

Shape Invariant Recognition of Segmented Human Faces using Eigenfaces

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Abstract— This paper describes an efficient approach for face recognition as a two step process: 1) segmenting the face region from an image by using an appearance based model, 2) using eigenfaces for person identification for segmented face region. The efficiency lies not only in generation of appearance models which uses the explicit approach for shape and texture but also the combined use of the aforementioned techniques. The result is an algorithm that is robust against facial expressions variances. Moreover it reduces the amount of texture up to 12% of the image texture instead of considering whole face image. Experiments have been performed on Cohn Kanade facial database using ten subjects for training and sever for testing purposes. This achieved a successful face recognition rate up to 92.85% with and without facial expressions. Face recognition using Principal Component Analysis (PCA) is fast and efficient to use, while the extracted appearance model can be further used for facial recognition and tracking under lighting and pose variations. This combination is simple to model and apply in real time.

Keywords- Active shape models, active appearance models, principal components analysis, eigenfaces, face recognition

I. INTRODUCTION

Since last three decades of face recognition technology, there exists many commercially available systems to identify human faces, however face recognition is still an outstanding challenge against different kinds of variations like facial expressions, poses, non-uniform light illuminations and occlusions. Meanwhile this technology has extended its role to Human-Computer-Interaction (HCI) and Human-Robot-Interaction (HRI). Person identity is one of the key tasks while interacting with the robots, exploiting the un-attentional system security and authentication of the human interacting with the system. This problem has been addressed in various scenarios by researchers resulting in commercially available face recognition systems [1,2]. However, other higher level applications like facial expression recognition and face tracking still remain outstanding along with person identity. This gives rise to an idea for generating a framework suitable for solving these issues together.

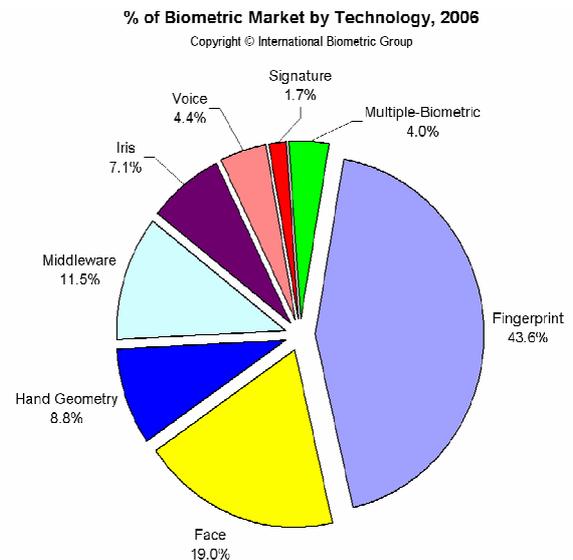
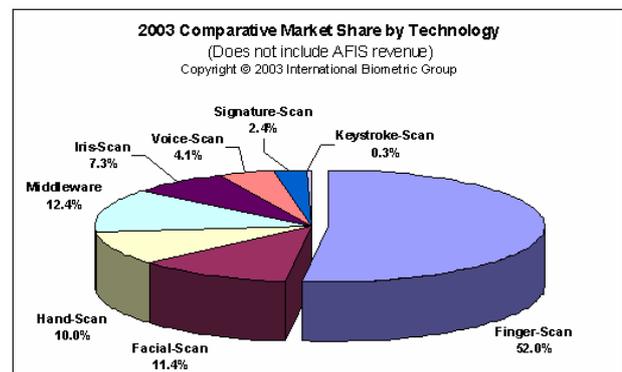


Figure 1 Face Recognition Technology compared to other Biometrics for years 2003 and 2006

As cameras are widely used and mounted on computer screens, embedded into mobiles and installed into everyday living and working environments they become valuable tools for human system interaction. A particular important aspect of this interaction is detection and recognition of faces and interpretation of facial expressions. These capabilities are

deeply rooted in the human visual system and a crucial building block for social interaction. Consequently, these capabilities are an important step towards the acceptance of many technical systems. Although faces are the most important and natural way for human-human interaction but some outstanding challenges like uniqueness, performance and circumvention made its market value a bit less than the other biometrics in year 2003. But in 2006 face recognition technology again raised up to 19% of the biometric market as shown comparably in Figure 1.

This publication focuses on one of aspects of natural human-computer interfaces. Our goal is to build a real-time system for facial recognition that could robustly run in real-world environments. We develop it using model-based image interpretation techniques, which have proven its great potential to fulfil current and future requests on real-world image understanding. Our approach comprises methods that robustly localize facial features, seamlessly track them through image sequences, and finally infer the facial recognition.

