
Performance comparison for face recognition using PCA and DCT

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Abstract: In this paper Performance of Principle Component Analysis and Discrete Cosine Transform methods for feature reduction in face recognition system is compared. In face recognition system, feature extraction is based on wavelet transform and Support Vector Machine classifier for training and recognition is employed. According to experimental results on ORL face dataset the PCA method gives better performance compared to using DCT method.

Keywords: Face Recognition, Wavelet Transform, PCA, DCT

1. Introduction

Over the past few years, the user authentication is important because the security control is required everywhere. ID cards and passwords are traditional way for authentication although the security is not so reliable and convenient. Recently, biological authentication technologies through fingerprints, iris print, retina, palm print, face, etc is playing an important role in modern personal identification systems [1]. The face is chosen for the suggested system.

The key to face recognition is discriminant feature extraction and classification designing [2]. The extraction of image features is one of the fundamental tasks in image recognition [3].

Wavelet Transform is a popular tool in image processing and computer vision. Many applications, such as compression, detection, recognition, image retrieval et al have been investigated [4].

A problem in face recognition system is the curse of dimensionality in the pattern recognition literature. A common way of dealing with it is to employ a dimensionality reduction technique such as Principal Component Analysis 'PCA' to pose the problem into a low-dimensional feature space such that the major modes of variation of the data are still preserved [5].

Another way to reduce dimensionality of feature vector is Discrete Cosine Transform 'DCT'. The DCT converts

high-dimensional face images into low-dimensional spaces in which more significant features are maintained [3].

Support vector machines (SVMs) have been recently proposed as new kinds of feedforward networks for pattern recognition [6]. It belongs to a family of generalized linear classifiers. The main idea of a SVM is to construct a hyperplane as the decision surface in such a way that the margin of separation between positive and negative examples is maximized. The separating hyperplane is defined as a linear function drawn in the feature space [7].

This paper is organized as follows. Section 2 reviews the background of Wavelet decomposition of an image. In section 3, two ways to reduce dimensionality of feature vector (PAC-DCT) are defined. The multi-class SVMs are presented in section 4. The proposed method and experimental results are presented in section 5 and finally, section 6 gives the conclusions.

2. Feature Extraction

2.1. Discrete Wavelet Transform

Wavelet Transform (WT) has been a very popular tool for image analysis in the past ten years [6]. The wavelet decomposition of an image can then be interpreted as a set of independent, spatially oriented frequency channels [8].

The DWT is closely related to multi-resolution analysis and sub-band decomposition. The 1D-DWT recursively

decomposes the input signal, $S_0(n)$, in approximation and detail at the next lowest resolution stages. Let $S_i(n)$ and $W_i(n)$ be the approximation and detail, respectively, of the signal at level i . The approximation of the signal at level $i+1$ is computed using[9]:

$$S_{i+1}(n) = \sum_{k=0}^{L-1} g(k)S_i(2n-k) \quad (1)$$

and the detail of the signal at level $i+1$ is computed using:

$$W_{i+1}(n) = \sum_{k=0}^{L-1} h(k)S_i(2n-k) \quad (2)$$

Where $g(k)$ and $h(k)$ are, respectively, the low-pass and high-pass filter coefficients, and L is the size of filters. This technique for computing the DWT is often referred to as the pyramid algorithm or Mallat's algorithm[10]. Output of the low-pass filter is approximation coefficients and high-pass filter is detail coefficients.

The two-dimensional wavelet transform is got by applying one-dimensional wavelet transform to the rows and columns of two-dimensional data. An approximation image is derived from 1-level wavelet decomposition of an image and three detail images in horizontal, vertical and diagonal directions respectively. The approximation image is used for the next level of decomposition[11]. Fig.1 show the process of decomposing an image.

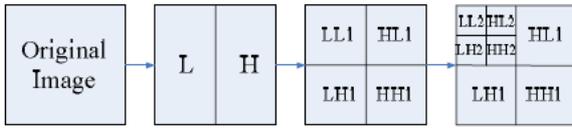


Figure 1. The process of decomposing an image

The LL sub band is the low frequency sub band of the original image. This sub band contributes to the global description of a face. LL sub band will be most stable sub band, so we use it as the feature representation of a face, in this paper.

