Fusing Local Binary Patterns with Wavelet Features for Ethnicity Identification

S. Hma Salah, H. Du, and N. Al-Jawad

Abstract—Ethnicity identification of face images is of interest in many areas of application, but existing methods are few and limited. This paper presents a fusion scheme that uses block-based uniform local binary patterns and Haar wavelet transform to combine local and global features. In particular, the LL subband coefficients of the whole face are fused with the histograms of uniform local binary patterns from block partitions of the face. We applied the principal component analysis on the fused features and managed to reduce the dimensionality of the feature space from 536 down to around 15 without sacrificing too much accuracy. We have conducted a number of preliminary experiments using a collection of 746 subject face images. The test results show good accuracy and demonstrate the potential of fusing global and local features. The fusion approach is robust, making it easy to further improve the identification at both feature and score levels.

Keywords—Ethnicity identification, fusion, local binary patterns, wavelet.

I. INTRODUCTION

ETHNICITY identification of face images refers to the process of recognizing the ethnic group to which the individual of a given face image belongs. The identification process involves extracting facial features, searching for similar facial images from a given database (or construct a classification model), and determining the ethnic group of the query face image. Ethnicity identification has a range of applications such as homeland security and automatic annotation of face images. Research in this field, sometimes known as demographic analysis of face images, intersects with face recognition, feature extraction and classification techniques. Unlike face recognition where the identity of an individual face is of interest, ethnicity identification involves the identity of a group of faces of an ethnicity. Also different from gender classification where either of two classes is of interest, ethnicity identification often deals with multiple classes. Technical challenges faced by ethnicity identification include the effective quantization of ethnical features and efficiency of the identification process.

Unlike face recognition [1], ethnicity identification for face images has received relatively less attention in the research community. Early works include a broad study of gender, ethnicity and pose identification of face images by Gutta et al.

[2] in which an ensemble of radial basis functions, decision tree and support vector machine classifiers was attempted with modest success. More recently, Lu and Jain used the linear discriminant analysis (LDA) in an ensemble approach for identification with good accuracy [3]. Manesh et al. employed support vector machine classifier on masked facial features such as eyes, nose and mouth also with good accuracy [4]. However, both [3] and [4] deal only with two-class situations (Asian vs. non-Asian). It is unclear about the effectiveness of their methods in more realistic situations of multiple ethnic groups. Duan et al. [5] later enhanced the LDA facial features in [3] with geometric features extracted using Gabor wavelet transform for a three-class scenario (Tibetan, Uygur and Zhuang) also with good levels of accuracy, but the geometric features rely on additional class-specific knowledge in the form of elastic templates.

In this paper, we present an empirical study of a new fusion scheme that combines Haar wavelet features in the low frequency subband (LL) with local binary patterns (LBP). In particular, the LL coefficients of the whole face at level 4 are fused with the block histograms of uniform LBPs from a 4x2 (4 horizontal and 2 vertical) partitioning of the image after local binary pattern transformation. We have conducted a number of tests on a mixed collection of 746 subject face images from our own face databases and some public domain databases. The results have shown the potential of fusing global and local features in face images. Our solution is simple and efficient since we employ simple techniques (Haar wavelet and LBP). To further improve efficiency, we applied the principal component analysis (PCA) on the fused features, and managed to reduce the number of combined features from 536 down to about 15 without sacrificing too much accuracy. This makes our scheme more feasible to be adapted in practical applications.

The rest of the paper is organized as follows. Section II briefly overviews Haar wavelets transform, uniform local binary patterns, and feature-based identification approaches. Section III describes the collection of face images used for this study and three initial tests from where the principle for the fusion approach emerges. These tests examine the relevance of Haar wavelet transform subbands at different levels, different ways of partitioning a face image into blocks, and the effectiveness of respective wavelet-based and LBP-based features. Section IV reports our fusion approach with experimental results. Section V discusses issues arising from our study before Section VI concludes the paper.