The remainder of this paper is divided in five sections. Section II deals with the work related to the proposed scheme. In section III the proposed scheme is described. Section IV describes face image segmentation using model based approach. Section V explains about feature extraction technique using eigenface approach. In the end, we showed experimentation results in Section VI.

II. RELATED WORK

The problem of person identity lies under area of pattern recognition. Various techniques have been used from last few decades. A formal method of classifying the faces was first proposed by Francis Galton [2] in 1888. Galton proposed collecting facial profiles as curves, finding their norm, and then classifying other profiles by their deviations from the norm. The classification was resulting in a vector of independent measure that could be compared with other vectors in the database. Traditional recognition systems have the abilities to recognise the human using various techniques like feature based recognition, face geometry based recognition, classifier design and model based methods. A term defined in [3] is Distinguishing Component Analysis (DCA) and is compared to Principal Components Analysis (PCA) attempting to capture what distinguishes one subject from the others. In [4] Luca and Roli have used the similar kind of technique, which is fusion of Linear Discriminant Analysis (LDA) and PCA is used. PCA is used to reduce the data size while LDA is used to classify the data. Similar application is performed by [5], which first used PCA and LDA in second step. The idea of combination of PCA and LDA is to improve generalization capability when few samples per class are given. Principle Component Analysis (PCA) and LDA are two commonly used techniques for data classification and dimensionality reduction, belonging to the same class [6]. In [7] authors have performed a review of Hidden Markov Models (HMM), Independent Components Analysis (ICA), Neural Networks and PCA.

This paper focuses on the modelling of human face using a two dimensional approach of shape and texture information and then utilising this model for recognition purposes. These type of models in literature are called *Active Appearance Models (AAMs)*, introduced by Edwards et al [8]. These models utilize the shape information based on a point distribution of various landmarks points marked on the face image. A parameterized recognition of the faces is performed by Edwards et al [9]. They have used models parameter for recognition using LDA. However, PCA were firstly used by Sirvovich and Kirby [10], which were latterly adopted by M. Turk and A. Pentland introducing the famous idea of *eigenfaces* [11,12], which was adopted by many researchers afterwards [13].

III. OUR APPROACH

The goal of this paper is to develop a system for face recognition that could be able to recognize persons in real time for HCI applications. The goal is the recognition of persons in the presence of facial expressions in daily life environment. A model based technique followed by eigenfaces is utilized in this regard. Active appearance models (AAM) are strongly applicable at this stage however we tried to achieve the accuracy using textural approach only.

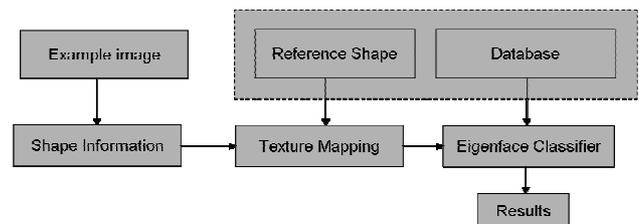


Figure 2 Our Approach

All the subjects in the database are labelled for identification. An active shape model (ASM) is fitted to all the face images in our database. Shape model could be fitted using any fitting algorithm [14,15]. A fitted shape model on training face images is then used for defining the reference shape which is actually mean shape of all the shapes in our database. Given a reference shape S_{ref} and an example image I fitted with shape S , it is suitable to apply texture mapping from example shape to reference shape using affine transformation. However prior to mapping we use planar subdivision i.e. delaunay triangulation for reference and example shape. The texture vector for corresponding image is stored as T . Instead of parametrizing our model we use this representative texture for eigenface classifier. The use of eigenspace at this stage is suitable in two major aspects, 1) reducing the amount of texture to be used in classification i.e. segmenting about 12% gray values information of the original image as compared to conventional eigenface approach, where we use full image texture, 2) Texture mapping on reference shape benefited in terms of shape normalization for all the available images, this makes facial expressions mould to reference shape. In this regard we can control the facial expressions in short extent. Further light variations are normalized in the extracted texture

to improve the segmented face for classification. The approach is shown in Figure 2.

This established framework could be used either to parameterize the appearance model or to use the texture information for eigenface classifier. Given a texture vector T , it could be projected to the eigenspace E using a linear combination:

$$T_{im} = \sum_n w_i \Phi_i$$

Where w_i are the weights for the example image and Φ_i are the corresponding eigenvectors over the whole space of n dimensions.

