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Application of DCT Blocks with Principal Component Analysis for Face Recognition

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Abstract Security is becoming one of the main human concerns nowadays. The need for an identity that cannot be destroyed, forgotten or stolen is greatly recommended in a world that is directed more and more toward automation. Hence, Biometrics is taking an important role in personal identification systems. A technique for automatic face recognition based on 2D Discrete Cosine Transform (2D-DCT) together with Principal Component Analysis (PCA) is suggested and tested. The achieved recognition rate varied according to the chosen threshold based on the security level of the application. The best achieved recognition result is 96.5%.

Key-words: face recognition, DCT, PCA, personal identification system.

1 Introduction

Over the past few years, the user authentication is increasingly important as the security control is required everywhere. Traditionally, ID cards and passwords are popular for authentication although the security is not so reliable and convenient. Recently, biological authentication technologies (i.e Biometrics) through voice, fingerprints, iris print, retina, palm print, face..etc is playing an important role in modern personal identification systems. The face, among them, is chosen for the suggested system. The face is user friendly as people are accustomed to taking photographs. It is economic due to the low cost of cameras and computers (it does not require any special devices).

The face features greatly change due to change in illumination, pose and expression. The need for a system that can overcome all of these variations and yet give good recognition results is greatly recommended.

The reliability of a face recognition system depends on the choice of a suitable feature vector. Several techniques for facial feature extraction have been proposed. They include methods based on geometrical features, statistical features [1], and neural networks [2], and [3].

The geometrical approach makes use of parameters such as ratios of distances, angles and areas between elementary features such as eyes, nose, mouth or facial templates as nose width and length, mouth position and chin type.

The statistical features are usually generated using algebraic methods such as the PCA, the independent component analysis (ICA) [4] and the linear discriminent analysis (LDA).

The Discrete wavetet transform (DWT) [5], [6], and [7] and the DCT [8], [9], [10], and [11] are also used to extract relevant face features.

Due to the large covariance matrix resulting from the PCA analysis which requires a computer with a very large memory and results in high computation time, the PCA is generally preceded with another transform for ex: the discrete wavelet transform (DWT) or the discrete cosine transform (DCT) as suggested in this paper.

The paper is organized as follows: A brief introduction to the DCT is presented section II. Each face in the database is transformed using the 2D-DCT. Several block sizes are chosen to be further transformed to a lower dimensional vector using the PCA which is discussed in section III. The recognition results are presented in section IV where the Euclidean distance is used in matching. Finally, the work is concluded in section V.

2 The Discrete Cosine Transform

The DCT is a popular technique in imaging and video compression, which was first applied in image compression in 1974 by Ahmed et al. In 1992, the first international standard for image compression, known as the Joint Photographic Experts Group (JPEG), was established with the DCT encoder and decoder.

Applying the DCT to an input sequence decomposes it into a weighted sum of basis cosine sequences.

The 2-D DCT is given by:

$$C(u,v) = \frac{2}{\sqrt{MN}}\alpha(u)\alpha(v)$$
$$\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\cos\left[\frac{(2x+1)u\pi}{2M}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

for u=0,1 2,….,W-1, v=0,1,2,….,H-1 (1).

The inverse transform is given by

$$I(x,y) = \frac{2}{\sqrt{WH}}\sum_{u=0}^{W-1}\sum_{v=0}^{H-1}\alpha(u)\alpha(v)$$
$$\times C(x,y)\cos\left[\frac{(2x+1)u\pi}{2W}\right]\cos\left[\frac{(2y+1)v\pi}{2H}\right] \quad (2).$$

The 2D-DCT was applied to the face image in Fig.1 to obtain the DCT coefficients shown in Fig.2.
A block size of 16×16, 32×32 and 64×64 are chosen to be further transformed using PCA.
The reconstructed face images from these block sizes are shown in figures 3, 4 and 5 respectively.

