



# Recognition of Phiz using Image Processing Techniques

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**Abstract :**A great challenge in automatic face recognition to achieve sequential invariance has been made. The aim is to come up with a representation and matching scheme that is robust to changes due to numerous facial poses.An image based face recognition and a novel method to model and recognize human faces in video sequences is also been performed.A discriminative paradigm has been proposed to address face matching in presence of pose variation by using different face databases. Scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) serve as the local descriptors. Since both of these descriptors have been shown to be very successful in image representation our approach gives the accurate result.

**Keywords :** Face recognition,SIFT,MLBP ,Boosting Algorithm,videostream

## 1. INTRODUCTION

Nowadays many commercial systems for face recognition are available. One of the biometric recognition modalities is face recognition which is non-intrusive, natural and easy to use. Thus, it has a higher commercial value in the market. Till the present date, the entry to restricted area systems has mostly been controlled by knowledge-based or security base on tokens, such as passwords and Identification cards. However, such security control can easily fail when a

password is divulged or a card is stolen. Furthermore, simple and short passwords are easy to guess by a fraudulent user, while long and complex passwords may be hard to memorize by a legitimate user. Therefore, the technologies of Biometric recognition are highly desired to address these problems.

### 1.1. BIOMETRIC RECOGNITION

Biometric recognition is the automatic recognition of individuals based on the characteristics of their behavioral and biological. It is introduced mainly to help terrorists' identification, provide better control of access to physical facilities and financial accounts, and increase the efficiency of access to services and their utilization.

It has been applied to identification of criminals, patient tracking in medical informatics, and personalization of social services, among other things. Further it has been used for public surveillance, finger imaging, military purposes etc.

Two main issues of biometric are biometric recognition systems are incredibly complex and need to be address and the other is, it is an inherently problematic endeavor.

Biometrics are being divided into physical and behavioral biometrics. Physiological biometrics analyses the physiological characteristics of an individual whereas behavioural biometrics deals with the identification or verification of individuals based on the manner in which they conduct themselves through various activities.



## 1.2. FACIAL RECOGNITION

Facial recognition (or face recognition) is a type of biometric software application that can identify a specific individual in a digital image by analyzing and comparing patterns or in a video streams, in which the input videos are converted to corresponding frames and are being analyze with certain algorithms .

Facial recognition systems based on face prints can quickly and accurately identify target individuals when the conditions are favourable. Currently, a lot of facial recognition development is focused on Smartphone applications. Smartphone facial recognition capacities include image tagging and other social networking integration purposes as well as personalized marketing. Facebook uses facial recognition software to help automate user tagging in photographs.

For a recognition mainly based on video, it must be able to classify the faces with ranges of image plane and 3-D orientations.

### Face recognition model

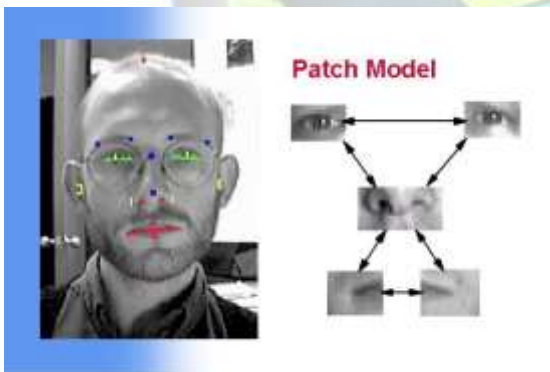


Fig 1. Face recognition model

In the above figure 1.4, the face recognition is done from the main areas of the facial patches as shown in the figure such as the patches of the eyes, nose, mouth etc. After matching of these particular patches if 90-100% matching could be achieved then it can be resulted that the face is being recognized.