IV. APPEARANCE MODEL FOR FACES

A. Active Shape Models (ASM)

Different kind of shape models have been utilized by the researchers depending upon different applications. Some are the landmark based models defining some fixed points annotated on the images and then defining the boundaries around the objects. However some rely on the contour based approach. Different contour define the shape of the object for outlining it along with covering the feature inside an object [16]. Landmark based models [17,18,19] however provide the exact location of the features inside the object. We utilize a 2D face model as shown in Figure 3. This point distributed model (PDM) consists of 134 landmarks which prominently describe the location of individual face features. This model covers full face area except some parts of the human head like hair, forehead and ears. By the analysis of human faces, it is observed that most of the expressional changes lie in this segmented region [20]. Shape model is projected on the image plane and fitted to the face. We used fitting of the shape on the face by training an objective function. This technique was devised by Wimmer et al [14].

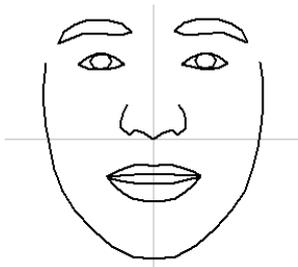


Figure 3 2D Shape model

An ASM is parameterized using PCA to form the shape feature vector.

$$x \approx x_m + P_s b_s$$

Where the shape x is parameterized by using mean shape x_m and matrix of eigenvectors P_s to obtain the parameter vector b_s [21]. However in our case face parameters are only required for model fitting.

B. Active Appearance Models (AAM)

For the various instances of the same person different types of variations are required to be modelled. For example, shape deformations including both expression changes and pose variations along with the texture variations caused by illuminations. Once we have information about the model for the example image, we can extract texture information easily.

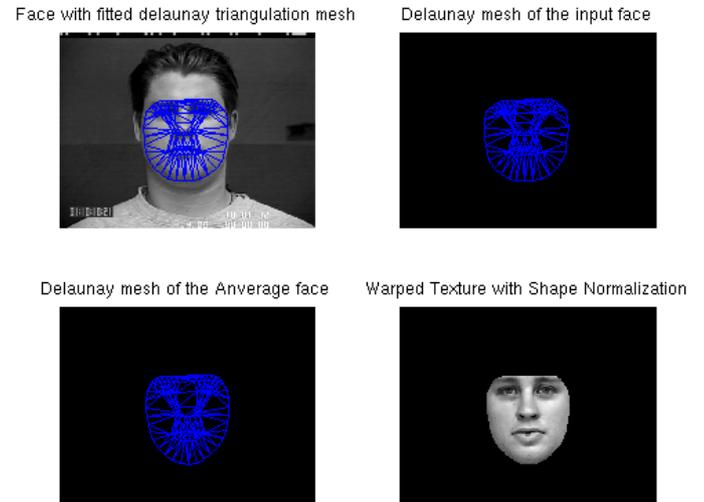


Figure 4 (Top Left) Face Fitted with Mesh, (Top Right) Mesh of the input image, (Bottom Left) Average shape where the texture is warped, (Bottom Right) Texture warping results on average face

At first, shape variation is required to be controlled in order to record the texture. This is achieved by defining a reference shape (mean shape in our case) for whole database. Figure 4 (bottom-left) shows the average shape (mean shape) of the subject in consideration. Delaunay triangulation is used to divide the shape into a set of different facets. The delaunay triangulation is a triangulation which is equivalent to the nerve of the cells in a voronoi diagram, i.e., that triangulation of the convex hull of the points in the diagram in which every circumcircle of a triangle is an empty circle [22].

Given a set of shape points x of the input example image and x_{avg} of the average image, we can find the texture vector g_{im} as follows:

- a) Compute the pixel position in the average shape.
- b) Find the relative position in example image using affine transformation.
- c) Sample the texture values at the points inside convex hull of the average image forming texture vector g_{im} .

The texture vector is normalized to remove global lighting effects. This is performed by applying the linear transformation [21],

$$g = (g_{im} - \beta 1) / \alpha$$

Where

$$\beta = (g_{im} \cdot 1) / n$$

$$\alpha = |g_{im}|^2 / n - \beta$$

Where, g is the texture vector obtained after light variations adjustment. Varying textural parameters cause changes in the image similar to eigenfaces [26]. Face images segmented after appearance model are shown in Figure 5.

