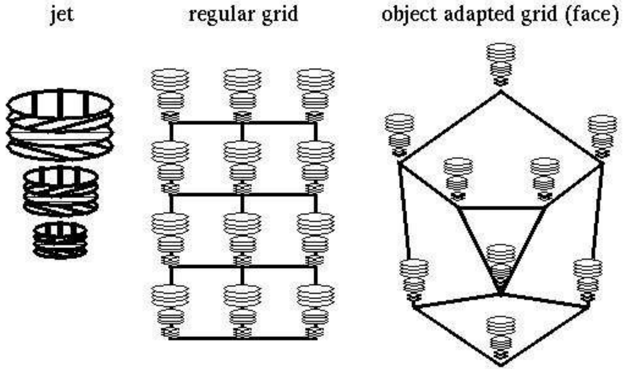
Given a set of points belonging to two classes, a Support Vector Machine(SVM) finds the hyper plane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyper plane. PCA is first used to extract features of face images and then discrimination functions between each pair of images are learned by SVMs.

Elastic Bunch Graph Matching (EBGM)

Elastic Bunch Graph Matching (EBGM). All human faces share a similar topological structure. Faces are represented as graphs, with nodes positioned at fiducially points. (Exes, nose...) and edges labeled with 2Ddistance vectors. Each node contains a set of 40 complex Gabor wavelet coefficients at different scales26and orientations (phase, amplitude). They are called "jets". Recognition is based on labeled graphs. A labeled graph is a set of nodes connected by edges, nodes are labeled with jets, and edges are labeled with distances.



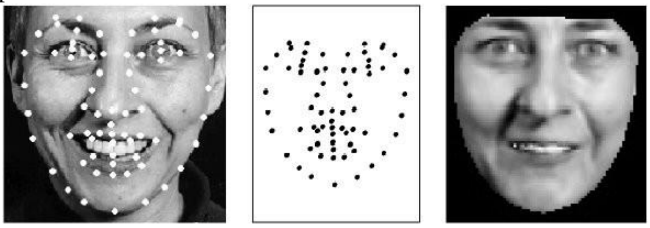
2.3 Jet



2.4 Labeled Graph

Active Appearance Model (AAM)

An Active Appearance Model (AAM) is an integrated statistical model which combines a model of shape variation with a model of the appearance variations in a shape normalized frame. An AAM contains a statistical model if the shape and graylevel appearance of the object of interest which can generalize to almost any valid example. Matching to an image involves finding27model parameters which minimize the difference between the image and a synthesized model example projected into the image. The AAM is constructed based on a training set of labeled images, where landmark points are marked on each example face at key positions to outline the main features.



2.5 The training image is split into shape and shape normalized texture.

3DMorphable Model

Human face is a surface lying in the 3Dspace intrinsically. Therefore the3Dmodel should be better for representing faces, especially to handle facial variations, such as pose, illumination etc. Blantz et al. proposed a method based on a 3Dmorphable face model that encodes shape and texture in terms of model parameters, and algorithm that recovers these parameters from a single image of a face.

3DFace Recognition

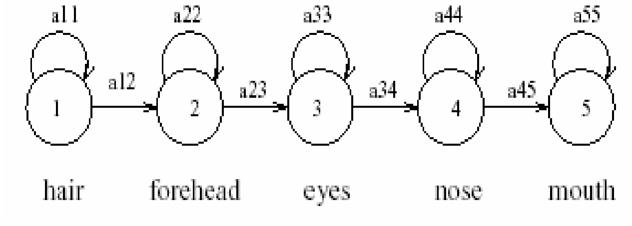
The main novelty of this approach is the ability to compare surfaces independent of natural deformations resulting from facial expressions. First, the range image and the texture of the face are acquired. Next, the range image is preprocessed by removing certain parts such as hair, which can complicate the recognition process. Finally, a canonical form of the facial surface is computed. Such a representation is insensitive to head orientations and facial expressions, thus significantly simplifying the recognition procedure. The recognition itself is performed on the canonical surfaces.