## 2. RELATED WORKS

In the method proposed by the A. Asthana,

T. Marks, M. Jones, and K. Tieu [4] which uses between 2D landmark points and 3D model vertices to synthesize frontal view. The drawbacks in this method is the dependence on the fitting of landmarks using the Active Appearance Model (AAM). A. Ashraf, S. Lucey, and T. Chen proposed a method [9] by using Gaussian probabilistic model and a Bayesian classifier has been adopted for learning the patch correspondences based on 2D affine transforms. The problem with these approaches is that the transformations are optimized locally without taking into account the global consistency of the patches because of drawbacks certain other approaches has been taken up. [7] S. Arashloo and J. Kittler proposed a method for estimating the deformation parameters of local patches using Markov Random Fields (MRFs). The disadvantage of this approach is that it depends on estimating the global geometric transformation between the template and the target images. [5] S. Biswas and Chellappa in their approach, they estimate the facial albedo and pose at the same time using a stochastic filtering framework and perform recognition on the reconstructed frontal faces. The disadvantage of this approach lies in the use of an iterative algorithm for updating the albedo and pose estimates leading to accumulation of errors from step to step.

## 3. THE FACE DATABASES

### Feret databases

The FERET program set out to establish a large database of facial images that was gathered.

The database collection was a collaborative effort between Dr. Wechsler and Dr. Phillips. The images were collected in a semi-controlled environment. To maintain a degree of consistency throughout the database, the same physical setup was used in each photography session. Because the equipment had to be reassembled for each session, there was some minor variation in images collected on different dates.

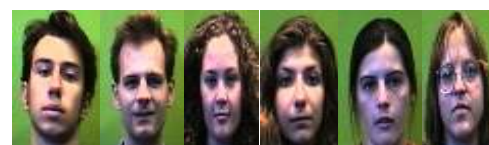


Fig 2.Feret databases

**CMU-PIE databases**

A close relationship exists between the advancement of face recognition algorithms and the availability of face databases varying factors that affect facial appearance in a controlled manner. The PIE database, collected at Carnegie Mellon University in 2000, has been very influential in advancing research in face recognition across pose and illumination. Despite its success the PIE database has several shortcomings: a limited number of subjects, a single recording session and only few expressions captured. To address these issues researchers at Carnegie Mellon University collected the Multi-PIE database. It contains 337 subjects, captured under 15 view points and 19 illumination conditions in four recording sessions for a total of more than 750,000 images. A database of 41,368 images of 68 people, each person under 13 different poses, 43 different illumination conditions, and with 4 different expressions was also taken.

**The Yale face database B**

Contains 165 gray scale images in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, and sleepy, surprised, and wink.

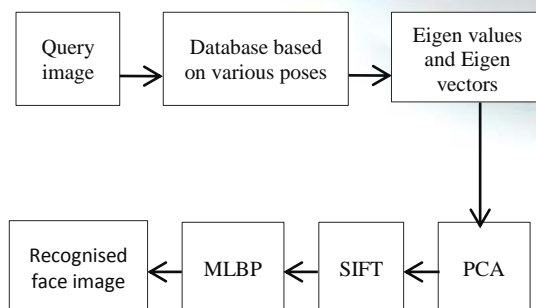
**4.THE SYSTEM**

Fig 3. Image based System block diagram

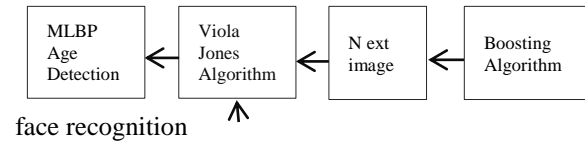
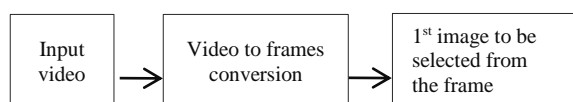


Fig 4. Video-based System block diagram

In the fig.3.the process of the system goes as, first, the query image which is to be recognized is taken as an input image. Second, the image which was already pre-process in terms of its different poses is then selected from the database. Third, the Eigen values and Eigenvectors calculation is performed. Then the PCA is being applied which reduces the dimensionality. The SIFT algorithm is applied to detect and describe local features in images. The MLBP algorithm is applied to obtain the large scale biometric pattern. Finally, the face image is recognized.