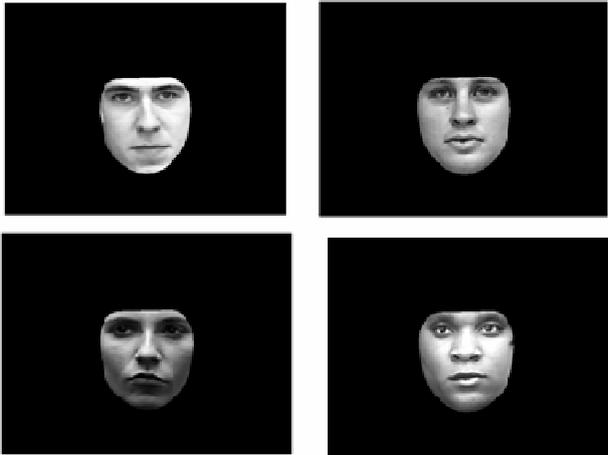


Figure 5 Segmenting face patches using AAM approach

V. EIGENFACES FOR FACE RECOGNITION

Eigenfaces are one of initial algorithms used for person identification. The underline approach is taken from information theory and consists of calculating Principal Components Analysis (PCA). PCA can predict, remove redundancy, extract features and can compress data. Using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the eigenspace projection. In [23] author has found the some limitations of the algorithm used: (i) that the face images should be normalized and frontal-view, (ii) the system is an auto associative memory. It is harmful to be over fitted and (ii) it is hard to decide suitable thresholds - It is kind of Art!

The idea of the eigenfaces was given by Turk and Pentland in early 1990's. The approach transforms face images into a small set of characteristic feature images, called eigenfaces, which are the principal components of the initial set of faces images. Recognition is performed by projecting a new image into the subspace spanned by the eigenfaces ("face space") and then classifying the face by comparing its position in face space with positions of known individuals. This is an information theory approach of coding and decoding face images and may give insight into the information content of face images, emphasizing the significant local and global features. Such features may or may not be directly related to intuition notion of the face features such as the eyes, nose, lips and hair [11,12].

In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. These eigenvectors can be thought of as a set of features, which together characterize the variation between the face images. Each image location contributes more or less to each eigenvector, so that these vectors can be displayed as a sort of ghostly face, which are called the eigenfaces. Figure 7 shows

the eigenfaces in our scenario, whereas Figure 6 shows an example standard eigenface. The amount of texture is reduced up to 12% of the original image along with the normalization in terms of shape and illuminations.



Figure 6 A conventional Eigenface for Cohn Kanade Database

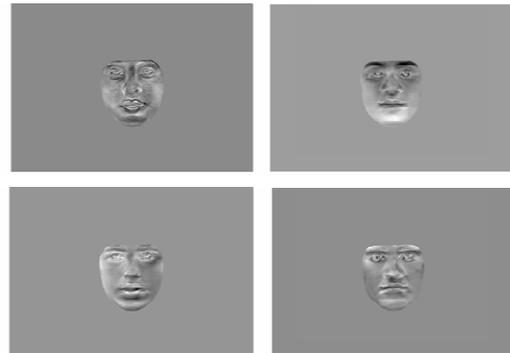


Figure 7 Eigenfaces for segmented face images

We use a nearest neighbour classifier. For a given example image ' I ', determine the ' k ' nearest neighbours, determine the class ' c ' which has the largest number of representative ' n '. If the $n > 1$ then ' I ' belongs to class ' c ', where ' T ' is the minimum threshold and distance used is *Euclidean distance* [24].

$$d(x_i, x_j) = \sqrt{\sum_N (x_i - x_j)^2}$$

VI. EXPERIMENTS

Keeping in view the facial expressional changes in daily life human-human interaction, we try to recognize a person under varying facial expression. In this regard we choose Cohn-Kanade-Facial-Expression database (CKFE-DB) [25]. CKFE-DB contains 488 short image sequences of 97 different persons performing the six universal facial expressions. Each sequence shows a neutral face at the beginning and then develops into the peak expression. Furthermore, a set of action units (AUs) has been manually specified by licensed Facial Expressions Coding System (FACS)-experts for each sequence. The subjects in this database were said to produce exaggerated expressions, hence expressions are not natural.

Experiments have been conducted on ten subjects of the database with different facial expressions variations. Training set consists of mixture of expression images along with neutral images. Some of the examples are used in our experiments are shown in Figure 8. Eigenfaces are extracted for the face image patches present in the database after AAM. Each new face is

projected on this eigenspace and its weight in face space is calculated.

Face images of ten subjects were selected for training the dataset for calculating eigenspace. Seven subjects were randomly selected from the dataset for testing. A successful recognition rate of 92.86% was obtained on testing images.



Figure 8 Images in database used for experiments purpose

VII. CONCLUSIONS

This paper discusses about a technique to segment the face images and then using eigenfaces for recognition purpose. In image segmentation phase, each image is mapped to a pre-defined shape and hence normalizes our shape information. Since faces contain facial expressions so after textural mapping the expressions mould to the expression of the target shape. This helps in transforming all the images towards neutral expressions and training the classifier for the optimum results. Eigenface approach is well-known and has computational ability to run efficiently in real time. We used a benchmark database to show our result, however this system can be applied in real time for daily life applications with slight modifications. The intention behind developing this system is not limited to human robot joint activities but equally useful in tradition biometric application. In future, this system could be coupled with other sources of variations like lighting, poses and occlusions.

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