Fig.1 Sample of a face image

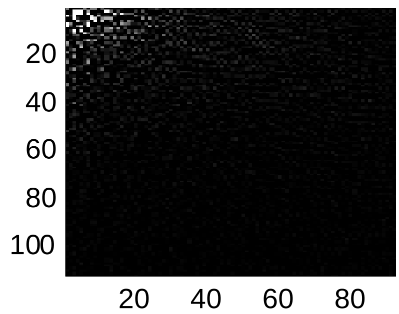

Fig.2 The 2D-DCT of the face image

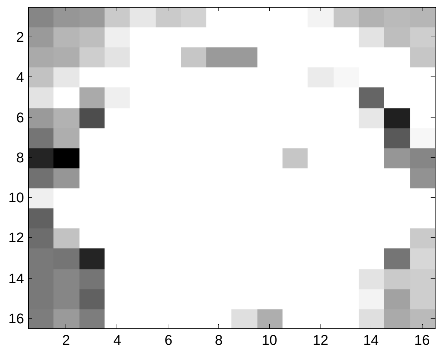

Fig.3 The reconstructed face image from a 16×16 Block

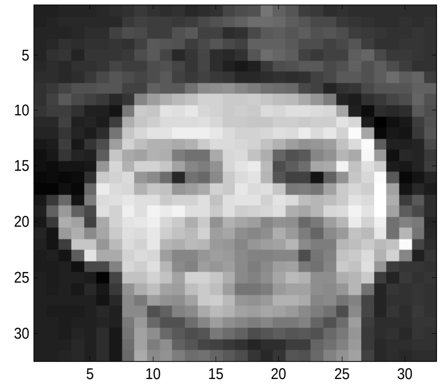

Fig.4 The reconstructed face image from a 32×32 block

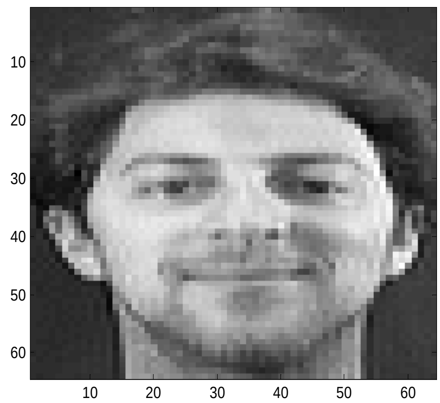

Fig.5 The reconstructed face image from a 64×64 block

As shown in figure 2, it is clear that most of the energies are located at low frequencies which is always the case when using the DCT transform.
Even that the reconstructed image using the block 16×16 does not represent a face, its recognition results are comparable to when using the 32×32 or the 64×64 block as will be seen later.
The DCT transformed face images using the different block sizes are transformed into a lower order feature size using the PCA as will be shown in the next section.

3 The Principal Component Analysis

Eigenface is one of the most thoroughly investigated approaches to face recognition. It is also known as Karhunen-Leove expansion, eigenpicture, eigenvector, and principal component [12]. Sirovich and Kirby and Kirby et al. used PCA to efficiently represent pictures of faces. They argued that any face image can be approximately reconstructed by a small collection of weights for each face and a standard face image (eigenpicture). The weights describing each face are obtained by projecting the face image onto the eigenpicture. In mathematical terms, eigenfaces are the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. The eigenvectors are ordered to represent different amounts of variation, respectively, among the faces. Each face can be represented exactly using only the best eigenvectors with the largest eigenvalues. The best M eigenfaces construct an M dimensional space called the "face space".
The covariance matrix is given by [13]

$$\sum_X = E\{[X - E(X)][X - E(X)]^t\} \quad (3)$$

where E(.) is the expectation vector, t is the transpose operation, and $\sum_X \in \Re^{N\times N}$. The PCA of a random vector X factorizes the covariance matrix $\sum_X$ into the following form:

$$\sum_X \Phi\Lambda\Phi$$

with $\Phi = [\Phi_1\Phi_2......\Phi_N]$
and $\Lambda = daig(\lambda_1, \lambda_2, ..., \lambda_N)$

where $\Phi \in \Re^{N\times N}$ is an orthogonal eigenvector matrix and $\Lambda \in \Re^{N\times N}$ is a diagonal matrix with diagonal elements in decreasing order $(\lambda_1 \geq \lambda_2 \geq .... \geq \lambda_N)$. $\Phi_1, \Phi_2, ..., \Phi_N$ and $\lambda_1, \lambda_2, ..., \lambda_N$ are the eigenvectors and eigenvalues of Σ_X respectively.
An important property of PCA is decorrelation, i.e., the components of the transformation, $X'=\Phi^t X$, are decorrelated since the covariance matrix of X' is diagonal, $\Sigma_{X'}=\Lambda$, and the diagonal elements are the variances of the corresponding components. Another property of PCA is its optimal signal reconstruction in the sense of minimum Mean Square Error (MSE) when only a subset of principal components where $P=[\Phi_1, \Phi_2, ..., \Phi_m]$, m<N and $P\in\Re^{N\times m}$ are used to represent the original signal. Therefore, an immediate application to this property is dimensionality reduction:

$$Y=P^t X \quad (4)$$

The lower dimensional vector $Y\in\Re^m$ captures the most dominant features of the original data X.

If the PCA is applied to the original face images (each face dimension is of size 112×92), it will result in a covariance matrix which cannot be calculated with most computers due to lack of memory. Therefore, as mentioned before, the face images are first DCT transformed and then a chosen block size of the DCT coefficients is introduced to the PCA resulting in a lower dimensional feature vector carrying the most dominant features.

