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RESEARCH ARTICLE

ACTIVE APPEARANCE MODEL AND PCA BASED FACE RECOGNITION SYSTEM

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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. We discuss how greater accuracy can be achieved by extracting features from the boundaries of the faces by using Active Shape Models and, the skin textures, using Active Appearance Models, originally proposed by Cootes and Talyor.*

***Index Terms* -** Eigenfaces, face recognition, Active shape models, PCA.

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. Available face recognition techniques are the eigenfaces technique, the information theory technique, the multiresolutional technique, the neural network technique, and the statistical approach. Different biometric indicators are suited for different kinds of identification applications due to their variations in intrusiveness, accuracy, cost, and ease of sensing. Features of face have highest compatibility then biometric indicator. Face recognition systems are examples of the general class of pattern recognition systems, and require similar components to locate and normalize the face; extract a set of features and match these to a gallery of stored.

An essential aspect is that the extracted facial features must appear on all faces and should be robustly detected despite any variation in the presentation: changes in pose, illumination, expression etc. Since faces may not be the only objects in the images presented to the system, all face recognition systems perform face detection which typically places a rectangular bounding box around the face or faces in the images. Describe 2D feature extraction methods that operate on all the image pixels in the face detected region: eigenfaces and fisherfaces which were first proposed by Turk and Pentland in the early 1990s. Eigenfaces can be made to work reasonably well for faces captured in controlled conditions: frontal faces under the same illumination. A certain amount of robustness to illumination and pose can be tolerated if non-linear feature space models are employed. Much better recognition performance can be achieved by extracting features from the boundaries of the faces by using Active Shape Models (ASM) and, the skin textures, using Active Appearance Models (AAM) [5].

The remainder of the chapter on face recognition is dedicated to ASMs and AAMs, their implementation and use. ASM and AAms readily extend to 3D, if multiple cameras are used or if the 3D geometry of the captured faces can otherwise be measured, such as by using laser scanning or structured light (e.g. Cyberware's scanning technology). ASMs and AAMs are statistical shape models and can be used to learn the variability of a face population. This then allows the system to better extract out the required face features and to deal with pose and lighting variation.

II. EXISTING SYSTEM

Face Detection

As we are dealing with faces it is important to know whether an image contains a face and, if so, where it is – this is termed face detection. This is not strictly required for face recognition algorithm development as the majority of the training images contain the face location in some form or another. However, it is an essential component of a complete system and allows for both demonstration and testing in a 'real' environment as identifying the a sub-region of the image containing a face will significantly reduce the subsequent processing and allow a more specific model to be applied to the recognition task.[6] Face detection also allows the faces within the image to be aligned to some extent. Under certain conditions, it can be sufficient to pose normalize the images enabling basic recognition to be attempted. Indeed, many systems currently in use only perform face detection to normalize the images. Although, greater recognition accuracy and invariance to pose can be achieved by detecting, for example, the location of the eyes and aligning those in addition to the required translation/scaling which the face detector can estimate.

A popular and robust face detection algorithm uses an object detector developed at MIT by Viola and Jones and later improved by Lienhart. The detector uses a cascade of boosted classifiers working with Haar-like features [6] to decide whether a region of an image is a face. Cascade means that the resultant classifier consists of several simpler classifiers that are applied subsequently to a region of interest until at some stage the candidate is rejected or all the stages are passed. Boosted means that the classifiers at every stage of the cascade are complex themselves and they are built out of basic classifiers using one of four different boosting techniques. Currently Discrete Adaboost, Real Adaboost, Gentle Adaboost and Logitboost are supported. The basic classifiers are decision-tree classifiers with at least 2 leaves. Haar-like features are the input to the basic classifier. The feature used in a particular classifier is specified by its shape, position within the region of interest and the scale. Normally only a small number of Haar features are considered, say the first 16×16 (256); features greater than this will be at a higher DPI than the image and therefore are redundant. Some degree of illumination invariance can be achieved firstly by ignoring the response of the first Haar-wavelet feature, H(0, 0), which is equivalent to the mean and would be zero for all illumination-corrected blocks.

The detector is trained on a few thousand small images (19x19) of positive and negative examples. The CBCL database contains the required set of examples. Once trained it can be applied to a region of interest of an input image to decide if the region is a face. To search for a face in an image the search window can be moved and resized and the classifier applied to every location in the image at every desired scale. Normally this would be very slow, but as the detector uses Haar-like features it can be done very quickly. An integral image is used, allowing the Haar-like features to be easily resized to arbitrary sizes and quickly compared with the region of interest. This allows the detector to run at a useful speed (10fps) and is accurate enough that it can be largely ignored, except for relying on its output.

