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A Novel Facial Recognition Method using Discrete Wavelet Transform Multiresolution Pyramid

G. Preethi
PG Scholar, Department of CSE,
Chendhuran College of Engineering & Technology,
Pudukkottai – 622507, India

ABSTRACT
Necessity for the facial recognition methods is increasing now-a-days as large number of applications need it. While implementing the facial recognition methods the cost of data storage and data transmission plays a vital role. Hence facial recognition methods require image compression techniques to full fill the requirements. Our paper is based on the discrete wavelet transform multiresolution pyramid. Various resolutions of the original image with different image qualities can be had without employing any image compression techniques. Principal Component Analysis is used to measure the facial recognition performance using various resolutions of the image. Facial images for testing are selected from standard FERET database. Experimental results show that the low resolution facial images also performs equal to the higher resolution images. So instead of using all the available wavelet coefficients, the minimum number of coefficients representing the lower resolution can be used and there is no need of image compression.

Keywords
Principal component analysis, discrete cosine transform, discrete wavelet transform, support vector machine words.

1. INTRODUCTION
Facial recognition methods are used to identify or verify an individual using the facial images already enrolled in a database. The general categories of facial recognition are holistic, feature-based, template-based and part-based methods. Among them holistic method requires the whole face region as input and utilizes its statistical moments. The basic and commonly used holistic methods are based on Principal Component Analysis (PCA) [1]. Facial recognition methods are used in large number of applications like e-visa, e-passport, entry control in organizations, criminal identification, forensic science, smart phones and laptops for authentication etc. The number of facial images to be stored increases the problems like data storage and the cost of transmitting images. As a solution to reduce both data storage and cost of transmission, image compression algorithms are utilized.

Efficient image compression can be achieved using transform based methods than the pixel based methods. Transform coding transforms the given image from spatial domain to transform domain where efficient compression can be carried out. Since the transformation is a linear process, there will not be any loss of information and the number of coefficients equals the number of pixels. As most of the image's energy is concentrated within a few large magnitude coefficients, the remaining very small magnitude coefficients can be coarsely quantized or even ignored while encoding. This will not affect the quality of the reconstructed image more. The available mathematical transforms are Karhunen-Loeve (KLT), Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) [2]. Among them DCT is utilized in large applications like JPEG and MPEG. Now DWT is replacing the DCT by its superior quality and various decoding options. Transforms which operates on the whole image instead of image blocks can avoid blocking artifacts at low compression rates. DWT decomposes the source signal into non-overlapping and contiguous frequency ranges called sub bands. The source sequence is fed to a bank of band pass filters which are contiguous and cover the full frequency range. This set of output signals are the sub band signals and can be recombined without degradation to produce the original signal [3] [4]. Fig.1 shows how a signal is separated into sub bands using band pass filters.

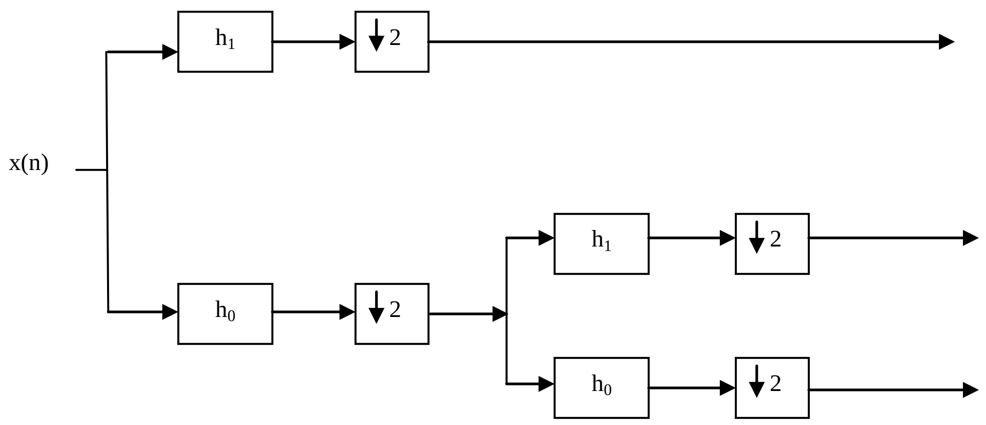

Figure 1. Sub band decomposition of a signal

When transforming a two dimensional digital image using the band pass (low pass and high pass) filters, it requires the first transform along horizontal axis and the second one along vertical axis to decompose the image into sub bands. The resulting four sub bands are named as LL, LH, HL and HH of a one level decomposition. LL, LH, HL and HH represents lowest frequencies, vertical high frequencies (horizontal edges), horizontal high frequencies (vertical edges) and high frequencies in both directions (the comers) respectively. Fig.2 shows various sub bands separated by a three level dyadic DWT [5].

