Face Identification Using Wavelet Transform & PCA

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ABSTRACT

Face recognition has recently attracted increasing attention and is beginning to be applied in a variety of domains, predominantly for security. In the past few decades' people used to create some passwords, key words or some other security measures to prevent maltransactions. But now a days with the advanced technology it is better to know the persons physical identity by recognizing some physical features. Because of the problem with traditional password/PIN system, biometric based technologies gained advantage. Face recognition is one of the biometric based technologies which use human faces for authentification. We use wavelet transform for the decomposition of images. Principal Component Analysis is used for the actual recognition. We considered Eigen faces as principal components Face images are projected onto a feature space ("face space") that best encodes the variation among known face images. This approach transforms face images into a small set of characteristic feature images, called "Eigen faces", which are the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the Eigen faces ("face space") and then classifying the face by comparing its position in face space with the positions of known.

Keywords—Wavelet Transform (WT), Principal Component Analysis (PCA), Face Recognition, Eigen value, Eigen Face.

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I. INTRODUCTION

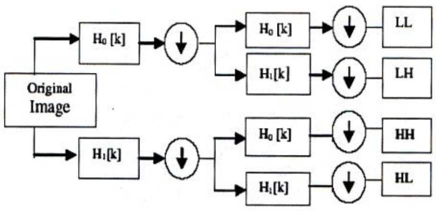
The face is our primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation [1,2].

This skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, Aging and distractions such as glasses, beards or changes in hairstyle. Face recognition can be roughly divided into two different groups; geometrical features matching the template matching. In the first Case, some geometrical measures about distinctive facial features such as eyes, mouth, nose and chin are extract. In the second case, the face image, represented as a two-dimensional array of intensity values, is compared to a single or several templates representing a whole face. The earliest methods for template matching are correlation-based, thus computationally very expensive and require great amount of storage and since a few years, the Principal Components Analysis (PCA) method also known as Karhunen-Loeve method, is successfully used in order to perform dimensionality reduction. Face recognition has become an important issue in many applications such as security systems, credit card verification and criminal identification. For example, the ability to model a particular face and distinguish it from a large number of stored face models would make it possible to vastly improve criminal Identification. Even the ability to merely detect faces, as opposed to recognizing them, can be important. Detecting faces in photographs for automating color film development can be very useful, since the effect of many enhancement and noise reduction techniques depend on the image content [3,4].

Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by the human brain. Human face recognition has been studied for more than twenty years. Unfortunately developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high-level computer vision task, in which many early vision techniques can be involved. To overcome the problems faced by humans, we implement Principal Component analysis.

II. WAVELET TRANSFORM

Wavelet transform is a transform of this type. It provides the time frequency representation. Often times a particular spectral component occurring at any instant can be of particular interest. In these cases it may be very beneficial to know the time intervals these particular spectral components occur. Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. The WT was developed, as an alternative to the STFT. It suffices at this time to say that the WT was developed to overcome some resolution related problems of the STFT. A wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet Transform has been a popular tool for multiresolution image analysis. Here wavelet is used to decompose the original image into wavelet sub bans each with different coefficients. An image, which is a 2D signal, is decomposed using the 2D wavelet tree decomposition algorithm [8,9].



Wavelet Decomposition Algorithm

The original image is process along the x and y direction by $H_0[k]$ and H1[k] Bank, which is the row representation of the original mage. It is decomposed row-wise for every row using 1D decomposition algorithm to produce 2 levels of Low (L) and High (H) components approximation. The term L and H refer to whether the processing filter is low pass or high pass. Because of the down sampling operation that is perform on the L and H image the resultant matrices are rectangular of size (N x N/2) . These matrices are then transposed and decomposed row-wise again to obtain four N/2 x N/2 square matrices. The down sampling that is then performs on these matrices will generate LL, LH, HH, HL components. Each of these images corresponds to four different wavelet sub band. The LL component (the approximation function component) decomposed to obtain further details of the image; the other wavelet component (LH, HH, HL) can also be decomposed further

