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Illumination and Expression Invariant Face Recognition: Toward Sample Quality-based Adaptive Fusion

Harin Sellahewa and Sabah A. Jassim

Abstract— **The performance of face recognition schemes is adversely affected as a result of significant to moderate variation in illumination, pose, and facial expressions. Most existing approaches to face recognition tend to deal with one of these problems by controlling the other conditions. Beside strong efficiency requirements, face recognition systems on constrained mobile devices and PDA's are expected to be robust against all variations in recording conditions that arise naturally as a result of the way such devices are used. Wavelet-based face recognition schemes have been shown to meet well the efficiency requirements. Wavelet transforms decompose face images into different frequency subbands at different scales, each giving rise to different representation of the face, and thereby providing the ingredients for a multi-stream approach to face recognition which stand a real chance of achieving acceptable level of robustness. This paper is concerned with the best fusion strategy for a multi-stream face recognition scheme. By investigating the robustness of different wavelet subbands against variation in lighting conditions and expressions, we shall demonstrate the shortcomings of current non-adaptive fusion strategies and argue for the need to develop an image quality based, intelligent, dynamic fusion strategy.**

I. Introduction

Over the past two decades, scientific researchers and commercial developers have made significant progress in developing robust algorithms and technology to transfer biometrics from theory to successful, large-scale automated identity verification systems. Human face is a natural choice in automated identification due to its unobtrusive nature. However, within-class variations due to occlusion, changes in illumination, pose, facial expressions and sensor quality make accurate automatic face recognition a challenging task [1]. This paper is primarily concerned with wavelet-based face recognition under varying illumination conditions and facial expressions.

Typical methods developed to address the challenges of face recognition under varying illumination conditions could be categorised as: *feature-based methods*, *holistic methods* and *generative methods*. In feature-based approaches, faces are represented by illumination invariant features. Typically these are geometrical measurements and relationships between local facial features such as the eyes, mouth, nose and chin [2]. Feature-based methods are known to be robust against varying illumination conditions, however, they rely on accurate face and facial feature detection.

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In holistic methods, the entire face image (image pixel values) is considered for face representation without taking into account any specific geometrical features. A face image could be thought of as a point in a high dimensional image space. To avoid computational complexities and to reduce redundant data, face images are first linearly transformed into a low dimensional subspace before extracting a feature vector. The most commonly used dimension reduction technique is the Principal Component Analysis (PCA), also known as Karhunen-Love transform (KLT) [3]. PCA is known to retain within-class variations due to illumination and pose. However, it has been demonstrated that leaving out the first 3 eigenfaces (that corresponds to the 3 largest eigenvalues) could reduce the effect of variations in illumination [4]. However this may also lead to the loss of information that is useful for accurate identification. An alternative approach to PCA based linear projection is Fisher's Linear Discriminant (FLD), or the Linear Discriminant Analysis (LDA) which is used to maximize the ratio of the determinant of the *between-class* scatter to that of *within-class* scatter [4], [5]. The downside of these approaches is that a number of training samples from different conditions are required in order to identify faces in uncontrolled environments.

Generative methods [6], [7], [8], [9] have been utilised to address the problem of varying illumination conditions in face recognition based on the assumption of the Lambertian model. Previous work has demonstrated that the variability of images under a fixed pose, consisting of only diffuse reflection components and varying illumination conditions can be represented by a linear combination of three basis images [10], [11]. Belhumeur and Kriegman [12] demonstrated that a set of images of an object under fixed posed, consisting of diffuse reflection components and shadows under arbitrary lighting conditions forms a convex cone, termed the illumination cone, in the image space and that this illumination cone can be approximated by a low-dimensional subspace. These generative methods have shown to perform well under varying illumination conditions. However, they require a number of training samples which represent extreme illumination conditions. It may be possible to acquire a number of training images for certain applications such as ID cards and drivers license, but not so for surveillance and counter terrorism related applications.

In recent years, wavelet transforms (WT) have been successfully used in a variety of face recognition schemes [13], [14], [15], [16], [17]. However, in most cases, only the approximation components at different scales of the WT are used to represent face images as these give the best overall recognition accuracy. The detail components (i.e. horizontal, vertical and diagonal features) of the WT face images are generally ignored. Our contribution in this paper is twofold. We first investigate the effect of variations in illumination and facial expressions on wavelet-based face recognition in order to identify which frequency components of the wavelet decomposed face image are robust against such varying conditions. Based on a number of experimental results, we argue for an image quality-based, adaptive fusion approach to wavelet-based multi-stream face recognition.