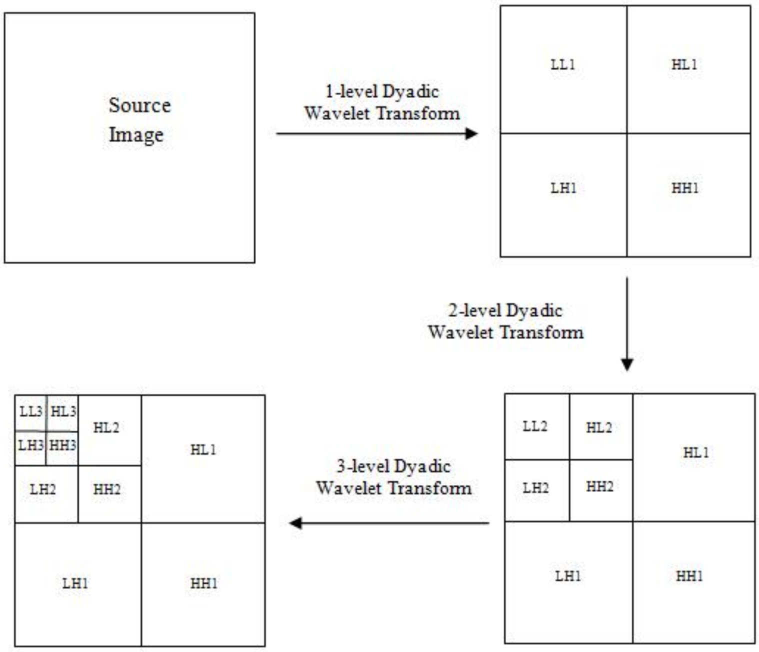

Figure 2. Sub bands separated by a three level dyadic DWT.

The multiresolution property [6] of DWT enables the user to have variable resolutions of the transformed image. While reconstructing the image, for a 3 level transformation, four resolutions (0 to 3) are possible. The LL3 sub band can reconstruct 0th resolution, LL3, HL3, LH3 and HH3 sub-bands can reconstruct 1st resolution, LL3, HL3, LH3, HH3, HL2, LH2 and HH2 sub-bands can reconstruct 2nd resolution and LL3, HL3, LH3, HH3, HL2, LH2, HH2, LL1, HL1, LH1 and HH1 sub-bands can reconstruct the third resolution.

When an image of dimension 128 x 128 pixels is transformed by DWT for 3 levels, the LH1, HL1, LL1 and HH1 will have a dimension of 64 x 64 pixels. LH2, HL2, LL2 and HH2 are of 32 x 32 pixels and LH3, HL3, LL3 and HH3 will have a dimension of 16 x 16 pixels. Hence the resolution 0 requires 256 (16 x 16) wavelet coefficients, 1 requires 1024 (32 x 32) wavelet coefficients, 2 needs 4096 (64 x 64) wavelet coefficients and 3 requires the whole 16384 (128 x 128) wavelet coefficients. With this multiresolution feature of the DWT, we propose a novel facial recognition method where the available resolutions of the facial image are used instead of the whole image.

2. MATERIALS AND METHODS

We briefly explain about the FERET database, PCA and the performance measure Recognition Rate here.

2.1 Database

FERET database is a standard database for testing facial recognition algorithms. This database is collected by Defense Advance Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST) of United States of America (USA) from 1993 to 1997 [7]. The total collection counts to 14051 grayscale facial images. Images are categorized into various groups depending upon the nature as Fa, Fb, Fc, Dup I and Dup II with 1196, 1195, 194, 722 and 234 images respectively. Moon and Philips [8] have analysed the computation and performance aspects of PCA based face recognition using Feret database.