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II. Related Work

A. Local Binary Patterns

Local binary pattern (LBP) was first proposed by Ojala et al [6]. A LBP normally refers to an 8-bit binary code derived from a neighborhood of a given grayscale image. Typically, for a 3x3 block of an image, the value of the centre pixel is subtracted from that of each of its 8 neighboring pixels, and a bit either 1 or 0 is derived depending on the sign of the subtraction result (+ or -). The generated bits for all the neighboring pixels are then encoded into a binary string (hence known as local binary pattern) in either clockwise or anticlockwise order starting from the top left position. Fig. 1 illustrates the transformation of pixel values of a 3x3 block to a LBP code.
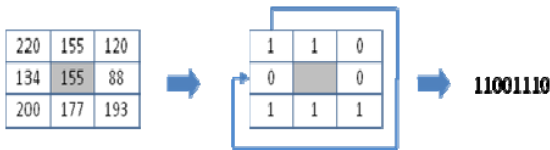

Fig. 1 Basic Local Binary Pattern Operation

The decimal value of the LBP code for the centre pixel is calculated as follows:

$$LBP(x_c, y_c) = \sum_{p=0}^{7} s(g_p - g_c) \times 2^p, \qquad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

where (x_c, y_c) represents the coordinate of the centre pixel of the block, g_c the color intensity value of the centre pixel, and g_p the value of the pth neighboring pixel ordered clockwise from the top left.

By replacing all pixel values by their LBP values, the original image is transformed into an LBP image. It is understood that the histogram of an LBP image captures the texture information of the image and is used as the texture feature vector for the image. However, research results show that not all 256 local binary patterns are equally useful in representing the texture. Some patterns, known as *uniform LBP*, that have at most two bitwise transitions are more useful than the others. In general, there are 58 uniform LBPs (2 for no transition + 14 for 1 transition + 42 for 2 transitions). Therefore, instead of a histogram of 256 bins, a histogram of 59 bins (58 for uniform LBPs and 1 for all the non-uniform patterns) can be used, greatly reducing the dimensionality of the feature vector.

Various forms of LBPs have been proposed and used for different purposes [7], but very little research about using LBPs for ethnicity identification has been reported. The work done by Yang and Ai [8] is the only reference found for the purpose. In their work, LBP is used in face demographic analysis, but the work is only concerned with a two-class (Asian vs Non-Asian) situation.

B. Wavelet Transformation

Discrete Wavelet Transform (DWT) is a transformation that decomposes an input signal into low and high frequency subbands. With two dimensional image signals, a set of high and low frequency subbands are obtained at a specific level of resolution by applying a transform filter. At level k, an image is decomposed into 3×k+1 (HL_1, LH_1, HH_1, …, HL_{k-1}, LH_{k-1}, HH_{k-1}, LL_k, HL_k, LH_k, HH_k) subbands. An illustration of level 3 transformation of an image is shown in Fig. 2.
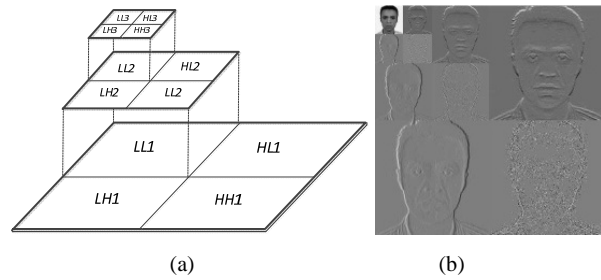

Fig. 2 Wavelet Transform (a) the pyramid scheme of resolutions; (b) an image transformed at level 3

The LL subband is the best approximation to the original image. The non-LL (high frequency) subbands represent fine details of changes of the original pixel values. The coefficients of each non-LL subband follow a Laplacian distribution with the mean close to zero. Increasing the level of decomposition makes the coefficients in the LL subbands coarser. There are many wavelet filters that can be used in the transformation [9]. Gabor filter is normally considered as being the most robust against local distortions caused by variance of illumination, expressions and poses, and it has been successfully applied for face recognition [9], [10]. Other wavelet filters, such as Haar, French hat, Mexican hat, Daubechies, Coiflet, Symlet, and 0-spline, have also been proven to be effective especially when they are used with frontal facial images [11].

