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Hybrid Wavelet and Discrete Cosine Transform Methods for Ethnicity Identification

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Abstract

Ethnic (Race) denotes to people who share common facial features that perceptually discriminate them from members of other ethnic groups. Ethnicity identification from face images is a process of facial features compilation of an individual compared to existing faces to inference his/her ethnic class, it play important role in face-related applications. In this paper, an improved ethnicity identification system's accuracy is proposed through hybrid Wavelet and DCT (Discrete Cosine Transform) global feature extractor. Firstly, a wavelet transform is applied to the face image with 4 levels of decomposition. And then the DCT transform is performed on the LL4 (Low-Low) approximation coefficients band. A frontal facial database containing (950) images of three different ethnic groups (European, Oriental, and African) with different conditions (lighting, expression, with glasses or without) is used for experimental tests. Results show that the proposed scheme is outperform other recent related works in terms of accuracy and efficiency.

Introduction

Comparing to face recognition [1] from face images ethnicity identification has received relatively less interest from researchers but in recent years, catch researchers attention for its importance application fields like consumer market research, access control, homeland security and automatic annotation, etc... .

Ethnic feature is one of most important face features and is influential characteristics for facial information expressing as well gender and age. Different ethnic groups differ in face characteristics.

To extract facial features from face images a global feature selection method a hybrid Haar wavelet and DCT is used.

The rest of the paper is organized as follows.

Section 2 presents a survey of some related works. Section 3 briefly overviews of Haar wavelet and DCT transforms. Section 4 depicts the face images that are been collected for this study. Section 5 reports experiment results for different cases and our hybrid approach with experimental results. These experiments examine the effective of selected feature numbers of respective Wavelet-based and DCT-based features. Section 6 discussion of issues growth before our study. Section 7 conclusion.

Survey of Related Works

More recently study, is described by fusion of color, Hue-Saturation-Value (HSV) and texture, Local Binary Pattern (LBP) features by Hongbo Du [2], and also K-NN and SVM (Support Vector Machine) classifier fusion to ethnicity decision for three ethnic classes.

Early example of ethnicity identification S. Hma Salah [3] fused global and local features by applying Haar wavelet and LBP extractors, for classification decision, K-NN classifier is applied. Lu and Jain present good identification accuracy they used Fisher linear discriminant analysis (LDA) in an ensemble approach [4] with two classes (Oriental vs. Non-Oriental). For three ethnic class (Tibetan, Uygur and Zhuang) and by enhancing the LDA facial features in [4] with geometric features extracted using Gabor wavelet transform Duan et al [5] obtain a good accuracy level, but the geometric features depend on additional class-specific knowledge in the form of elastic templates.

Global Feature Selection Methods

1. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is the most familiar decomposition approach, which used frequently in image processing and used for feature extraction, denoising, compression, face recognition, and image super-resolution, etc....

Two-dimensional DWT decomposes the original grayscale image into four regions called wavelets and this decomposition known as the resolution of the image.

The received output is the decomposition of the input image into four multi-resolution sub-bands: LL, LH, HL and HH.

The LL (low–low) subband is an approximation of the original image. The LH (low–high) subband represents the alterations in the image along horizontal directions whereas the HL (high–low) subband represents alterations along vertical directions. The subband HH (high–high) shows the higher frequency factor or the detail of the image.

This is the first level of image decomposition. The upper left corner approximation region of image further decomposed into four smaller regions at the next level of decomposition and this process continues see Fig. 1, Fig. 2.