3. Feature Reduction

3.1. Principal Component Analysis

The Principle Component Analysis method, also called Eigenface method, is the most classical, and commonly used algorithm in modern face recognition field [12]. PCA is used to find a low dimensional representation of data [13]. Let us have a brief view of the principle of PCA [11]:

Step1: A set of M images with size $N \times N$ can be represented by vectors of size N^2

$$F_1, F_2, F_3, \dots, F_M$$

Step2: The average training set is defined by

$$\varphi = \frac{1}{M} \sum_{i=1}^M F_i \quad (3)$$

Step3: Each face differs from the average by vector

$$\varphi_i = F_i - \varphi \quad (4)$$

Step4: A covariance matrix is constructed as follows:

$$c = A^T A \quad (5)$$

Step5: Finding eigenvectors of $N^2 \times N^2$ matrix is very difficult. Therefore, we use the matrix $A^T A$ of size $M \times M$ and find eigenvectors of this small matrix.

Step6: If v is a nonzero vector and λ is a number such as $Av = \lambda v$, then v is an eigenvector of A with eigenvalue λ .

Step7: Consider the eigenvectors v_i of $A^T A$

$$A^T A v_i = u_i v_i \quad (6)$$

Step8: Multiply both sides by A , we can obtain the result:

$$A A^T (A v_i) = u_i (A v_i) \quad (7)$$

Step9: A face image can be projected into this face space by

$$\Omega_k = U^T (\Gamma^k - \varphi) k = 1, \dots, M \quad (8)$$

3.2. Discrete Cosine Transform

The DCT is a popular technique in imaging and video compression, which transforms signals in the spatial representation into a frequency representation [14]. The DCT of an image basically consists of three frequency components namely low, middle, high each containing some detail and information in an image [15]. DCT is conceptually similar to Discrete Fourier Transform (DFT)[16].

The forward 2D-DCT [20] of a $M \times N$ block image is defined as

$$C(u, v) = \alpha(u)\alpha(v) \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(x, y) * \cos \frac{\pi(2x+1)u}{2M} \cos \frac{\pi(2y+1)v}{2N} \quad (9)$$

The inverse transform is defined as

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \alpha(u)\alpha(v) C(u, v) \cos \frac{\pi(2x+1)u}{2M} \cos \frac{\pi(2y+1)v}{2N} \quad (10)$$

where

$$a_p = \begin{cases} \frac{1}{\sqrt{M}} u = 0 \\ \sqrt{\frac{2}{M}} u = 1, 2, \dots, M-1 \end{cases}$$

$$a_q = \begin{cases} \frac{1}{\sqrt{N}} v = 0 \\ \sqrt{\frac{2}{N}} v = 1, 2, \dots, N-1 \end{cases}$$

and, x and y are spatial coordinates in the image block, and u and v are coordinates in the DCT coefficients block.

4. Support Vector Machine

Support Vector Machine (SVM) is a known supervised learning methods used for classification and regression. The

SVM is widely used in face detection and recognition. The support vector machine views the training data as two sets of vectors in an n-dimensional space, and then it will find a hyperplane which maximizes the margin between the two closest points in the training set which are termed as support vectors, and the calculation of SVM is only related with the support vectors. The optimal hyperplane can be computed as a decision of the form [2].

$$f(x) = \text{sgn}\left(\sum_{i=1}^l y_i \alpha_i K(x_i, x) + b\right) \quad (11)$$

Where x_i is the training vectors, x is the testing vector and $K(.,.)$ is the kernel function that must satisfy Mercer's condition. The coefficient α_i and b can be determined by solving the following quadratic programming (QP) problem:

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \sum_{i,j} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_j \alpha_j \quad (12) \\ \text{s.t} \quad & \sum_i y_i \alpha_i = 0 \\ & 0 \leq \alpha_i \leq C, \quad \forall i \end{aligned}$$

The unbound C is the penalty parameter that represents the tradeoff between minimizing the training set error and maximizing the margin [2].

The basic SVM is a binary classifier, so there are tree developed methods for c-class recognition ($C > 2$). The first method is one against all approach, which needs to construct c SVM classifiers and each one separates one signal class from all other classes. The second method is one against one approach and the third method is based on tree algorithm. In this paper, we use first method.

5. Experimental Results and Analysis

To evaluate the effectiveness of the proposed method, we used Cambridge ORL¹ face database. This face database contains 40 individuals, and each individual has 10 images with variations in pose, illumination, facial expression and accessories [11].