2.2 Image Types

There are three types of images: Gallery images are the collection of facial images from known individuals which forms the search dataset. Probe images are the collection facial images of unknown persons to be identified or verified by matching the gallery images. Training images are the random collection facial images from all the available categories. These training images are used to train the PCA algorithm for facial recognition.

2.3 Principal Component Analysis

An applied linear algebra tool used for dimensionality reduction of the given data set. It decorrelates the second-order statistics of the data. A 2-D facial image is converted into a single dimensional vector by joining all the rows one after another having r (row) x c (columns) elements. For M training images, there will be M single dimensional vectors. A mean centered image is calculated by subtracting the mean image from each vector. Based on the covariance matrix of the mean centered image, Eigen vectors are computed. The basis vectors which represent the maximum variance direction from the original image are selected as feature vectors. These feature vectors are named as Eigen faces or face space. It is not necessary that the number of feature vectors should be equal to the number of training images. Every image in the gallery image set is projected into the face space and the weights are stored in the memory. The face to be probed is also projected into the face space. The distance between the projected probe image weights and every projected gallery image weight is computed. The gallery image having the shortest distance will be treated as the recognized face. Many PCA based face recognition methods are available. Hybrid versions of PCA and other methods like Gabor wavelets [9], Support Vector Machine (SVM) Classifiers [10], etc. are used for face recognition.

2.4 Distance Measure

The distance measures are used to compare the similarity between the probe and gallery images. The distance measure used in our work is L1. Let x and y are two vectors of size n and d is the distance between the vectors x and y. L1 distance or City-Block or Manhattan distance is defined as the sum of the absolute differences between these two vectors x and y. L1 distance is given in the following equation:

$$d(x, y) = |x - y| = \sum_{i=1}^{n} |x_i - y_i|$$

2.5 Performance Measure - Recognition Rate (RR)

We adopted the performance measure from Delac et. al. [12]. The recognition rate is defined as the ratio between the number of probe images recognized correctly and the total number of probe images used for recognition. Both the gallery and probe images are projected in the face space and the individual similarity score of the probe images are calculated. Distance measure is used to find out the gallery image having higher similarity with the probe image. If the identified gallery image is exactly equal to the probe image then it is declared that it is correctly identified. For example out of 1000 probe images if 786 are correctly identified than the RR is 786/1000 = 78.6%.

3. PROPOSED METHOD

Facial image sets of Fa, Fb, Fc, Dup I and Dup II from FERET database are normalized as per the ISO/IEC 19794-5 standard for facial image data using the algorithm of Somasundaram and Palaniappan [12]. From the resultant images of the normalization method, the facial features region (area covering eyes, nose, mouth) is segmented to the dimension of 128 x 128 pixels. Few of the test images are shown in Fig.3.

Figure 3. Few segmented test images from FERET database

Every segmented facial image is de-noised using median filter and the intensity values are equalized using histogram equalization. These images are transformed using DWT with Cohen-Daubechies-Feauveau 9/7 (CDF9/7) filter for 3 levels. The wavelet coefficients of LL3 (16 x 16) are used for the reconstruction of resolution 0. Wavelet coefficients of LH3, HL3, LL3 and HH3 (32 x 32) are used for the reconstruction of resolution 1. All the wavelet coefficients except LH1, HL1 and HH1 (64 x 64) are used to reconstruct resolution 2. Whole wavelet coefficients representing all the levels (128 x 128) are used to reconstruct resolution 3. Fig.4 shows the various resolutions available.