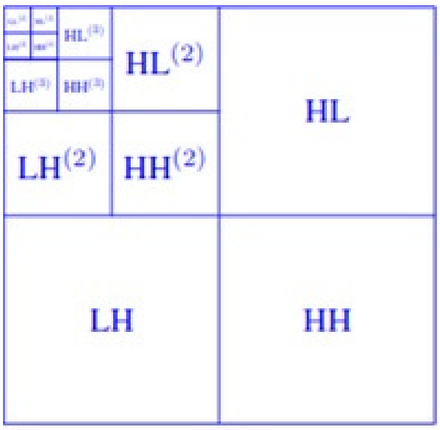

Fig. 1: Four levels of 2D-DWT

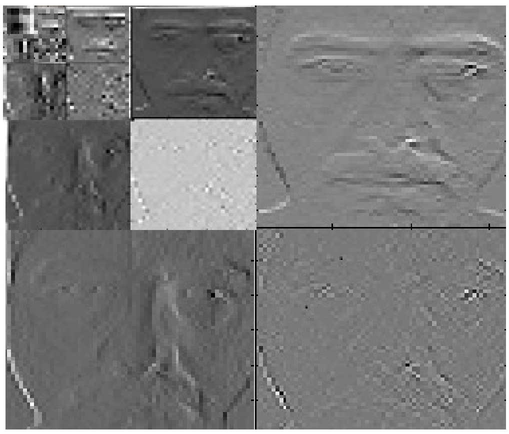

Fig. 2: Multi-resolution scheme after four levels of wavelet transform.

[(3*k) + 1] sub-bands available for a k level DWT.

All sub-band coefficients energy used as feature vectors individually which is called as sub-band energy vector (E). Each sub-band energy is calculated using the equation (1) [22].

$$E_k = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}|x_k(i,j)| \quad \text{…………..(1)}$$

Where $x_k(i,j)$ is the pixel value of the k^{th} subband and R, C is width and height of the subband respectively.
The Haar transform is the simplest of all wavelet transforms yet it has some profound applications to digital image processing [6] [7].
In this paper, the simplicity and effectiveness in capturing the image sharp edges is the reason of selecting the Discrete Haar Wavelet Transform (DHWT). DHWT realized by applying a low or high pass filter along the rows then columns of image respectively. DHWT computationally considered as efficient technique since the pair of low and high pass filter only operates on adjacent values.

2. *Discrete Cosine Transform (DCT)*

Transform coding depend on that the pixels in an image exhibit a certain level of correlation with their neighboring pixels. Consequently, this correlation can be involve to predict the value of a pixel from its respective neighbors. Mapping spatial (correlated) data into transformed (uncorrelated) coefficients defined as transformation. Clearly, that the small information content of an individual pixel utilized by the fact of transformation i.e., largely visual contribution of a pixel can be predicted using its neighbors.
Ahmed, Natarajan and Rao (1974) first introduced the discrete cosine transform (DCT) in the early seventies. DCT used in many image processing applications like image compression, face recognition [8], Gender classification [9], etc... .
The 2D-DCT distribute the source image into (N x N) matrix or block. In practice (N) most often equals 8 because performing larger block takes a great deal of time. Then the discrete cosine transform is applied on the matrix.
The mathematical functions for a two-dimensional DCT are [8]:

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

for $u,\ v=0,1,2,\dots,N-1$

$\alpha(u),\alpha(v)=\sqrt{1/N}$ for u,v=0 , $\alpha(u),\alpha(v)=\sqrt{2/N}$ for $u,v\neq 0$

It is clear from equation (2) that for u,v=0

$$C(u,v)=1/N \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)$$

Thus, the first transform coefficient is the average value of the sample sequence. In literature, this value referred to as the DC Coefficient. All other transform coefficients are called the AC Coefficients [9].
DC coefficients in the upper-left corner of the DCT matrix describes most of the information contained in the image, can utilize to be selected features for identification, few information are distributing along other AC values.

3. *K-NN Classifier*

In pattern recognition, for classifying objects based on closest training examples in the feature space the k-nearest neighbor algorithm (K-NN) is the generally used method. KNN is a type of instance-based learning where the function only approximated locally and all computation deferred until classification. Classified of an object in K-NN, is obtained by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small). The object is simply assigned to the class of its nearest neighbor if k = 1. The neighbors are taken from a set of objects for which the correct classification is known.