4 Recognition Results

The used data set is from the Olivetti Oracle Research Lab (The ORL database found in [14]). The ORL database consists of 400 frontal faces; 10 tightly cropped images of 40 individuals with variations in pose, illumination, facial expressions and accessories. The size of each image is 92×112. The training set is composed of five persons each having five different expressions resulting in a training matrix of 25 face images. These face images are DCT transformed and a block size of 16×16 is transformed using PCA to get a feature vector of 25 features.
Two other block sizes are chosen to be further transformed using PCA; namely a 32×32 and a 64×64 DCT coefficients so as to see the effect of changing the block size on the recognition rate. Also, a feature vector of 25 features is calculated in each case.
The rest of the data set (35 individuals each having 10 different images) are also DCT transformed and the chosen block size is transformed via the PCA transformation matrix to get the feature vector required to be tested. The system matches the input test sample with all the training samples and measures the minimum distance between them using the Euclidean

distance nearest-neighbor classifier. If the feature vector of the input test sample is v and that of the database is f, then the Euclidean distance between the two is given by [8]:

$$d = \sqrt{(f_0 - v_0)^2 + (f_1 - v_1)^2 + \ldots\ldots + (f_{M-1} - v_{M-1})^2}$$
(5)

Where

$$v = [v_0\ v_1 \ldots\ldots\quad v_{M-1}]^T$$

$$f = [f_0\ f_1 \ldots\quad f_{M-1}]^T$$

And M is the number of used feature. A match is found by minimizing d.

The recognition rate depends on a chosen threshold based on the security level of the application. Two important aspects must be investigated namely the False Accept rate (FAR) and the False Reject Rate (FRR). The FAR is the success probability of an unauthorized user to be falsely recognized as a legally registered user. A low threshold leads to lower FAR value, but to higher values of FRR. In contrast, the FRR is the probability of the legally registered user to be falsely rejected by the biometric system when presenting his features. High thresholds lead to low FRR but high FAR. Both values FAR and FRR are negatively correlated. If the value of the FAR and FRR is equal, then this point is called the equal error rate.
The ROC (receiver operating characteristics) curve analysis is a method to compare classifiers on natural datasets using accuracy. The ROC curve shows the trade off between the FAR and the GAR (genuine accept rate). The derived ROC curve is plotted using the percentage FAR and GAR values for a given threshold value. In general, the ROC curve demonstrates the performance of the system.
The ROC curve is plotted using the FAR and GAR values resulting from the features generated when using a 16×16 DCT block followed by PCA, a 32×32 and a 64×64 DCT block sizes both followed by PCA. The ROC curve is shown in fig. 6.

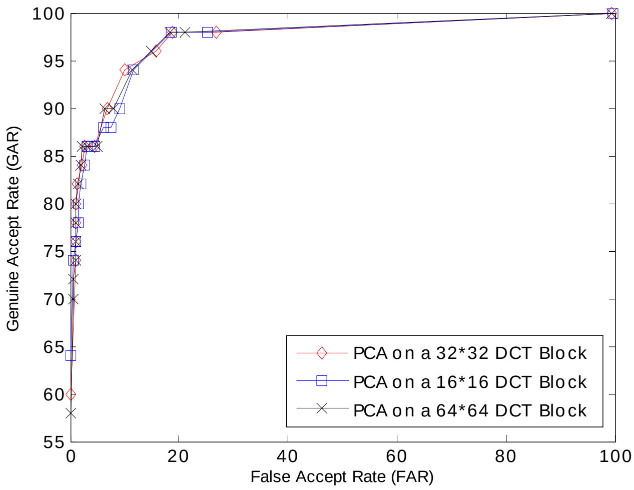

Fig.6 ROC curve of the recorded features using different block sizes

As can be seen from the curve, the features resulting from the three chosen block sizes result in ROC curves that almost coincide. The performance differ a bit at GAR values greater than 85% where the 32×32 and the 64×64 perform better than the 16×16 block.

The results are illustrated in Table 1.

Block Size	**GAR (%)**	**FAR (%)**	**Best Recognition Rate (%)**
16×16	98.57	20	96.25
32×32	98.29	18	96.25
64×64	98.57	18	96.5

Table 1 shows that the best recognition result was achieved when using a block size of 64×64 DCT coefficients. Nevertheless, the recognition results achieved with the other chosen blocks are still acceptable.

5 Conclusion

A face recognition system is suggested and tested. The systems performs overall 2D-DCT on face images, chooses a block of DCT coefficients to be further transformed using PCA. The technique is simple and in-spite of the small number of used features, it can overcome variations in pose and illumination giving results that are comparable to the published techniques found in the references without any pre-processing. The recognition results illustrate that the chosen block size does not have a recognizable effect on the recognition rate.

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