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FACE RECOGNITION USING DIFFERENT LEVEL OF ALGORITHMS

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***Abstract*:** This paper proposes the automatic face recognition method based on the face representation with five major processing modules- Filters, Face Location, Feature Location, Normalization, and Face Recognition. This precisely reflects the geometric features of the specific subject. We test our proposed algorithm database, and experimental results, show the effectiveness and competitive performance of the proposed method.

Keywords: face recognition, Filters, Face Detection, and Normalization, computation of eigenface.

INTRODUCTION

Face Recognition is one of the most important characteristics. All the biometric features, the face is so common and reachable that face recognition remains one of the most active research issues in pattern recognition and image processing. In the past decades, most researches focus on feature extraction from 2D intensity or color images. The recognition accuracy is sensitive to the lighting conditions, expressions, viewing position or variety of subordinates such as hair, glasses. So far, it is very difficult to develop a robust automatic face recognition system. Face recognition is an area of research that has been explored for many years. It is one of the popular biometric systems that can be used for security purposes. An automatic face recognition system is able to identify unknown people in a crowd without the intervention of humans. This makes it an important security tool and therefore warrants extensive research on it to help create a robust automatic face recognition system.

In [1] the single image per person face recognition methods have been classified into two ways: first way is Holistic methods and second way related to Local methods. Holistic methods address the face recognition problem in two ways. The first tries to obtain as much information as possible from the single face image in the database, either in the high dimensional face space or more commonly, in the dimensionality-reduced eigenspace. Examples of the latter are (PC) 2A [2], Enhanced (PC) 2A [3], Singular Value Perturbation [4] and 2DPCA [5]; all use extensions of the Principal Component Analysis (PCA) method to recognize faces from single images. The second approach enlarges the available dataset by artificially constructing novel views for each of the prior available images. In [6, 7, 8] the database of single training images are extended by synthesizing new facial images, and then by applying standard face recognition techniques on the enlarged dataset. Also E(PC)2A and the Singular Value Perturbation methods, mentioned above, can be used to generate new training images for enlarging the dataset. Local methods are subdivided into local feature based methods and local appearance based methods. Early local feature based methods used distinguishing facial features like width of the head, distance between eyes etc. for recognizing faces. In later feature based techniques, topological graphs were constructed based on face images and the face recognition was formulated as a graph-matching problem. Local appearance based methods define local regions on the face images; the regions may be rectangular elliptical or strips. PCA, LDA or texture measures are used on these local regions for feature extraction. The information from different regions is finally combined for recognition. In a recent work [9], Wang et al departed from the traditional methods of recognizing face images from single samples. They used a generic face dataset that contained multiple facial samples for each person. This is 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.

The eigenface technique is simple, efficient, and yields generally good results in controlled circumstances [10]. The system was even tested to track faces on film. There are also some limitations of eigenfaces. There is limited robustness to changes in lighting, angle, and distance [12]. 2D recognition systems do not capture the actual size of the face, which is a fundamental problem [11]. These limits affect the technique's application with security cameras because frontal shots and consistent lighting cannot be relied upon.

PROPOSED ALGORITHM

This section we describes the design of the face recognition system on an different level. Fig 1 shows the following four steps of face recognition.

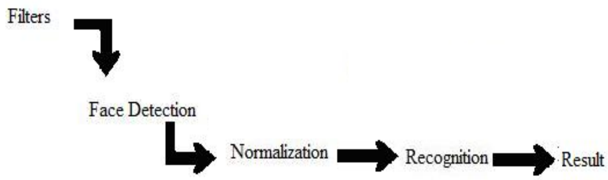


Figure 1. Face Recognition Using different level of Algorithms

First we Computation of the eigenface for human faces have to be represented before recognition can take place. The role played by representation is mostly important, known as classification and identification. Verification checks if the biometric signature presented is genuine and belongs to the identity declared by the client. Identification usually corresponds to closed set face recognition and is implemented as iterative verification. It always finds a mate for identification, the most similar one, even if there is none. Rejection an option available only during open set face recognition is appropriate for the case when there is no enrolled for the unknown face.

FIRSTLY CHECKS THE COMPUTATION OF THE EIGENFACE IF (IT IS DONE) GO TO NEXT STAGE.