Facial Image Database

Face Images used in this Study

In the proposed ethnicity identification system with 950 frontal passport style images which are divided in to three ethnic group (European, Oriental, and African) are collected based upon the demographic information given by participants carried out from a number of different ethnic databases [10] [11] [12] [13] [14] [15]. The images selected manually under variations such as lighting condition, expression, with glasses or without, etc... . Since individuals of same ethnicity has common face features, we select as many subjects of each ethnicity as possible, but only take one image per subject. Table 1 shows the details of the collected images database. Figure 3 presents some samples of the image database.

Table1: Image sources of used database.

Ethnicity Class	Image Source	No. of Images	Total
European	GUFD	210	400
	PUT	86	
	FERET	104	
Oriental	CUHK	160	400
	HKU	89	
	FERET	100	
	CASIA	51	
African	FERET	50	150
	MUCT	37	
	Faces from www	63	
		Total	950

In the experimental test, leave-one-out test strategy for test and training dataset is followed.

Fig. 3: Sample facial images.

Hybrid Scheme for Ethnicity Identification

1. Hybrid Wavelet and DCT Scheme

The framework of the proposed hybrid scheme for ethnicity identification is shown in Fig. 6. proposed ethnicity identification method consists of three main modules: face detection, feature extraction/selection, and identification. For face detection, first the image is undergoing over some image preprocessing. In preprocessing, the image is cropping and removing the background, noise and other components of the face that can affect the identification rate. The face image is resized to pre-determined standard (128x128) pixels and converted into a gray scale image (see Fig. 6). For feature extraction, first apply Haar wavelet transform at level 4. Second, a DCT transform is applied on LL4 subband coefficients as a result we get (256) DCT coefficients.

The facial feature selection plays an important role in the classification problem. It is to reduce the search space, reduce error rate and given an accurate result. A 25 (i.e. a square sub vector 5x5) significant features is selected from the top left corner of coefficients vector, where most energy (less frequent intensity) coefficients considered for ethnicity identification depending on previous initial experiments in section 4.

In the identification phase, first by applying 'City Block' algorithm eq. (3) to the tested image feature vector with the training feature vectors in the database we find dissimilarity between them. Then by using the K-Nearest Neighbor classifier, the decision will obtained. The value of k is set to (5) to guarantee majority voting to one of three ethnicities at least.

K-NN classification engine steps:-

1- Apply 'City Block' distance measurement to tested image and training images.

2- Distance sort in ascending order.

3- Minimum 5 distance is taken.

4- Finding the 5 class values.

5- In last step identified 5 classes are formed a ratio and the class which has maximum ratio is taken. This taken class gives us the class of desired data.

In addition to, a level of confidence is assigned to the majority vote where 5 out of 5 voting of a class yields 100%, 4 of 5 80%, 3 of 5 60%, 2 of 5 40%, or 1 of 5 20% of confidence.

$$L1 = \sum_{j=1}^{n} | x_{rj} - x_{sj} | \quad \text{............(3)}$$

where $L1$ is 'City Block' distance between r and s images, n is the dimension of the feature vector, and x is the j^{th} feature of image r.