In the fig.4 process of the system goes as,first, the query input video is first taken and then it is converted to frames. Second, the 1<sup>st</sup> frame is chosen in terms of its different poses is then selected from the frames database. Third, the Boosting Algorithm is being applied inorder to calculate feature values of the eyes,nose and mouth.Fourth,the next frame is chosen.Through Viola Jones Algorithm, the face is being recognized with the 1<sup>st</sup> frame which is a childhood photo and the next frame is the adulthood photo.Last,MLBP algorithm is applied to detect the age of query person. Finally, the face image is recognized and age detected.

**Eigen faces**

Eigen faces are based on the dimensionality reduction approach of Principle Components Analysis (PCA). The basic idea is to treat each image as a vector in a high dimensional space. Then, PCA is applied to the set of images to produce a new reduced subspace that captures most of the variability between the input images.

An input image is transformed into the Eigen space, and the nearest face is identified using a Nearest Neighbor approach. Two versions of Nearest Neighbor classifiers can be used. The first compares the input image against all the images in the database. The second,





called Nearest Cluster Center, computes the means of each cluster (faces of the same person) and uses those cluster means for comparison.

### Principle Component Analysis(PCA)

The main idea of using Principle component analysis(PCA) for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principle components of feature space. This is can be called Eigen space projection.

Using PCA, we find a subset of principle components in a set of training faces. Then, we project faces into this principle components space and get Eigen face vectors. Comparison is performed by calculating the distance between these vectors. Usually comparison of faces is performed by calculating the Euclidean distance between these feature vectors but other measures are possible.

After we perform a PCA, our original data is expressed in terms of eigenvectors found from the covariance matrix.

The way this is done is to measure the difference between the new image and original images, but not along the original axes, along the new axes derived from the PCA analysis. It turns out that these axes work much better for recognition faces, because the PCA analysis has given us the original images in terms of differences and similarities between them. PCA has identified the statistical patterns in the data.

### Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) features are features extracted from images to help in reliable matching between different views of the same object. The extracted features are invariant to scale and orientation, and are highly distinctive of the image.

They are extracted in four steps: In the first stage, interest points called key points, are identified in the scale space by looking for image locations that represent maxima or minima of the difference-of-Gaussian function. The scale space of an image is defined as a function  $(x; y; \sigma)$ ,

that is produced from the convolution of a variable-scale Gaussian,

$G(x; y; \sigma)$ , with the input image,  $I(x; y)$ :

$$L(x; y; \sigma) = G(x; y; \sigma) * I(x; y); \quad \text{-----1}$$

with

$$G(x; y; \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}; \quad \text{-----2}$$

where  $\sigma$  denotes the standard deviation of the Gaussian  $G(x; y; \sigma)$ .

The difference-of-Gaussian function  $D(x; y; \sigma)$  can be computed from the difference of Gaussians of two scales that are separated by a factor  $k$ :

$$\begin{aligned} D(x; y; \sigma) &= (G(x; y; k\sigma) - G(x; y; \sigma)) * I(x; y) \\ &= L(x; y; k\sigma) - L(x; y; \sigma) \quad \text{-----3} \end{aligned}$$

Local maxima and minima of  $D(x; y; \sigma)$  are computed based on the comparison of the sample point and its eight neighbours in the current image as well as the nine neighbours in the scale above and below. If the pixel represents a local maximum or minimum, it is selected as a candidate key point.

In the second stage, removal of unreliable key points is done. The final key points are selected based on measures of their stability. During this stage low contrast points (sensitive to noise) and poorly localized points along edges (unstable) are discarded. Two criteria are used for the detection of unreliable key points. The first criterion evaluates the value of  $|D(x; y; \sigma)|$  at each candidate keypoint. If the value is below some threshold, which means that the structure has low contrast, the keypoint is removed. The second criterion evaluates the ratio of principal curvatures of each candidate keypoint to search for poorly defined peaks in the Difference-of-Gaussian function.