Step 1: obtain face images I1, I2... IM (training faces)
(**Very important:** the face images must be centered and of the same size)
Step 2: represent every image Ii as a vector □i
Step 3: compute the average face vector □:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i$$

Step 4: subtract the mean face:□i ̣□i ̃ □
Step 5: compute the covariance matrix C:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \quad (N^2\mathrm{x}N^2 \text{ matrix})$$

where A ̣[□$_1$ □$_2$ . . . □$_M$] (N^2xM matrix)
Step 6: compute the eigenvectors u_i of AA^T
The matrix AA^T is very large --> not practical !!
Step 6.1: consider the matrix A^TA (M x M matrix)
Step 6.2: compute the eigenvectors v_i of A^TA: A^TAv_i ̣$\mu_i v_i$
Correspond to the M largest eigenvalues of A A^T (alongwith their corresponding eigenvectors)
Step 6.3: compute the M best eigenvectors of AA^T: u_i ̣Av_i
(**important:** normalize u_i such that ǁuiǁ ̣1)
Step 7: keep only K eigenvectors (corresponding to the K largest eigen values)

STAGE 1-FILTERS- WE USE THE FILTERS FOR SCENE.

When there is a large movement in the scene, the system postulates multiple individuals and hence become more selective in its detected regions of movement, decreasing the horizontal and vertical spans or in other words, when there is little movement within the scene, the temporal filter becomes more accepting in it's detected regions of movement and the horizontal and vertical spans are increased. The idea of using this form of adaptive temporal filtering has not been encountered in literature and is considered to be a novel approach.

The first image contains s the result of temporal convolution; the second image contains the result of zero crossing detection and the third image contains the predicated head location. One the predicted head location is found this information is passed to the face location module.
If (it this stage done successfully) then go to next stage.

STAGE 2-FACE LOCATION-

Locates the face within the regions of movement detected by the filters. The basis functions, similar in concept to receptive field profiles, are the dimensions that define the face space.

The construction of Multi Scale Pyramids enables the eigen-face detection paradigm to be extended into multi scale searches. Multi Scale Pyramidsare three-dimensional structures containing scaled versions of the eigenfaces. By searching with the eigenfaces from each level of the pyramid, we effectively conduct a Multi Scale face search within our image. This is equivalent to scaling our input image, however since the FFT over the scaled eigenfaces can be pre-calculated, scaling the eigen and average face results in a more computationally efficient algorithm.
Given an unknown image □
Step 1: compute ̣□ ̣□ ̣̃□ □

Step 2: compute
$$\hat{\Phi} = \sum_{i=1}^{K} w_i u_i \quad (w_i = u_i^T\Phi)$$

Step 3: compute
$$e_d = \|\Phi - \hat{\Phi}\|$$

Step 4: if ed < Td, then ̣is a face.The distance ed is called distance from face space (dffs)
If (it this stage done successfully) then go to next stage.

STAGE 3-NORMALIZATION-

Accepts the geometrically normalized face produced by the scale and rotation normalization module and compensates for variations in lighting conditions. These include global lighting changes as well as non-uniform gradients.

There are three different lighting normalization techniques implemented and the method used by the system can be specified by the end user.Global lighting variations by setting the mean of the facial image to zero and the norm to one:
□normalized=(□$_{extracted}$-mean (□$_{extracted}$))/ǁ □$_{extracted}$ǁ

A non-linear block-processing algorithm is also available. This algorithm estimates local lighting conditions by determining the median intensity value of the region surrounding the pixel of interest. The third technique available is a sobell filter. Commonly used in edge detection algorithms, the sobell filter acts as a bimodal bandpass filter.
If (it this stage done successfully) then go to next stage.

STAGE 4-FACE RECOGNITION-

Projects the normalized face in to face-space to determine it's identity. A certainty measure is also produced.
Given an unknown face image ̣ (centered and of the same size like the training faces) follow these steps:
Step 1: normalize □: ̣□ ̣□ ̣̃□ □

$$\Phi = \sum_{i=1}^{K} \Sigma w_i u_i \; (w_i = uT_i \Phi)$$

Step 2: project on the eigenspace
Step 3: represent ̣as: ̣□ ̣

$$\begin{bmatrix} w1 \\ w2 \\ \cdots \\ wK \end{bmatrix}$$

Step 4: find er □minl ||□̃□□^{l}||
Step 5: if er < Tr, then □is recognized as face 1 from the training set.
- The distance er is called distance within the face space (difs)
Comment: we can use the common Euclidean distance to compute , however, it has been reported that the Mahalanobis distance performs better:

$$\|\Omega - \Omega^k\| = \sum_{i=1}^{K} \frac{1}{\lambda_i} (w_i - w_i^k)^2$$

(Variations along all axes are treated as equally significant)

A. One the face has been located, extracted and normalized for scale and lighting it is ready to be processed by the Face Recognition. The Face Recognition is the final stage of the system and is responsible for determining both the closest match for the identity of the located person, and the probability of that match.
B. The probability generated by the mahalanobis distance is actually conditional. What we have found is the probability that image □ belongs to face class n on the assumption that □ is a member of the general face class. To convert this conditional probability to an absolute one our system takes the product of the conditional probability to an identity match with the probability that □ is a facial image . thus:
   P(□□Ω_n)= P((□□Ω_n) | (□□$\tilde{\Omega}$P(□□Ω)

Where Ω_n represents face class n and Ω represents the face class in general.