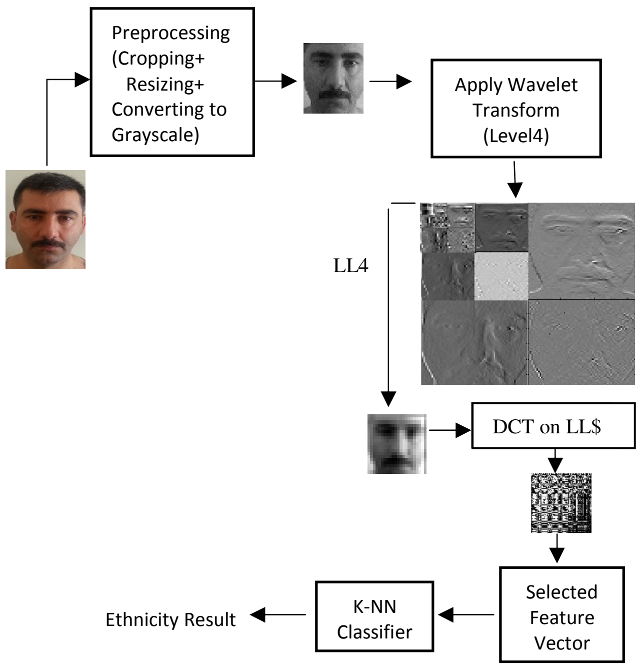

Fig. 6: Hybrid Wavelet (LL4) and DCT method framework Block Diagram

2. *Performing Test Results*

Wavelet transform has been widely reported in face recognition systems [19], but relatively there is a few use of wavelet transform for ethnicity identification. Salah [3], in applying Haar wavelet transformation at level 4 they discovered that ethnicity features better represents the whole face in LL subband than other subbands at different levels for a mixed image database consist of (746) images. Tests have conducted on the dataset for LL subband in 3 different level of Haar wavelet decomposition, and the results is presented in Table 2.

Table 2: LL Subband Accuracy in Different Levels.

Haar Wavelet	Level 2	Level 3	Level 4
Avg. Accuracy	94.4167	95.3056	96.1944

The results indicates that the LL subband at level 4 gives a better average accuracy than other levels. This observation provides the fact for selecting the LL subband at level 4 in capturing global features of a face in the proposed hybrid method. To get a better understanding about the effect of selected features reduction using PCA in LL4 and LL3, we have conducted three tests for identification with (16, 25 and 64) features. The results shown in Fig. 4.

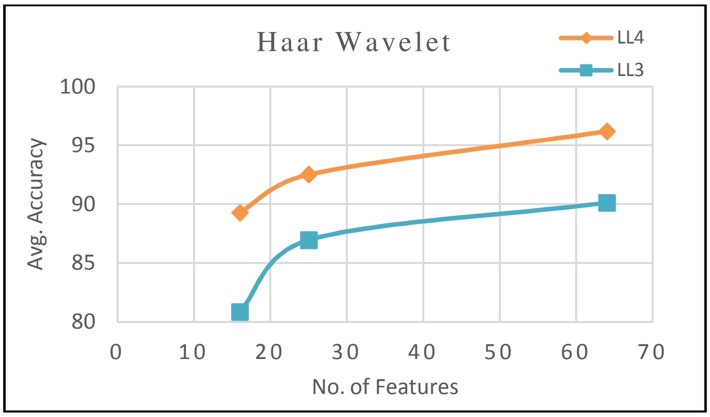

Fig. 4: Average accuracy comparison with different No. of features.

According to the above figure, the best value of the average accuracy is in LL4 with 64 features (%96.1945). the average accuracy is decreased when the number of selected features is decreased too.

Discrete cosine transform also used in many face recognition papers [20] [21].

After applying DCT over all face images for the global feature extraction, we select from upper left corner of feature vector 64, 25 and 16 features. The results of the ethnic identification accuracy is shown in Fig. 5.

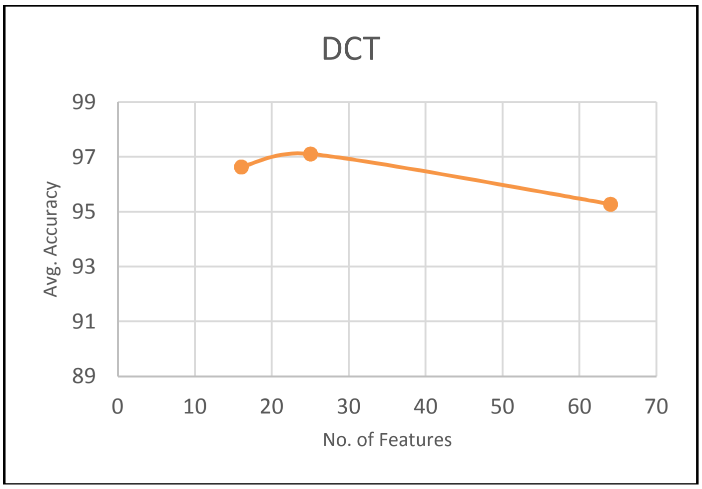

Fig. 5: DCT Average Accuracy comparison with different No. of features.