Bayesian Framework

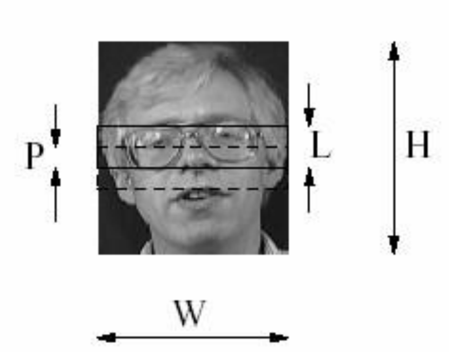
A probabilistic similarity measure based on Bayesian belief that the image intensity differences are characteristic of typical variations in appearance of an Individual. Two classes of facial image variations are defined: intra personal variations and extra personal variations. Similarity among faces is measured by using Bayesian rule.

Hidden Markov Models (HMM)

Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal. HMM consists of two interrelated processes: (1) an underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and (2) a set of probability density functions associated with each state.HMM approach for face recognition based on the extraction of 2dimensionaldiscrete cosine transformation (DCT) feature vectors. The author takes advantage of DCT compression property for feature extraction. An image is divided by blocks of a sub image associated with observation vector. In HHM, There are unobservable Markov chain with limited number of status in the model, the observation symbol probability matrix **B**, a state transition probability matrix **A**, initial state distribution **π**, and set of probability density functions (PDF). AHMM is defined as the triplet's **λ** = (**A**, **B**, ***π***). For frontal human face images, the important facial components appear in top to bottom order such as hair, forehead, eyes, nose, mouth, and chin. This still holds although the image rotates slightly in the image plane. Each of the facial regions is assigned to one state in1Dcontinuous HMM. The transition probability *ai j* and structure of face model is illustrated in following Figure.



2.6 HMM for face recognition image



2.7 Block extraction Form

Boosting & Ensemble Solutions

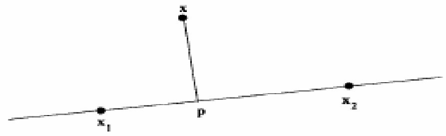
The idea behind Boosting is to sequentially employ a weak learner on a weighted version of a given training sample set to generalize a set of classifiers of its kind. Although any individual classifier may perform slightly better than random guessing, the formed ensemble can provide a very accurate (strong)classifier. Viola and Jones build the first real-time face detection system by using AdaBoost, which is considered a dramatic breakthrough in the face detection research. On the other hand, papers by Guo et al. are the first approaches on face recognition using the AdaBoost methods.

Nearest Feature Line Method

Its one of holistic matching methods to deal with problems in Eigenfaces approach. To create a feature point in feature space, it is assumed that there should be at least two prototype feature points available from the same class(image). A line passing the two prototype features forms a feature line (FL) that generalizes the two feature points. A feature line represents an approximate of two prototypes (images) that are captured under different conditions, such as different head gaze direction or different light illumination. An input image is then identified with a corresponding class, according to the distance between feature point of the given image and FL of the prototype images. Facial image is represented as a point in the feature space, which is an eigenspace. The line **x**1 through **x**2 of same class denoted as **x**1 **x**2 is called30feature line of that class. The query which is input image **x** is projected K onto an FL, and the FL distance **x** and **x**1**x**2 is defined as d(**x,** **x**1**x**2) = |**x** – **p**|, where | **.**|is some norm. The projection point can be found by setting up a vector line

Equation with parameter. Depending μ on the sign of μ **,**the position of **p** can be left of **x1**, right of **x2**, or between ***x1*** and ***x2*** on the line. The greater the value of

the parameter is, the further the position of p from **x1** or **x2** becomes. The classification of the input image is done as follows: Let ***c x*** and ***c j x*** be two distinct prototype points in feature space.



2.8 Generalizing two prototype feature points x1 and x2

Result Analysis:

Classification Results for Four Individual Data Bases.