Image-Based Face Recognition

Correlation, Eigenfaces and Fisher faces are face recognition methods which can be categorized as image-based (as opposed to feature based). By image-based we mean that only the pixel intensity or colour within the face detected region is used to score the face as belonging to the enrolled set. For the purposes of the following, we assume that the face has been detected and that a rectangular region has been identified and normalized in scale and intensity. A common approach is to make the images have some fixed resolution, e.g.128 × 128, and the intensity be zero mean and unit variance.

The simplest method of comparison between images is correlation where the similarity is determined by distances measured in the image space. If y is a flattend vector of image pixels of size $l \times l$, then we can score a match against our enrolled data, gi, $1 \leq i \leq m$, of m faces by some distance measure $D(y, g_i)$, such as $y^T g_i$. Besides suffering from the problems of robustness of the face detection in correcting for shift and scale, this method is also computationally expensive and requires large amounts of memory. This is due to full images being stored and compared directly, it is therefore natural to pursue dimensionality reduction schemes by performing linear projections to some lower-dimensional space in which faces can be more easily compared. Prinicpal component analysis (PCA)[20] can be used as the dimensionality reduction scheme, and hence, the coining of the term Eigenface by Turk and Pentland.

Statistical Shape Models:

The shape of an object, x, is represented by a set of n points:

$$x = (x1, \ldots, xn, y1, \ldots, yn)^T.$$

Given a training set of s examples, xj , before we can perform statistical analysis it is important to remove the variation which could be attributed to an allowed similarity transformation.

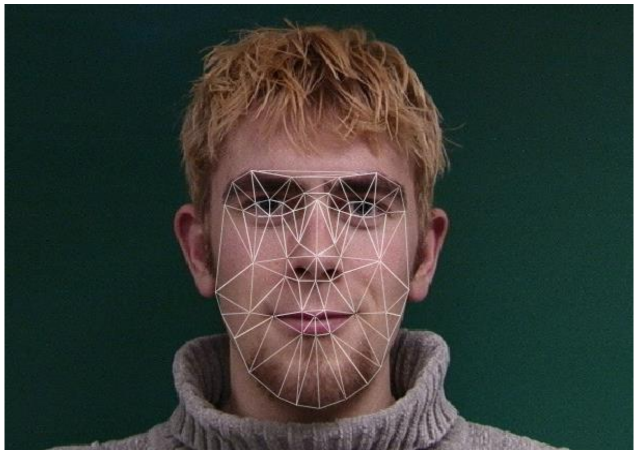


Fig 1: A training image with automatically marked feature points from IMM database[16].

The marked feature points have been converted to triangles to create a face mask from which texture information can be gathered. Points line only on the eyebrows, around the eyes, lips and chin. These shapes form a distribution in a 2n dimensional space that we model using a form of Point Distribution Model (PDM) [20]. It typically comprises the mean shape and associated modes of variation computed as follows.

- Compute the mean of the data,

$$\bar{\boldsymbol{x}} = \frac{1}{s}\sum_{i=1}^{s}\boldsymbol{x}_i.$$

- Compute the covariance of the data,

$$\boldsymbol{S} = \frac{1}{s-1}\sum_{i=1}^{s}(\boldsymbol{x}_i - \bar{\boldsymbol{x}})(\boldsymbol{x}_i - \bar{\boldsymbol{x}})^{\mathrm{T}}.$$

- Compute the eigenvectors Φi and corresponding eigenvalues λi of S, sorted so that λi ≥ λi+1.

If Φ contains the t eigenvectors corresponding to the largest eigenvalues, then we can approximate any of the training set, x, using x ~ x + Φb, where Φ = (Φ1|Φ2| . . . |Φt) and b is a t dimensional vector given by

$$b = \Phi^{T}(x - x).$$

The vector b defines a set of parameters of a deformable model; by varying the elements of b we can vary the shape, x. The number of eigenvectors, t, is chosen such that 95% of the variation is represented. In order to constrain the generated shape to be similar to those in the training set,we can simply truncate the elements bi such that |bi| ≤ 3(p^λi). Alternatively we can scale b until

$$\left(\sum_{i=1}^{t}\frac{b_i^2}{\lambda_i}\right) \leq M_t,$$

Where the threshold, Mt, is chosen using the X^2 distribution.