Third, the Orientation assignment. An orientation is assigned to each key point by building a histogram of gradient orientations  $\theta(x; y)$  weighted by the gradient magnitudes  $m(x; y)$  from the key point's neighbourhood:

$$m(x; y) = \sqrt{((L(x+1; y) - L(x-1; y))^2 + (L(x; y+1) - L(x; y-1))^2)}; \quad \text{-----4}$$

$$\theta(x; y) = \tanh(L(x; y+1) - L(x; y-1)) = (L(x+1; y) - L(x-1; y)); \quad \text{-----5}$$



where  $L$  is a Gaussian smoothed image with a closest scale to that of a keypoint. By assigning a consistent orientation to each key point, the keypoint descriptor can be represented relative to this orientation and, therefore, invariance to image rotation is achieved.

Finally, a local feature descriptor is computed at each key point. This descriptor is based on the local image gradient, transformed according to the orientation of the key point to provide orientation invariance. Every feature is a vector of dimension 128 distinctively identifying the neighbourhood around the key point.

#### Multi Local Binary Pattern (MLBP) for image

An approach based on Multi Local Binary Pattern (MLBP) features for face recognition has been proposed. The MLBP features are extracted from all the faces in the database. Then, given a new face image, the features extracted from that face are compared against the features from each face in the database. The face in the database with the largest number of matching points is considered the nearest face, and is used for the classification of the new face.

A feature is considered matched with another feature when the distance to that feature is less than a specific fraction of the distance to the next nearest feature. This guarantees that we reduce the number of false matches. This is because in case of a false match, there will be a number of other near features with close distances, due to the high dimensionality of the features. And further, MLBP is used for video-based face recognition.

#### Video-based face Recognition Description

##### Boosting Algorithm

Aim at learning a sequence of weak classifiers and best combining weights. Solves three fundamental problems: learning effective features from a large features set, constructing weak classifiers, each of which is based on one of the selected features (most significant feature selected) and boosting the weak classifiers to construct a strong classifier.

##### Viola Jones Algorithm

It is for detecting people's faces, noses, eyes, mouth or upper body. Features types involve detection by sums of image pixels within rectangular areas.

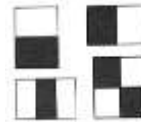


Fig.5: Four types of rectangular Haar wavelet-like features.

## 5. EXPERIMENTAL RESULTS

Experimental results show that by using the input image selected from the standard databases which are particularly the FERET, CMU-PIE databases having different facial poses with different illuminations, facial recognition could be done. Facial recognition could be said to be recognized if the matching percentage of the test image and the images which is taken as the input image has a matching percentage from 90-100%. In this experiment, the matching percentage of the input and the test image using the FERET and CMU-PIE shows a matching factor of 94.6845% and 94.0845%. Thus, the face image has been recognized. And in video-based face is recognized and the age detection is done successfully.

## 6. CONCLUSION

In this paper, different pose input image has been divided into database overlapping patches, a globally optimal set of local warps can be estimated to transform the patches to the frontal view. Each patch is aligned with images from a training database of frontal faces in order to obtain a set of possible warps for that node. The determinate Eigen Values and Eigen Vectors a  $3 \times 3$  matrix. The matrix have changed but need to know how to calculate my matrix up to get the equation. The Scale Invariant Fourier Transform (SIFT) Algorithm SIFT descriptors, an efficient algorithm was also designed to classify whether the pose of the input face image is frontal or nonfrontal. The multi large scale biometric pattern (MLBP refers to the automatic identification or identity verification of living persons using their enduring physical or behavioral characteristics and age detection is done through MLBP. Principal Components Analysis (PCA) is a mathematical technique which transforms the original image data, typically highly



correlated, to a new set of uncorrelated variables called principal components.

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