In this paper, the Discrete Haar Wavelet Transform (DHWT) is selected for its simplicity and effectiveness in capturing the sharp edges. DHWT is realized by applying a low pass or high pass filter along the rows then columns of image respectively. Since the pair of low pass and high pass filter only operates on adjacent values, DHWT is considered a computationally efficient technique.

C. Facial Features and Feature Extraction

Many approaches and methods have been developed to capture facial features from the spatial or frequency domain for various recognition purposes [1]. Some methods can be generally applicable to more than one recognition purpose, but specific methods for a specific type of recognition may be needed. The amount of the information in spatial domain is relatively more compared with that in the frequency domain. As a result, the facial feature vector captured from the spatial domain needs more computational time. The colored bands captured from the spatial domain are often used as a step of preprocessing for face verification but not for identification of ethnicity. Some pilot studies in the authors' own institution,

have revealed that skin color alone is not a strong indicator for ethnicity in a number of different color spaces such as RGB, HSV, YUV and YCbCr.

Bagherian and Rahmat in [12] discussed the ranking of the significance of the facial features. Hair, eyes, mouth and face outline have been described as important factors for face recognition. The eye regions in particular are considered as being very descriptive for the face, and therefore the top part of a face image is more important than the lower part. Based on that, some face recognition approaches consider dividing the face image to different horizontal blocks and use the blocks to construct their feature vector.

III. FACE IMAGES AND SOME INITIAL STUDIES

A. Face Images and Test Protocol

Many databases of face images have been constructed [13]-[17]. These databases contain purposely introduced variations, such as different lighting conditions, various facial expressions, etc., interested by face recognition research community. Although the databases could be and have been used for ethnicity identification in the past, the very fact that they include many variations for different purposes makes it difficult to focus on demographic feature analysis and compare different methods. A database of good quality frontal passport-style face images that are taken under relatively similar and constant lighting conditions would be ideal. Unfortunately, it appears that there is no such a purposely built benchmark database. The EGA database [18] is in fact merely a gateway to the existing databases rather than a purposely built database. Because of this difficulty, we have manually selected a collection of images from different data sources including our own ([19] and [20]). The selection criteria are straightforward. We use only frontal face images taken in reasonable lighting conditions (not extreme dark, nor extreme bright). We focus on 3 ethnicities: European (including Caucasian), Oriental (East Asian) and African (including nationals with African origins). Since ethnicity is a common feature of individual faces, we select as many subjects of each ethnicity as possible, but only take one image per subject. Table I summarizes the sampling details of our final mixed collection of face images. Fig. 3 shows a selection of face images from our mixed collection.

Fig. 3 Sample face images used for the study

TABLE I
DATASET FOR THIS STUDY

Ethnicity	Data Source	No. of Subjects (Images)	Total
European	GUFD	265	380
	PUT	100	
	PDA	9	
	Fanar	6	
Oriental	CUHK	188	301
	HKU	98	
	PDA	9	
	Fanar	6	
African	PDA	8	65
	Fanar	7	
	MUCT	50	
	Total		746

It is quite obvious that we have a class imbalance problem: the number of African images is far fewer than the other two ethnicities. We recognize this problem and have decided to draw a random sample of 65 Europeans and 65 Orientals, use them together with the 65 African images in our tests for 3 ethnicities. We repeat the tests 10 times to reduce the effects of randomness. We utilize more European and Oriental images for a separate 2 ethnicity study (see Section IV).