III. PROPOSED WORK

Active Shape Models

Active Shape Models employ a statistical shape model (PDM) as a prior on the co-location of a set of points and a data-driven local feature search around each point of the model.[8]

A PDM consisting of a set of distinctive feature locations is trained on a set of faces. This PDM captures the variation of shapes of faces, such as their overall size and the shapes of facial features such as eyes and lips. The greater the variation that exists in the training set, the greater the number of corresponding feature points which have to be marked on each example. This can be a laborious process and it is hard to judge sometimes if certain points are truly corresponding.

Model fitting

The process of fitting the ASM to a test face consists the following. The PDM is first initialized at the mean shape and scaled and rotated to lie within the bounding box of the face detection, then ASM is run iteratively until convergence by:

1. Searching around each point for the best location for that point with respect to a Bmodel of local appearance.
2. Constraning the new points to a 'plausible' shape.

The process is considered to have converged when either,

• the number of completed iterations have reached some limit small number;

• The percentage of points that have moved less than some fraction of the search distance since the previous iteration.

Modelling Local Texture

In addition to capturing the covariation of the point locations, during training, the intensity variation in a region around the point is also modeled[10]. In the simplest form of an ASM, this can be a 1D profile of the local intensity in a direction normal to the curve. A 2D local texture can also be built which contains richer and more reliable pattern information - potentially allowing for better localization of features and a wider area of convergence. The local appearance model is therefore based on a small block of pixels centered at each feature point.

An examination of local feature patterns in face images shows that they usually contain relatively simple patterns having strong contrast.[20] The 2D basis images of Haar-wavelets match very well with these patterns and so provide an efficient form of representation. Furthermore, their simplicity allows for efficient computation using an 'integral image'. In order to provides some degree of invariance to lighting, it can be assumed that the local appearance of a feature is uniformly affected by illumination. The interference can therefore be reduced by normalisation based on the local mean, and variance.

$$P_N(x,y) = \frac{P(x,y) - \mu_B}{\sigma_B^2}.$$

This can be efficiently combined with the Haar-wavelet decomposition. The local texture model is trained on a set of samples face images. For each point the decomposition of a block around the pixel is calculated. The size may be 16 pixels or so; larger block sizes increase robustness but reduce location accuracy. The mean across all images is then calculated and only a subset of Haar-features with the largest responses are kept, such that about 95% of the total variation is retained. This significantly increases the search speed of the algorithm and reduces the influence of noise. When searching for the next position for a point, a local search for the pixel with the response that has the smallest Euclidean distance to the mean is sought. The search area is set to in the order of 1 feature block centered on the point, however, checking every pixel is prohibitively slow and so only those lying in particular directions can be considered.

Multiresolution Fitting

For robustness, the ASM itself can be run multiple times at different resolutions. A Gaussian pyramid could be used, starting at some coarse scale and returning to the full image resolution. The resultant fit at each level is used as the initial PDM at the subsequent level. At each level the ASM is run iteratively until convergence.

The PCA method was developed in 1991 [Turk and Pentland, 1991]. In [Belhumeur, Hespanha and Kriegman, 1997], the PCA method is used for dimension reduction for linear discriminate analysis (LDA), generating a new paradigm, and called fisherface. The fisherface approach is more insensitive to variations of lighting, illumination and facial expressions. However, this approach is more computationally expensive than the PCA [20] approach.

In this paper, we propose a new method for face recognition using PCA and RBF neural networks. The RBF neural networks have been used due to its simple structure and faster learning ability [Moody and Darken, 1989; Girosi and Poggio, 1990]. The face features are extracted by the PCA method, reducing the dimensionality of input space. It has been seen that variations between the

Images of the same subject due to variation in pose, orientation, etc. are quite high. Therefore, to achieve high recognition rate, structural information of face images of the same subject is considered for classification process.

This has been realized by identifying sub-clusters corresponding to a subject separately using a clustering algorithm. Then the prototypes of these sub-clusters are used to model the hidden layer neurons of the RBF neural networks. This process also improves its generalization capabilities.

FACE RECOGNITION USING PRINCIPAL COMPONENT ANALYSIS (PCA)

In statistics, **principal components analysis (PCA)** is a technique that can be used to simplify a dataset. It is alinear transformation that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a dataset while retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. The idea is that such low-order components often contain the "most important" aspects of the data. The task of facial recognition is discriminating input signals into several classes. The input signals are highly noisy, yet the input images are not completely random and in spite of their differences there are patterns which occur in any input signal. Such patterns, which can be observed in all signals, could be - in the domain of facial recognition - the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called ***eigenfaces*** in the facial recognition domain (or ***principal components*** generally). They can be extracted out of original image data by means of the mathematical tool called *Principal Component Analysis* (PCA) [19].