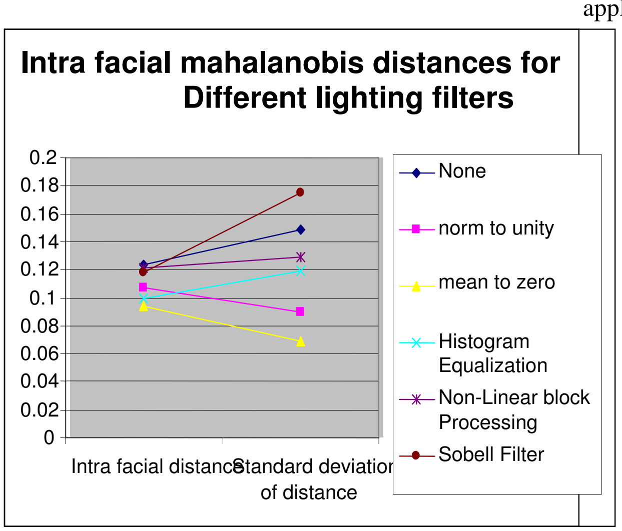
While the use of multiple training images for each individual improves the performance, this implementation does not take full advantage of the intra-personal information available.

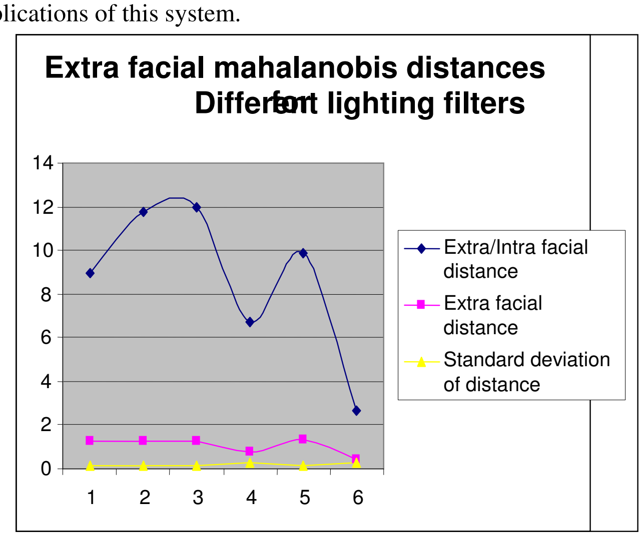
RESULTS

Using the filter this measure, 20 runs of 5 frames each where processed using both the adaptive and standard temporal filter. The temporal performance for adaptive filter was found to be 45.3%, which compares well to the 16.2 % obtained by the standard filter.

Face detection performance can be evaluated in terms of the mean location error. This is the mean error between the position of the face found by the algorithm and that found by manual location. We evaluated the mean error of our system in locating the face center over 40 frames of varying pose, lighting and position. The mean error in location was found to be 8.822 pixels. Our system has multi-scale face location capabilities in that it can locate faces at different pre-defined scales. As a result the system constantly detects faces in the larger scale, whether they are there or not. The theory is supported by our system's ability to perform simultaneous multi scale location on synthetic images accurately. as a result the system experiences success in recognition.

The lighting normalization algorithms were evaluated based on their ability to improve recognition performance under a broad range of variations in lighting. A database of 7 individuals was generated with 11 images per individual. One of these images was taken under standardized lighting conditions and used to train face recognition system. The other 12 were taken under various lighting conditions and used to test the system recognition performance. These images were selected as representatives for the lighting condition experienced in applications of this system.





The face recognition module was evaluated using a database of 9 individuals containing 1 training image and 10 test images for each individual. Here the correct recognition rate is simply defined as the ratio of correct recognitions to total trials. Here the recognition accuracy is greater than 70%.20 recognition runs were made on each individual and the mean recognition accuracy was found to be 94%.fac recognition was evaluated offline and shown to have a maximum recognition rate of 94.5%. Test subject were acquired by the system for training and the system's ability to recognize the individual was tested.

CONCLUSION

The approach is definitely robust, simple, and easy and fast to implement compared to other algorithms. It provides a practical solution to the recognition problem. We are currently investigating in more detail the issues of robustness to changes in head size and orientation. Also we are trying to recognize the gender of a person using the same algorithm.

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