III. EIGEN FACE-BASED FACIAL RECOGNITION

The task of facial recognition is discriminating input signals (image data) into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.), 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, and mouth) in any face as well as relative distances between these objects. These characteristic features are called Eigen faces in the facial recognition domain (or principal components generally). They can be extracted out of original image data by means of a mathematical tool called Principal Component Analysis (PCA). By means of PCA one can transform each original image of the training set into a corresponding Eigen face. An important feature of PCA is that one can reconstruct any original image from the training set by combining the Eigen faces. Remember that Eigen faces are nothing less than characteristic features of the face. Therefore one could say that the original face image can be reconstructed from Eigen faces if one adds up all the Eigen faces (features) in the right proportion. Each Eigen face represents only certain features of the face, which may or may not be present in the original image. If the feature is present the original image to a higher degree, the share of the corresponding Eigen face in the “sum” of the Eigen faces should be greater. If, contrary, the particular feature is not (or almost not) present in the original image, then the corresponding Eigen face should contribute a smaller (or not at all) part to the sum of eigen faces. So, in order to reconstruct the original image from the Eigen faces, one has to build a kind of weighted sum of all Eigen faces. That is, the reconstructed original image is equal to a sum of all Eigen faces, with each Eigen face having a certain weight. This weight species, to what degree the specific feature (Eigen face) is present in the original image. If one uses all the Eigen faces extracted from original images, one can reconstruct the original images from the Eigen faces exactly. But one can also use only a part of the Eigen faces. Then the reconstructed image is an approximation of the original image. However, one can ensure that losses due to omitting some of the Eigen faces can be minimized. This happens by choosing only the most important features (Eigen faces) [5-7].

Omission of Eigen faces is necessary due to scarcity of computational resources. How does this relate to facial recognition? The clue is that it is possible not only to extract the face from Eigen faces given a set of weights, but also to go the opposite way. This opposite way would be to extract the weights from Eigen faces 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 Eigen faces. Therefore, using these 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 (Eigen faces) 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 [5-7].

(i) Eigenvectors and Eigen values

An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding Eigen value of the eigenvector. This relationship can be described by $M \times u = \lambda \times u$, where u is and eigenvector of the matrix M and λ is the corresponding eigen value. Eigenvectors possess following properties:

(a) They can be determined only for square matrices.

(b) There are eigenvectors (and corresponding eigen values) in an n x n matrix.

(c) All eigenvectors are perpendicular, i.e. at right angel with each other.

(ii) Calculation of Eigen faces with PCA

In this section, the original scheme for determination of the Eigen faces using PCA will be presented. The algorithm described in scope of this paper is a variation of the one outlined here.

Step 1 : Prepare the data

In this step, the faces constituting the training set (Γi) should be prepared for processing.

Step 2 : Subtract the mean

The average matrix ψ has to be calculated, then subtracted from the original faces (Γi) and the result stored in the variable ϕi:

$$\psi = \frac{1}{M} \sum_{n-1}^{M} \Gamma n \qquad (1)$$

$$\psi = \Gamma n - \psi \qquad (2)$$

Step 3: Calculate the covariance matrix

In the next step the covariance matrix C is calculated according to

$$C = \frac{1}{M} \sum_{n-1}^{M} \phi_n \phi^T_n \qquad (3)$$

Step 4 : Calculate the eigenvectors and eigenvalues of the co-variance matrix

In this step, the eigenvectos (eigenfaces) ui and the corresponding engenvalues λi should are calculated. The eigenvectors (eigenfaces) must be normalized so that they are unit vectors, i.e. of length. 1. The description of the exact algorithm for determination of eigevectors and eigenvalues is omitted here, as it belongs to the standard arsenal of most math programming libraries.

Step 5 : Select the principal components

From M eigenvectors (eigen faces) ui, only M should be chosen, which have the highest eigen values. The higher the more characteristic features of a face does the particular eigenvector describe. Eigen faces with low eigen values can be omitted, as they explain only a small part of characteristic features of a faces. After M eigen faces Ui are determined, the "training" phase of the algorithm is finished [4,5-7].