By means of PCA one can transform each original image of the training set into a corresponding eigenface. Original image. If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenfaces *exactly*. But one can also use only a part of the eigenfaces. Then the reconstructed image is an approximation of the original image. However, losses due to omitting some of the eigenfaces can be minimized. This happens by choosing only the most important features (eigenfaces). Omission of eigenfaces is necessary due to scarcity of computational resources. Thus the purpose of PCA is to reduce the large dimensionality of the face space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables.

To generate a **set of eigenfaces**, a large set of digitized images of human faces, taken under the same lighting conditions, are normalized to line up the eyes and mouths. They are then all resample at the same pixel resolution (say $m \times n$), and then treated as mn-dimensional vectors whose components are the values of their pixels. The eigenvectors of the covariance matrix of the statistical distribution of face image vectors are then extracted. Since the eigenvectors belong to the same vector space as face images, they can be viewed as if they were $m \times n$ pixel face images: hence the name *eigenfaces*. Viewed in this way, the principal eigenface looks like a bland androgynous average human face. Some subsequent eigenfaces can be seen to correspond to generalized features such as left-right and top-bottom asymmetry, or the presence or lack of a beard. Other eigenfaces are hard to categorize, and look rather strange. When properly weighted, eigenfaces can be summed together to create an approximate gray-scale rendering of a human face. Remarkably few eigenvector terms are needed to give a fair likeness of most people's faces, so eigenfaces provide a means of applying data compression to faces for identification purposes. It is possible not only to extract the face from eigenfaces given a set of weights, but also to go the opposite way. This opposite way would be to extract the weights from eigenfaces and the face to be recognized. These weights tell nothing less, as the amount by which the face in question differs from "typical" faces represented by the eigenfaces.

Therefore, using this weights one can determine two important things:

• Determine if the image in question is a face at all. In the case the weights of the image differ too much from the weights of face images (i.e. images, from which we know for sure that they are faces) the image probably is not a face.

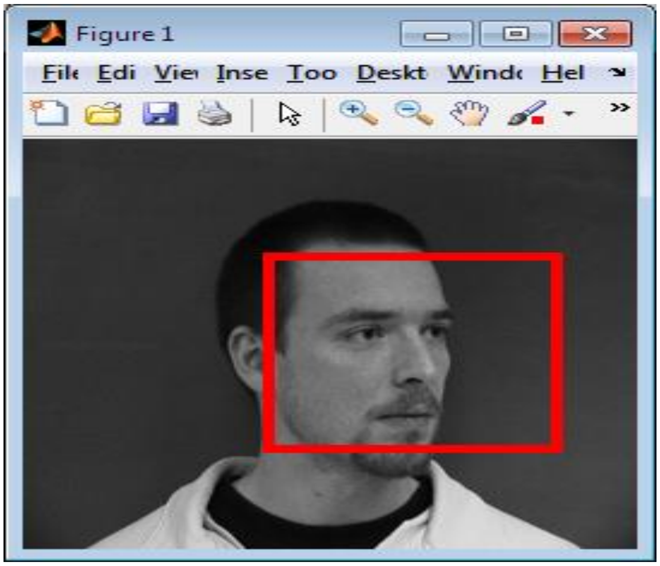
• Similar faces (images) possess similar features (eigenfaces) to similar degrees (weights). If one extracts weights from all the images available, the images could be grouped to clusters. That is, all images having similar weights are likely to be similar faces.