We use the cross validation for evaluation of accuracy. We essentially follow the stratified leave-one-out test strategy, and hence divide the sampled data set into 65 folds, and each fold contains 3 images (1 for each ethnicity). The reason is that the number of images for our study is limited and we want to utilize as many training images as possible. The leave-one-out strategy has been widely used in machine learning and has been considered as unbiased [21]. Having said this, we have also attempted cross validations using fewer folds in order to give a more balanced view on accuracy (see Section IV).

Attempts in the past have been made in exploiting novel classification techniques such as decision tree, support vector machine, mixture models, etc. [2]. In this study, we are more interested in the effectiveness of the extracted features, and the fusion of these features. For simplicity, we only use the basic k-nearest neighbor classifier with class scores, i.e. 1-distance. To avoid sensitivity, we set k > 1 (e.g. 4). The dissimilarity measure is simply the Euclidean distance function.

B. Preliminary Investigations

Although using wavelet transform for face recognition has been widely reported [9], using wavelet transform for ethnicity identification are relatively few. In a pilot study in the authors' own institution, Mustafa [22] investigated the effectiveness of Haar wavelet subbands on the whole face image for ethnicity identification at different levels, but due to the limited number of subjects in the PDA database, it was inconclusive which subband is better. We have conducted a similar test on our dataset, and the result is presented in Table II. The result indicates that the LL subband better represents a whole face in terms of ethnicity features than other subbands at different levels. This observation provides the ground for selecting the LL subband in capturing global features of a face in our fusion method.

TABLE II
EFFECTS OF HAAR WAVELET SUBBANDS ON ETHNICITY IDENTIFICATION
ACCURACY

Haar Subbands	Level 4	Level 3	Level 2
LL	90.6154	90.4101	90.3076
HL	79.0769	70.205	60.6153
LH	76.9231	74.5642	59.8975
HH	71.7949	57.5386	33.7949

Assam et al [23] has reported three interesting findings: (a) the amount of relative entropy differs from one horizontal block of a face image to another and the blocks nearer to the eye regions have higher amount of information; (b) there exists a strong degree of correlation between the amount of relative entropy and accuracy of face recognition; and (c) using blocks with higher level of relative entropy can result in high and even better accuracy than using all the blocks. These findings together with the general understanding in the face recognition literature as explained in Section II *C* motivate us to consider dividing a face image into blocks when local features are extracted. We have conducted another initial experiment on different ways of decomposing a face image into blocks, and investigated the effects of the ways of decomposition on the accuracy of a block-based identification using our dataset. We first performed local binary pattern transformation to obtain the LBP codes of the face. We then generated histograms of uniform LBPs for different blocks and then used the concatenation of the histograms as the facial feature. Table III shows the average accuracy rates across the three ethnicities when a LBP face is divided into X blocks horizontally and Y blocks vertically. For instance, 2×1 means 2 horizontal blocks and 1×2 means 2 vertical blocks.

TABLE III
BLOCKING ON IDENTIFICATION ACCURACY

No. of Blocks	Average Accuracy
1x1	68.6154
2x1	76.3075
4x1	87.3847
1x2	70.7692
1x4	81.4358
4x2	89.2308
2x4	84.0001
2x2	80.1540

We concluded that using 4×2 blocking (4 horizontal blocks and 2 vertical blocks) is the best. These blocks correspond roughly to the regions of a face such as forehead, eyes, nose and chin.

In order to gain better understanding towards the effects of the wavelet features and LBP features on the three ethnicities, we summarize the more detailed results of the two initial tests in Table IV. It appears that accuracies of classification by different types of features vary from ethnicity to ethnicity. The accuracy levels do not match the best reported in the literature, and hence we investigate a fusion approach.