There is a problem with the algorithm described in above is that The covariance matrix C in step 2 (see equation 3) has a dimensionality of $N^2 \times N^2$, so one would have N^2 Eigen faces and eigen values. For a 256×256 image that means that one must compute a $65{,}536 \times 65{,}536$ eigen faces. Computationally, this is not very efficient as most of those Eigen faces are not useful for our task. So, the step 3 and 4 is replaced by the scheme proposed by Truck and Pent land.

$$C = \frac{1}{M} \sum^{M} \phi_n \phi^T_n = AA^T \qquad (4)$$

$$L = A^T A \quad L_{n,m} = \phi^T_m \phi_n$$

$$u_l = \sum_{k-1}^{M} u_{lk} \phi_k = l = 1, \ldots, M \qquad (5)$$

Where L is a M x M matrix, v are M eigenvectors of L and u are eigen faces. Note that the covariance matrix C is calculated using the formula $C=AA^T$, the original (inefficient) formula is given only for the sake of explanation of A. The advantage of this method is that one has to evaluate only M numbers and not N^2 Usually, M, N^2 as only a few principal components (eigen faces) will be relevant. The amount of calculations to be performed is reduced from the number of pixels ($N^2 \times N^2$) to the number of images in the training (M). In the step 5, the associated eigen values allow one to rant the eigen faces according to their usefulness [10]. Usually, we will use only a subset of M eigen faces, the M eigen faces with the largest eigen values.

IV. RESULTS & CONCLUSION

Face recognition has been an attractive field of research for engineering, computer vision scientists and security prupose. Humans are able to identify reliably a large number of faces and scientists are interested in understanding the perceptual and cognitive mechanisms at the base of the face recognition process. Since 1888, many algorithms have been proposed as a solution to automatic face recognition. Although none of them could reach the human recognition performance. We presented an algorithm for face recognition by performing PCA on Wavelet Transform. The Wavelet Transform is used to decompose the original image into four Wavelet sub bands, each with a different frequency component. PCA is them applied on this Wavelet to reconstruct the image into vector representation.