The rest of this paper is organised as follows: In section II, we give a brief introduction to wavelet transforms and review existing work on wavelet-based face recognition. Section III and Section IV analyse the effects of varying illumination conditions and facial expressions on different wavelet subbands. In section V, we present an existing wavelet-based multi-stream approach to face recognition [18] and argue that the fusion of different wavelet subbands should be performed adaptively, based on the quality of the live sample image. Finally, the conclusions and our future direction of work are discussed in section VI.

II. Wavelet Transforms

A WT is a multiresolution signal analysis tool which allows one to view a signal's regular patterns as well as its anomalies by hierarchically decomposing the signal into low- and high-frequency components. Similar to the Fourier analysis representing a signal in terms of sine waves of different frequencies, a WT represents a signal by a linear combination of *wavelets*. This set of wavelets are the *dilated* and *translated* versions of a *mother wavelet* [19], [20]. The mathematical properties of the discrete wavelet transform (DWT) is equivalent to filtering the input signal with a bank of band-pass filters whose impulse responses are approximated by different scales of the same mother wavelet.

There are a number of different ways of applying a 2D-wavelet transform. The most commonly used wavelet decomposition is the pyramid (the non-standard) scheme, which we have adopted here. At a resolution depth of k, the pyramid scheme decomposes an image I into $3k+1$ subbands, (LL_k, HL_k, LH_k, HH_k, ..., HL_1, LH_1, HH_1), with the lowest-pass subband LL_k representing the $k-level$ approximation of the image I. The subbands LH_1, HH_1 and HL_1 contain finest scale (highest frequencies) wavelet coefficients, and the coefficients get coarser as k increases, LL_k being the coarsest.

A. Wavelet Transforms in Face Recognition

The use of wavelet transforms in face recognition tasks has been studied on previous occasions. Etemad and Chellappa suggested to estimate the discriminant powers of each subband of a wavelet transformed image for their proposed LDA method [5]. They found that the *LL* components are the most informative and indicated that the LDA scheme can be applied on wavelet-based multiscale representation of face images. Lai et al. [13] proposed *spectroface*, a face representation scheme based on wavelet and Fourier transforms (FT). In order to attenuate the effect of facial expressions, the authors used the *LL* subbands of WT face images rather than the original image to derive FT-based facial features. In [14], [15], the *LL* subband coefficients were used as the facial feature representation on its own (wavelet-only) or as a dimensionality reduced space for further statistical analysis using PCA or LDA. Sellahewa and Jassim [21] also demonstrated that the wavelet-only scheme using *LL* for face representation is robust against varying facial expressions. Since we are investigating the recognition accuracy of different wavelet subbands under varying illumination and facial expressions, we based our study on the wavelet-only face feature representation.

Consider the training set $\Gamma = \{T_{i,1}, T_{i,2}, T_{i,3}, \ldots, T_{i,m}\}$ of N×N face images of n subjects with m images per subject. Applying a WT on each of the training images results in a set $W_k(\Gamma)$ of multi-resolution decomposed images. Let $LL_k(\Gamma)$ be the set of all k-level *LL* subbands obtained from the elements in the set $W_k(\Gamma)$. The new set of features for the given training set Γ on this occasion is the set $LL_k(\Gamma)$. Hence, the image j of subject i in the training set is represented by its feature vectors $LL_{k,i,j}$. Similar to the facial feature representation by LL_k, we can also construct 3 more independent representations at the same decomposition level k: $HL_k(\Gamma)$, $LH_k(\Gamma)$ and $HH_k(\Gamma)$ based on the k^{th}-level *HL*-, *LH*- and *HH*-subbands respectively.

When a new face image T is presented for identification, a WT is applied on T and the appropriate frequency channel (e.g LL_k) is selected as the feature vector. We now calculate a match score $S_{i,j}$ between the test feature vector and each of the feature vectors j of subject i in the enrolled feature set $LL_k(\Gamma)$ using a nearest-neighbour (NN) classifier (e.g. Euclidean or CityBlock distance). The score associated with the test image and the enrolled identity i is

$$S_i = \min(S_{i,j}) \qquad \text{(for j = 1, ..., m)}$$

The identity associated with the test image is the identity of subject i where $\min(S_i)$. Subbands of two different wavelet filters, Haar and Daubechie-2 were tested in our experiments. All the results presented in this paper are based on the Daubechie-2 filter and the NN classifier is the CityBlock distance.