Database	Eigenface	Elastic Matching	Auto-Association and classification Networks
MIT	97%	97%	72%
Olivetti	80%	80%	20%
Weizmann	84%	100%	41%
Bern	87%	93%	43%

Result for combined databases

Eigenface	Elastic Matching	Auto-Association and classification Networks
66%	93%	Not tested

METHOD	Error rate (%)	Trianing Time	Classification Time
PDBNN	4.0	20min	<0.1s
SOM+CN	3.8	4hours	<0.5s
Top-down HMM	13.0	n/a	n/a
Pseudo-2d HMM	5.0	n/a	240s
Eigenface	10.0	n/a	n/a
n-tuple	14.0	0.9s	0.025s
cont n-tuple	2.7	0.9s	0.33s
cont n-tuple*	4.2	30min	0.025s
1-nearest-neighbour	3.7	0s	1s

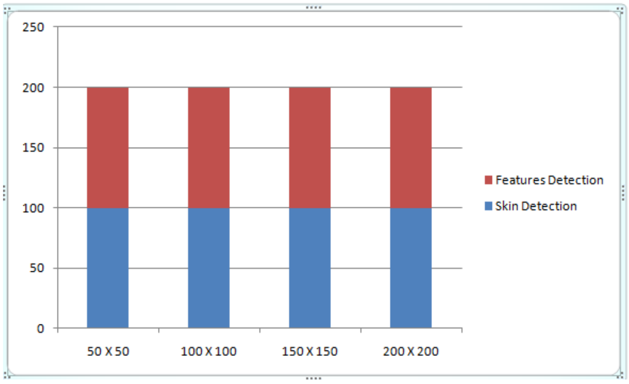
Existing Methods Results

Sr.No	Image Type	Size	Skin Detected	Accuracy of Detection(skin)	Features Detected	Accuracy of Detection(Features)
1	RGB	50X 50	Yes	100%	yes	100 %
2	RGB	100 X 100	Yes	100%	yes	100 %
3	RGB	150 X 150	Yes	100%	yes	100 %
4	RGB	200 X 200	Yes	100%	yes	100 %
5	RGB	250 X 250	Yes	100%	yes	100 %
6	RGB	300 X 300	Yes	100%	yes	100 %
7	RGB	350 X 350	Yes	100%	yes	100 %

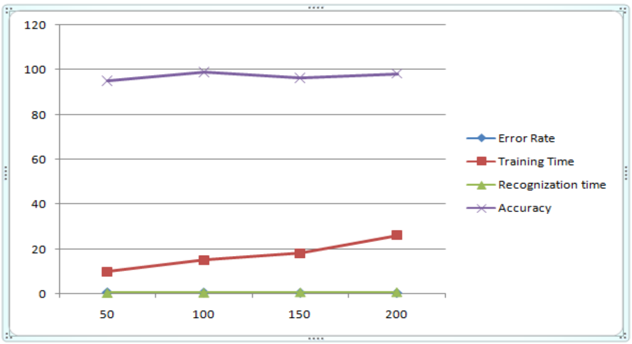
Skin Color Detection & Features Detection Result

Sr.No	Neural Network Training Time	Error Rate	No of Images	Size of an Image	Recognization Time	Accuracy (%)
1	10 Sec	0.67	50	200 X 200	0.32 Sec	95%
2	15 Sec	0.60	100	200 X 200	0.50 Sec	99%
3	18 Sec	0.47	150	200 X 200	0.67 Sec	96.43%
4	26 Sec	0.38	200	200 X 200	0.73 Sec	98.32%

Project Face Recognization Results



Skin detection & Face features Extraction Chart representation



Comparative Study

III. CONCLUSION

We have used a specific method for generating features vector of the whole face in an image, by first detecting face regions using the color of skin which presents a robust overlooked in different background, accessory and clothing. It is a fast algorithm for extracting human faces in color images and easy to implement. GA is then applied to perform the recognition task. This solution was implemented using Matlab environment. Results indicate that the proposed method achieves good results.

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