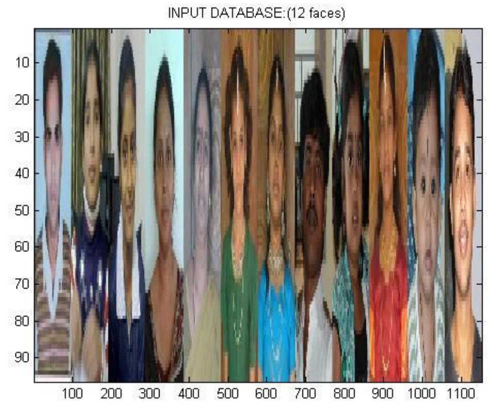


Figure 1. Input database 12 faces

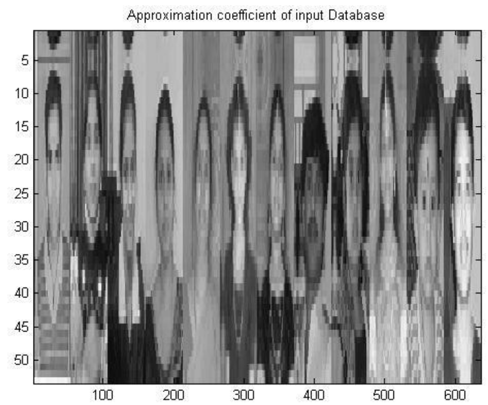


Figure 2. The approximation coefficient of input database

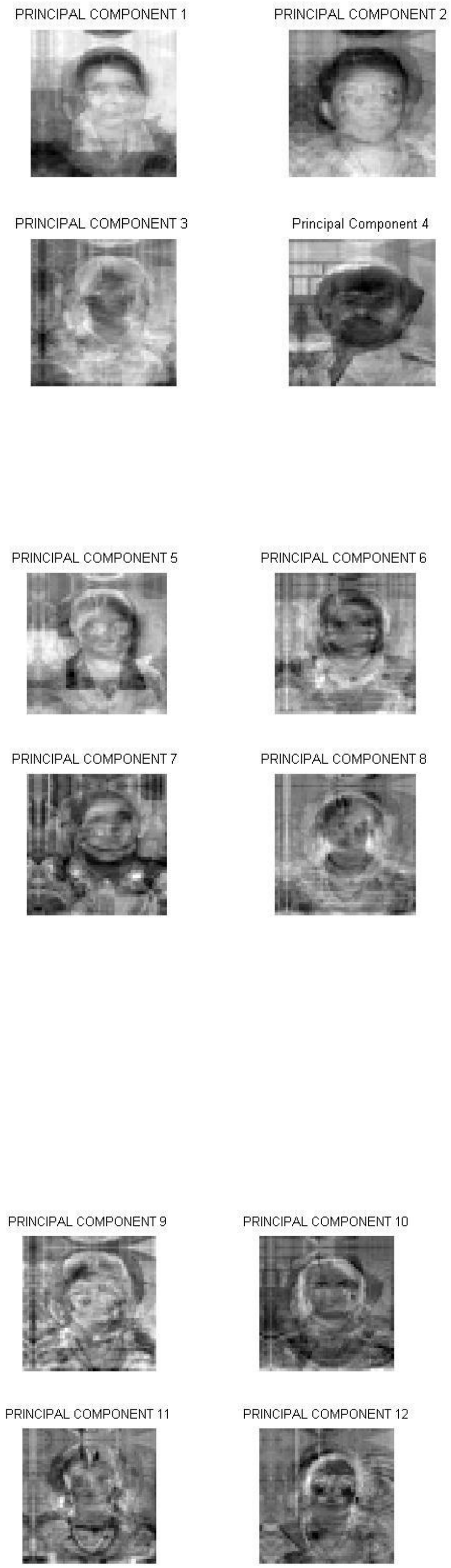


Figure 3. The principal component of 12 faces

Figure 4. Eigen component

Figure 5. Test face for detection

Figure 6. The difference new image is considered as test face

Wavelet Transform provides and excellent image decomposition and texture description. The combination of Wavelet Transform and PCA gives a better recognition accuracy and significant performance improvement when the database has large number of images. It reduces computational load and increase accuracy of the system. The paper has resulted in an overall success being able to perform reliable recognition in a constrained environment. A recognition accuracy of 86% has been achieved. While the problem of recognizing faces under gross variations remains largely unsolved, a through analysis of the strengths and weakness of face recognition using PCA has been presented.

REFERENCES

1. Matthew A. Turk and Alex P.Pentland. “*Eigenfaces for ecognisatoin”.* Journal of cognitive neurosciences, Volume 3, Number 1, Nov 27, 2002.
2. Mohamed Rizon, Muhammad Firdaus Hashim, Puteh Saad, Sazali Yaacob, Mohd Rozailan Mamat, Ali Yeon Md Shakaff, Abdul Rahman Saad, Hazri Desa and M. Karthigayan, "Face Recognition using Eigenfaces and Neural Networks", *American Journal of Applied Sciences*, Vol. 2, No. 6, 2006, pp. 1872-1875.
3. http://www.cs.dartmouth.edu/~farid/teaching/cs88/kimo.pdf
4. Chi-Fa Chen, Yu-Shan Tseng and Chia-Yen Chen “Combination of PCA and Wavelet Transforms for Face Recognition on 2.5D Images”, Palmerston North, November 2003, Department of Electrical Engineering, I-Shou University, Kaohsiung, Taiwan.
5. O. O. Khalifa, M.Yusuf, S.Gagula, “Face Recognition Using PCA Wavelet Decomposition”, Electrical & Computer Department, Kulliyyah of Engineering, International Islamic University Malaysia Jalan Gomabak, Malaysia.
6. B. Fasel and J.Luettin, “Automatic Facial Expression Analysis : A Survey,” *Pattern Recognition*, vol. 36, pp.259-275, 2003.
7. M. Almas Anjum, M. Younus Javed, and A. Basit, "A New Approach to Face Recognition Using Dual Dimension Reduction", *International Journal of Signal Processing* Vol. 2, No.1, 2006, pp1-6.
8. Charles K. Chui, 1992. An Introduction to Wavelets, Academic Press, 1992.
9. Chin-Chen Chang, Jun-Chou Chuang and Yih-Shin Hu, "Similar Image Retrieval Based On Wavelet Transformation", *International Journal Of Wavelets, Multiresolution And Information Processing*, Vol. 2, No. 2, 2004, pp.111–120.
10. Ilker atalay, “Face Recognition using eigen faces”, Istanbul technical university Jan 1996.