From Fig. 5, one conclude that the best accuracy is with 25 features selection (%97.111), unlike wavelet the decrement of selected features tends to the increasing of the accuracy.

3. *Accuracy*

Our task in these experiments is to classify (950) subjects as European (400) or Oriental (400) or African (150) ethnic and evaluate the system performance. For the training and testing set images, we chose (Leave-One-Out) strategy.

Identification average accuracy of the proposed hybrid method for (16, 25 and 64) selected features are (96.94%, 97.72% and 95.94%) respectively.

The results show that the best accuracy is in 25 features selection; then these features are chosen as demographic information for our hybrid system to ethnicity identification.

In Table 3 the detail of correct and wrong identification rate of three ethnic group is presented. Hybrid scheme improved average accuracy by nearly 5%, 0.5% compared to Wavelet and DCT respectively.

Table 3: Hybrid Scheme Accuracy for Identification.

Ethnicity Estimation Results

Actual Ethnicity

Ethnicity	European	Oriental	African
European	99.25	0.75	0
Oriental	0.5	99.25	0.25
African	2.6667	2.6667	94.6666

In Table 3 the results show that the correct identification rate of European reaches to 99.25%, the false rate of European, which is identified as Oriental is 0.75%, and wrongly classified as African is 0%. The correct identification rate of Oriental reaches to 99.25%, the false rate of Oriental, which is identified as European, is 0.5%, and wrongly classified as African is 0.25%. Finally, the correct identification rate of African reaches to 94.6666%, the false rate of African, which is identified as European, is 2.6667%, and wrongly classified as Oriental is 2.6667%.

4. *Efficiency*

Efficiency is one of the important parameters that affect the performance of the system, it has important role in image processing problems especially in real time applications. The proposed method is efficiently working because of the few number of features that selected using hybrid DWT/DCT scheme and the simplicity of the classifier K-NN.

Discussion

Comparison to Existing Results

The comparison of the proposed method with other recently related works is not easy because of non-availability of the common frontal facial image database that take into consideration a standard environment conditions. However, a comparison is done with some previous works. In table 5 the test results of the proposed scheme is compared with [2] [3] [17] and results show that the accuracy of identification is better than them with 25 selected features. On the other hand, comparing the proposed method to [4] and [18] ostensibly does not fair because both of them deals with binary-class (Asian vs. Non-Asian) situation. Third class addition affect accuracy passively.

Table 5: Proposed scheme comparison with recent works.

Ref. No.	Feature Selected	European	Oriental	African	Average
[2]	HSV+LBP	94.78	95.36	96.23	95.46
[3]	LBP +Wavelet	97.3846	95.5385	97.8462	96.9231
[17]	GWT +Retina Sampling	93.1	96.3	94.3	94.5667
Proposed Scheme	Wavelet +DCT	99.25	99.25	94.6666	97.7222

Conclusions

The ethnicity classification based on the hybrid DWT/DCT scheme for global feature extraction is proposed. The facial images are first subjected to the some image preprocessing algorithm to help the process of identification. A special database containing 950 images is created for three different ethnic groups (Asian, European and African). Test results show that the proposed scheme is outperforming the DWT and DCT separately. The average accuracy is attained (%97.722) with 25 features which is very optimal in terms of accuracy and efficiency. To further improve the performance, another feature extractor method and classifier can be used.

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