III. Effects of Varying Illumination on Wavelet-based Face Representations

We studied how the changes in illumination between the enrolled and test face images affect the recognition accuracy of different wavelet-based face representations through a number of identification experiments. The effects of two commonly used illumination normalisation methods: (1) histogram equalisation (HE) and (2) z-score normalisation (ZN) were also compared. HE was applied on the spatial domain while ZN was performed on the selected wavelet subband.

A. Experimental Data

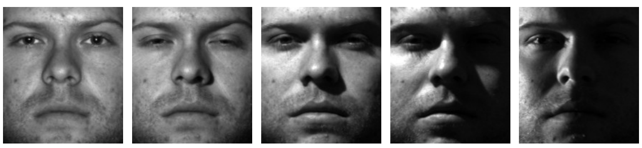
We used the 168×192 cropped face images [9] from the Yale Face Database B and the Extended Yale Face Database

B for our experiments. The Yale Face Database B consists of 5850 images of 10 subjects. Each subject was imaged under 576 viewing conditions (9 poses $\times$ 64 illumination conditions). In addition to these images, an image was captured under ambient illumination for each of the poses. The Extended Yale Face Database B consists images of an additional 28 subjects to those subjects that are already in the Yale Face Database B, but only for frontal pose. Since we are concerned with varying illumination conditions, we only used the 64 images (i.e. excluding the image in ambient light) of each subject in frontal pose (i.e. images with pose P00). These images were divided into 5 subsets according to the angle θ of the light-source with respect to the optical axis of the camera. The subsets are: subset 1 – $\theta < 12^\circ$ (70 images), subset 2 – $20^\circ < \theta < 25^\circ$ (120 images), subset 3 – $35^\circ < \theta < 50^\circ$ (120 images), subset 4 – $60^\circ < \theta < 77^\circ$ (140 images) and subset 5 – $85^\circ < \theta < 128^\circ$ (190 images). All our experiments were conducted on resampled images of size 80×96. Fig. 1 shows an example image of each one of the 5 subsets in Yale Face Database B.

B. Experiments: Yale Face Database B

We used only one training image per subject (i.e. the image that was captured with a light-source on the optical axis of the camera in subset 1) and the remaining 630 images of the 10 subjects were used for testing. Table I shows identification error rate for each illumination subset as well as the total error rate for different face feature representations at different scales. It is evident that the feature representation based on the approximation subband (i.e. LL) is the most affected by the changes in illumination while the LH subband is the least affected representation. However, LL features under small variations in lighting conditions (e.g. subset 1) performs as well as the non-LL features. Table II shows the effects of applying HE and/or ZN as a pre-processing step to normalise variations in illumination. The normalisation step significantly reduced the identification error, especially of the LH_2 feature representation, which achieved a total accuracy rate of 96%. Consindering the use of only a single training image, the identification error of the wavelet-based approach using the LH subband is significantly lower than the error rates of most existing methods as reported in [7], [8], [9].

Above observations are further confirmed by the results shown in Table III: identification errors rates of the Extended Yale Face Database B which consists a total of 38 subjects. Interestingly, LL-subband acheived the lowest identification error for test images in subset 1 which suggests that under controlled lighting conditions, the LL-subband is the suitable feature representation. We also noted that the normalisation by ZN method alone led to a significant reduction in identification error for subsets 1, 2, 3 and 4 while HE being the better choice for subset 5. Applying HE and ZN resulted in the lowest identification for subsets 4 and 5. This indicates that the choice of the illumination normalisation method should be adaptive, based on the illumination quality of the sample image. However, in existing approaches to face recognition, the illumination normalisation step is performed at all times, irrespective of the lighting conditions.



(a) Subset 1 (b) Subset 2 (c) Subset 3 (d) Subset 4 (e) Subset 5

Fig. 1: Example images of Yale Face Database B

IV. Effects of Varying Facial Expressions on Wavelet-based Face Representations

In section III we investigated the effects of varying illumination on different frequency components of the WT face images when used as face feature represenation for person recognition and found that the LH subband is the most suitable representation under varying illumination while the LL subband representation is significantly affected by extreme changes in illumination. Here we analyse the effects of varying facial expressions on different wavelet feature representations using the Yale Face Database.

A. Experimental Data and Results

The Yale Face database [4] consists of 15 subjects and there are 11 different 320×243 grey scale images per subject. These images include:

- expressions - normal, happy, sad, sleepy, surprised and wink,
- face details - with glasses and without glasses.
- illuminations - center-light, left-light and right-light,

The 11 different images of a subject in the Yale Face Database are shown in Fig. 2. All original images of the Yale Face database were manually cropped around the face and resized to 80×96 pixels for our experiments.