TABLE IV
USING WAVELET AND LBP FEATURES SEPARATELY

Features Selected	European	Oriental	African
4x2 Block LBP Histograms	88.7692	86.0000	92.9231
Haar Wavelet LL Subband at Level 4	93.2308	88.7692	89.8462

IV. A FUSION SCHEME FOR ETHNICITY IDENTIFICATION

A. The Framework and Main Steps

Based on our preliminary investigations reported in the previous section, we propose a fusion scheme that combines both global and local features of face images. The framework of the scheme is illustrated as a block diagram in Fig. 4. It consists of pre-processing, feature extraction, feature fusion, dimension reduction and classification. In the pre-processing step, a color image is first converted into a grayscale image, cropped, and probably resized depending on the image size. In this study, the image size is fixed to 120x128 pixels. Using grayscale image instead of the original color image is based on the finding that facial features rather than skin color is more relevant to the intended purpose.

In the feature extraction step, the global features are extracted by first conducting Haar wavelet transform at level 4 to the whole image and then selecting the coefficients of the LL subband. The local features are extracted by conducting local binary pattern transformation to the whole face first. The transformed image of LBP values is then divided into 4×2 equal size horizontal and vertical blocks. The histogram of the uniform local binary patterns in each block is then obtained. The rationale behind this local feaure extraction method is that (a) local binary patterns represent textures of a small local area (e.g. 3×3), and (b) the histograms of uniform local binary patterns of the blocks tend to further capture the local textural features of different regions of a face.
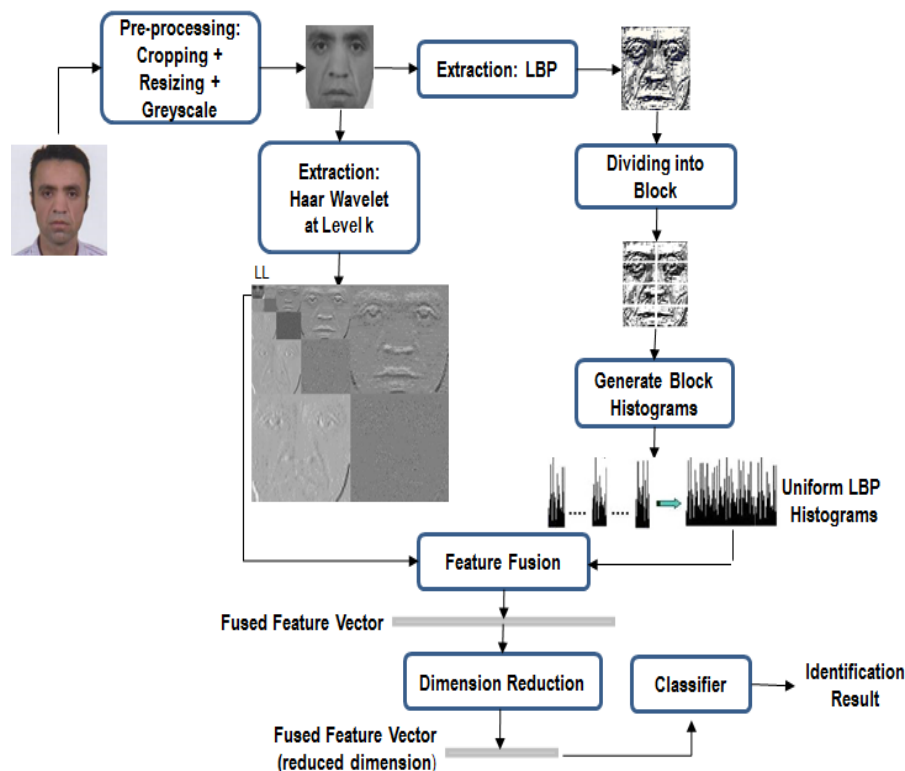
Fig. 4 The Framework of the Proposed Fusion Method

In the fusion step, the feature-level fusion is simply the concatenation of the LL subband coefficients and the uniform LBP hisgtograms (59 bins) of the blocks after the coefficients and the values of the histograms are normalized using the division-by-norm normalization technique. This feature-level fusion yields a feature vector for the face image. In this study, the vector has initially 536 (i.e. $64 + 59 \times 4 \times 2$) components. The high dimensionality not only slows down the speed of identification, but also affects the level of accuracy and the robustness of the classification model. Therefore, we use PCA to reduce the dimensionality of the feature vector space.