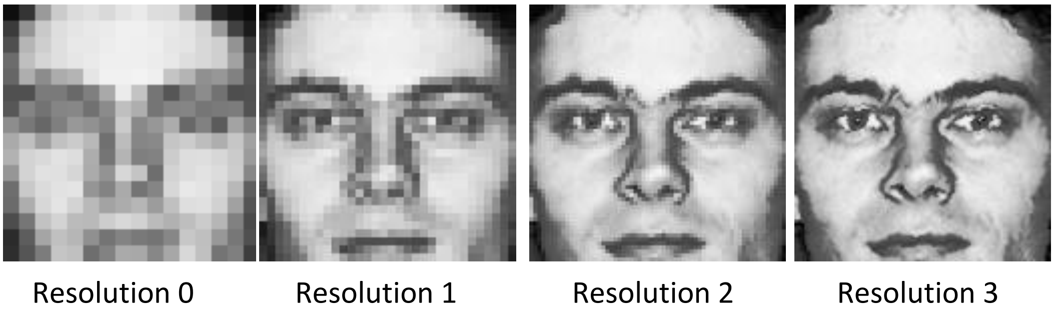

Figure 4. Various resolutions available for a 3 level DWT decomposition

The FERET image set Fa is used as gallery image set. Sets Fb, Fc, Dup I and Dup II are used as probe image sets. A training set of 501 images from FERET data set obtained from the CSU Face Identification Evaluation System of Colorado State University is used in our experiment. Among these training images 80% are from gallery images and 20% from Dup I images. While performing PCA on the training set, it generates 500 Eigen vectors. Among these 500 Eigen vectors only the top 200 Eigen vectors (40% of the total Eigen vectors) are selected as basis vectors. These basis vectors are used with PCA algorithm to generate the PCA face space (W_{PCA}).

We performed two types of experiments where in the first experiment the training and gallery images are of resolution 3 and only the probe images are varied from resolution 3 to resolution 0. For the second experiment all the gallery and probe images are varied from resolution 3 to 0. These two experiments are carried over for every individual probe sets Fb, Fc, Dup I and Dup II. Initially the face spaces are generated using PCA using training images for every resolution. While carrying out the experiments the gallery and probe images are projected to the respective face space as per the requirement. The L1 distance measure is used to find the similarity scores of the gallery images.

4. RESULTS AND DISCUSSION

The FERET facial images are transformed using DWT using Matlab (Version 7) software. The PCA face space generation, projection of gallery, probe image and similarity score computation are also carried out using Matlab programs. For every experiment the recognition rates are individual calculated for every probe image using all the resolution levels.

4.1 Experiment 1

The recognition rates of the probe image sets Fb, Fc, Dup I and Dup II for the resolution levels 3, 2, 1 and 0 with the gallery and training images of resolution 3 are given in Table 1.

Table 1. Recognition rate for resolution 3 training and gallery images

Image Type	Recognition Rate (%)			
	Res-3	**Res-2**	**Res-1**	**Res-0**
Fb	86.78	86.78	86.61	81.92
Fc	38.66	37.63	32.47	25.77
Dup I	41.83	41.69	40.58	35.73
Dup II	19.66	19.23	18.80	14.96

For Fb image set the resolutions 3,2 and 1, the RR is more or less equal and the resolution 0 decreases much. For all the resolution levels 3 to 0, the RR drops significantly in Fc image sets. In the image sets Dup I and Dup II also the RR resembles the image set Fc. As an overall observation the RR drops significantly as the resolution decreases.

4.2 Experiment 2

The recognition rates of the probe image sets Fb, Fc, Dup I and Dup II for the resolution levels 3, 2, 1 and 0 with the gallery and training images of the same resolution level are given in Table 2.

Table 2. Recognition rate for all the resolutions

Image Type	Recognition Rate (%)			
	Res-3	**Res-2**	**Res-1**	**Res-0**
Fb	86.78	88.03	88.77	88.87
Fc	38.66	41.75	41.24	42.27
Dup I	41.83	42.11	41.13	40.44
Dup II	19.66	20.09	19.52	18.80

When the training, gallery and probe image sets belong to the same resolution give better results than the first experiment. For Fb image set the RR increases for resolutions 3, 2, 1 and 0 steadily. The RR of resolutions 2 to 0 differ by a minimum of 1.25% from the resolution 3. The RR of Fc shows a good difference between the resolution 3 and others. Even the resolution 3 differs by 3.5% with resolution 0. For the image sets Dup I and Dup II the RR increases for resolution 2 from 3, but decreases for resolution 1 and 0 than the resolution 3.

Based on the results of the above two experiments, it is evident that the facial recognition rates of the lower resolution also equals the higher resolution. So instead of using the overall wavelet coefficients a minimum number of coefficients which can give higher recognition rate can be used without using any image compression.

5. CONCLUSIONS

Our proposed method presents a facial recognition algorithm based on the resolution scalability of DWT using PCA. The lower resolution images require very low bit rate when compared to higher resolution images. But the lower resolution images give recognition rate more or less equal to the higher resolution images. This can save the cost of transmission time and data storage. Our method can fulfill the requirements of a basic facial recognition with low resolution images.

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