The procedure of the algorithm design in this paper is as follows:

Step1: Perform wavelet transform on ORL database,

Step2: LL sub-image of wavelet decomposition levels are selected,

Step3: For each person three images are selected as training images, and seven images as testing images,

Step4: Apply reduce methods on extracted features:

- Apply PCA on features vector,
- Apply DCT on features matrix and the next convert it to vector,

Step5: Train SVM with sample feature,

Step6: Exert test vectors on SVM to calculate error.

In this paper, application of different mother wavelet such as, Haar, Db1 and Sym1 were tested. Also we assay

different level of wavelet transform to find best result. Result shows the third level of Haar wavelet is the best.

In order to find efficient feature by DCT, this algorithm applied on different level. The resolution of images is changed in from of 48x48 to 6x6 using the third level of wavelet decomposition so, the size of DCT coefficients matrix is 6*6. Fig 2 and Table 1 show result of choice different level of DCT.

Table 1. Error from different level of DCT

Size of DCT block	Error percent
1*1	93/3333
2*2	73/3333
3*3	25
4*4	14/1667
5*5	5/8333
6*6	5/7776

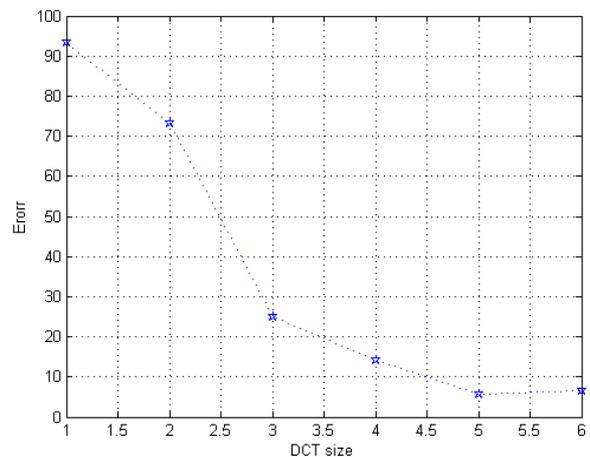


Figure 2. Changes of error by increasing the size of the DCT block

In order to find efficient feature by PCA, we employ PCA algorithm for distinct number of feature. Fig 3 shows changes of error by difference number of feature that selected by PCA. Reduce the feature in from of 36 to 22 bringing best result that is 95% recognition rate.

To show effect of proposed combination algorithm, each method tested alone. DWT, PCA and DCT algorithms are tested. The result is shown in table 2. The exported result is the best effect after do algorithms with different number of feature.

Table 2. Recognition rate

Algorithm	recognition rate
Original image	%83/33
DWT	%87/5
PCA	%90
DCT	%87/5
DWT/PCA	%95
DWT/DCT	%94/17

Table 2 shows that our method performs better than other algorithms.

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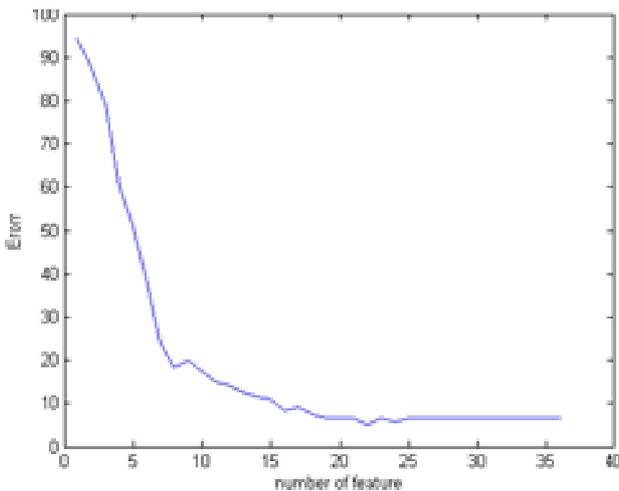


Figure 3. Changes of error by increasing the number of feature that reduction by PCA

6. Discussion and Conclusion

Our experimental results can be summarized as follows: The use of DWT as a feature extractor and DCT-PCA as featurereduction methodsto train and test support vector machine. The combination of DWT and DCT-PCA methods shows a very satisfactory result.

In the future, we plan to continue our research by investigating other possible methods (both feature extractors and classifiers) to achieve a better system performance.

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