The k-nearest neighbor classifier used in this study finds 4 nearest subjects according to the euclidean distance between the feature vectors of training images and that of a test image. Rather than a simple majority voting, we use the distance-based scoring mechanism for each of the three ethnicity as explained in Section III. The scoring mechanism is more sophisticated than the majority voting by taking into account the distance from each of the 4 neighbors to the test image.

B. Experiments and Results

We followed the experiment protocol as outlined in Section III. Namely, we draw 65 out of 380 Europeans, 65 out of 301 Orientals, and combine them with the 65 Africans images to form a random sample. We then use 65-fold stratified cross validation, i.e. 3 images for testing (1 for each ethnicity) and the remaining for training, and then measure the recall rate as the level of accuracy. We repeat this test 10 times and then take the average on accuracy over the 10 rounds. As explained

in Section III, we have also attempted 5-fold and 13-fold cross validations. Table V lists the average accuracy across the three different ethnicities. The table shows a clear improvement of the fusion over the results reported in Table IV.

TABLE V
AVERAGE ACCURACY BY CROSS VALIDATION TESTS

Features	Average Accuracy		
	65 folds	13 folds	5 folds
Fusion of 4x2ULBP + LL4	96.3077	95.1796	93.9487

For some insight, we present a confusion matrix for the 65-fold (leave-one-out) case in Table VI. Across ethnicities, the accuracy rates are similar, slightly better in the European and African classes and slightly worse in the Oriental class.

TABLE VI
A CONFUSION MATRIX (DIM = 536, K = 4, 65-FOLD)

		Predicted Ethnicity		
		European	Oriental	African
Actual Ethnicity	European	96.9231	1.8462	1.2308
	Oriental	2.1538	95.3846	2.4615
	African	2.4615	0.9231	96.6154

To get a better understanding about the effect of PCA dimension reduction, we have collected the classification results when we raise the threshold on eiguevalues in reducing dimensions. Table VII summarises the test results for the average accuracy of identification at different thresholds.

TABLE VII
IDENTIFICATION ACCURACY FOR THE FUSION METHOD

Features Selection (PCA)	European	Oriental	African	Average
536	96.9233	95.3846	96.6154	96.3077
450	96.9231	95.3846	96.6154	96.3077
350	96.9231	95.3846	96.6154	96.3077
250	96.9231	95.3846	96.6154	96.3077
150	97.0769	95.2308	96.6154	96.3077
100	96.9231	95.2308	96.3077	96.1538
50	96.9231	94.9231	95.8462	95.8974
15	97.3846	95.5385	97.8462	96.9231
10	96.1538	95.3846	97.8462	96.4615
5	95.8462	93.5385	98.3077	95.8974

The table illustrates that the classification accuracies for the Europeans class are not affected when the dimensionality is greatly reduced to around 15 or 10, whereas the accuracies of the African class is in fact increasing as the dimensionality reduces. The accuracies for the Oriental class are also not affected much but marginally more than the other two classes. Further dimension reduction has a bigger impact on the accuracy for the Oriental class. The optimal result across all ethnicities is at the time when the dimensionality is reduced to 15. This results indicates that (a) there still a great degree of redundancy among the fused feature vectors across the face images of different ethnicities, and (b) the PCA process is effective in minimizing the redundancy but at the same time maintaining ethnic features.

In order to better understand the impact of Haar wavelet features and the LBP features on distance measurements, we have also conducted another experiment by assigning different weights to the distance measures based on the global wavelet features and those based on local LBP features. To do so, we first normalize the Euclidean distances calculated on Haar wavelet features and on LBP features (which explains why the figures are different from those in Table IV when the weight on one feature is 0 and the weight on another is 1), and then apply the weights. Table VIII summarizes the levels of accuracy for each ethnicity. The table shows that the best accuracies are achieved when the distance measure based on LBP features have higher weights.