STEPS FOR RECOGNITION USING PCA

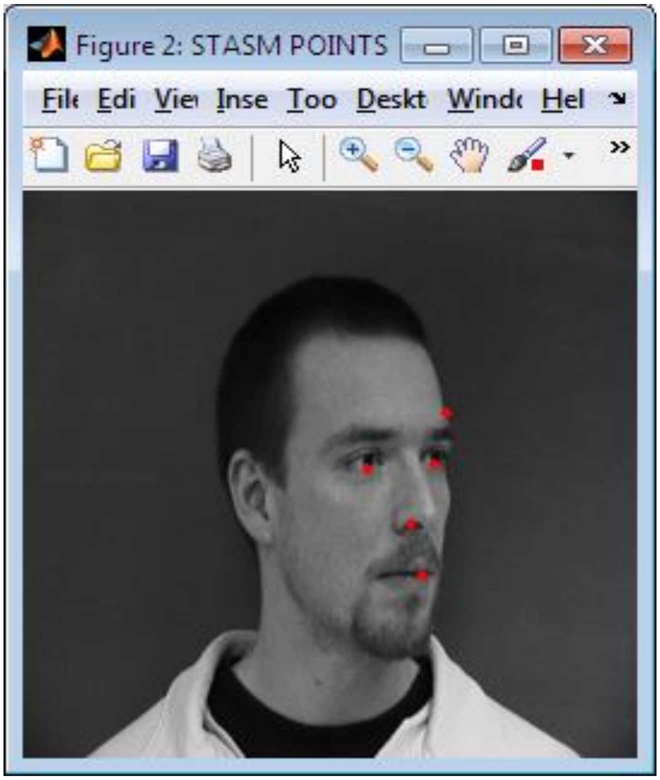
STEP 1: Prepare the Data
STEP 2: Obtain the Mean
STEP 3: Subtract the Mean from Original Image
STEP 4: Calculate the Covariance Matrix
STEP 5: Calculate the Eigenvectors and Eigenvalues of the Covariance Matrix and Select the Principal Components

IV. EXPERIMENTAL RESULTS

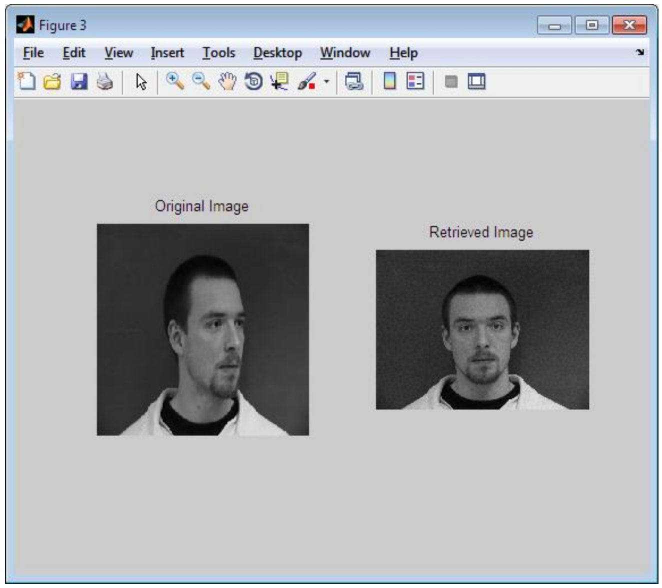
Face detection algorithm:



Active appearance points:



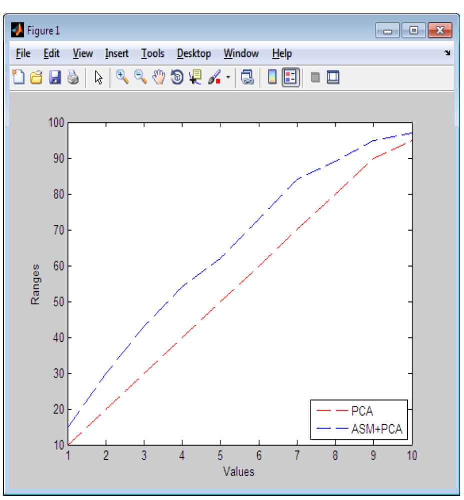
Recognition image:

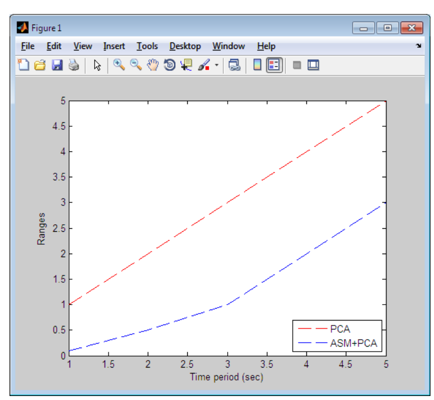


Si.no.	Algorithm	Accuracy	Time period
1	ASM	92.3	5.31 sec
2	PCA	94.5	4.5 sec
3	ASM+PCA	96.7	3.3 sec

V. CONCLUSION AND FUTURE SCOPE

The paper has presented a face recognition system using ACM and PCA with neural networks in the context of face verification and face recognition using photometric normalization for comparison. The experimental results show the N.N. Euclidean distance rules using PCA for overall performance for verification. However, for recognition, ASM+PCA gives the highest accuracy using the original face image. Thus, applying histogram equalization techniques on the face image do not give much impact to the performance of the system if conducted under controlled environment.





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