TABLE VIII
APPLYING WEIGHTING TO WAVELET AND LBP FEATURES IN THE DISTANCE MEASUREMENT

Weight on Haar wavelet	Weight on LBP	European	Oriental	African	Average
0	1	93.8462	90.9231	93.8462	92.8718
0.1	0.9	96.0000	94.3077	96.9231	95.7436
0.2	0.8	97.3846	95.2308	97.2308	96.6154
0.3	0.7	97.3846	95.2308	96.9231	96.5128
0.4	0.6	97.6923	94.7692	96.6154	96.3590
0.5	0.5	97.8462	93.8462	96.3077	96.0000
0.6	0.4	97.2308	93.6923	96.0000	95.6410
0.7	0.3	96.7692	93.5385	95.3846	95.2308
0.8	0.2	95.6923	92.4615	95.3846	94.5128
0.9	0.1	94.6154	92.0000	95.2308	93.9487
1	0	94.1538	90.1538	92.0000	92.1026

V. DISCUSSION

A. Comparison to Existing Results

Comparing to the existing results reported in the literature, the accuracy rates presented in the tables in Section IV are better than that in [24] or match the best reported in [3] and [4]. However, a direct comparison appears not very sensible for three reasons. First, both [3] and [4] were dealing with the two-class situation. The presence of a third class is inevitably having an impact on accuracy (most likely to be negative). In order to obtain a better understanding how well our approach performs for a 2-class ethnicity identification problem, we did run a separate experiment fully utilizing all 380 European subjects (images) and 300 Oriental subjects (images). Table IX provides a brief summary of the accuracy levels for European vs. Non-European (Oriental + African) and Oriental vs. Non-Oriental (European + African). This table is only provided as a reference.

Second, while we only used a simple k-nearest neighbor method with a rudimentary scoring scheme for classification, both [3] and [4] used more sophisticated classification techniques. It is also our desire to investigate the use of better performing classifiers in our future work. Finally, the database that we used can be quite different from those used by other researchers. As we have stated before, there is an urgent need for a purposely built benchmark database for demographic feature (ethnicity, age, gender, etc.) analysis.

TABLE IX
APPLYING THE FUSION APPROACH IN 2 ETHNICITY CASES

Fusion Approach for 2-Class Scenarios	Average Accuracy		
	65 folds	10 folds	5 folds
European vs. Non-European	97.6389	96.94444	96.9444
Oriental vs. Non-Oriental	98.6667	97.1667	97.3333

B. Use of Haar Wavelet Levels and Blocking of LBP Face

In our study, we selected LL subband of Haar wavelet at level 4 and 4×2 partitioning of a LBP face mainly because of the good performance of the extracted features (the level 4 choice is also subject to the image size used from the database). In fact, it may be possible that LL subbands at higher levels and other form of partitioning may also lead to good performance. As for the Haar wavelet features, we expect that LL subband outperforms other high frequency subbands consistently at higher levels due to the type of information captured in that subband. As for the portioning, we argue that partitioning the LBP face into blocks lead to better results than using the whole LBP face, and horizontal blocking performs better than vertical blocking. This is very much due to the human facial structure. Our arguments have been supported by tests that have not been reported in this paper due to space limitations.

VI. CONCLUDING REMARKS

In this paper, we have presented a fusion scheme for ethnicity identification that combines Haar wavelet-based global features and uniform LBP-based local features of a face image. The experiment results show good level of accuracy

for identification. The use of PCA reduces the dimensionality of the feature vector space greatly without sacrificing much accuracy. Due to lack of a benchmark database, it is difficult to compare this scheme against the best in the literature. As a part of our immediate future work, we shall conduct a proper comparative study and evaluation of our work against a number of methods reported in the literature using our own collections of data as well as some larger public domain databases from the face recognition community.

Other future work includes further investigation of dynamic partitioning of the LBP face, the possible weighting for different blocks according to its information content, the score-level fusion and use of better classification techniques.

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