TABLE I: Effects of varying illumination on wavelet-based face recognition using different wavelet subbands. Only one image per person from Subset 1 (i.e. frontal pose, frontal light source) was used for enrolment.

Yale Database B: Identification Error Rates						
Wavelet Subband	Error Rate (%) vs. Illumination Subset					
	Set 1	Set 2	Set 3	Set 4	Set 5	Total
LL_1	1.67	7.50	55.83	81.43	87.89	56.83
LL_2	1.67	10.83	57.50	82.14	87.89	57.94
LL_3	6.67	16.67	67.50	82.86	88.95	61.90
LL_4	8.33	30.83	75.00	82.14	86.84	65.40
HL_1	13.33	15.83	47.50	80.00	91.58	58.73
HL_2	5.00	9.17	26.67	85.00	93.68	54.44
HL_3	1.67	10.00	40.00	86.43	91.58	56.51
HL_4	3.33	32.50	70.00	87.86	91.05	66.83
LH_1	8.33	0.00	24.17	58.57	85.26	44.13
LH_2	0.00	0.00	7.50	48.57	81.05	36.67
LH_3	0.00	0.00	14.17	46.43	77.37	36.35
LH_4	1.67	17.50	50.00	65.00	87.89	53.97
HH_1	25.00	21.67	60.83	77.14	88.42	61.90
HH_2	13.33	7.50	36.67	68.57	88.42	51.59
HH_3	0.00	0.00	24.17	72.86	92.11	48.57
HH_4	0.00	0.00	45.00	85.71	93.16	55.71

TABLE II: Effects of illumination normalisation on wavelet-based face recognition using different wavelet subbands. Only one image per person from Subset 1 (frontal pose, frontal light source) was used for enrolment.

Yale Database B: Identification Error Rates (including pre-processing to normalise illumination)							
Wavelet subband /Illumin. Norm		Error Rate (%) vs. Illumination Subset					
		Set 1	Set 2	Set 3	Set 4	Set 5	Total
LL_1	None	1.67	7.50	55.83	81.43	87.89	56.83
	HE	0.00	5.83	30.83	61.43	56.32	37.62
	ZN	0.00	4.17	30.83	69.29	82.63	46.98
	HE, ZN	0.00	5.83	31.67	60.71	56.32	37.62
LL_2	None	1.67	10.83	57.50	82.14	87.89	57.94
	HE	0.00	8.33	35.83	61.43	60.53	40.32
	ZN	0.00	5.00	35.00	70.71	85.26	49.05
	HE, ZN	0.00	8.33	37.50	61.43	63.16	41.43
HL_2	None	5.00	9.17	26.67	85.00	93.68	54.44
	HE	0.00	8.33	30.00	73.57	70.00	44.76
	ZN	5.00	6.67	21.67	67.14	88.42	47.46
	HE, ZN	3.33	7.50	26.67	65.00	68.95	42.06
LH_2	None	0.00	0.00	7.50	48.57	81.05	36.67
	HE	0.00	0.00	10.83	40.71	18.42	16.67
	ZN	0.00	0.00	2.50	22.14	36.32	16.35
	HE, ZN	0.00	0.00	3.33	12.14	2.63	4.13
HH_2	None	13.33	7.50	36.67	68.57	88.42	51.59
	HE	1.67	3.33	15.83	32.86	34.74	21.59
	ZN	10.00	3.33	16.67	34.29	65.26	32.06
	HE, ZN	1.67	3.33	16.67	28.57	29.47	19.21

TABLE III: Extended Yale Face Database B: Effects of illumination normalisation on wavelet-based face recognition using different wavelet subbands. Only one image per person from Subset 1 (frontal pose, frontal light source) was used for enrolment. The remaining 2376 images were used to test the identification accuracy.

Extended Yale Database B: Identification Error Rates (including pre-processing to normalise illumination)							
Wavelet subband /Illumin. Norm		Error Rate (%) vs. Illumination Subset					
		Set 1	Set 2	Set 3	Set 4	Set 5	Total
LL_2	None	8.44	14.25	80.66	95.63	97.20	69.36
	HE	1.33	20.39	67.91	90.30	86.27	62.96
	ZN	0.89	17.32	65.27	93.92	96.22	65.61
	HE, ZN	1.78	20.83	67.47	90.30	85.71	62.84
HL_2	None	17.33	5.70	54.29	94.11	98.32	63.51
	HE	17.33	3.51	59.34	91.06	86.27	59.76
	ZN	16.00	5.26	61.32	93.54	95.66	63.72
	HE, ZN	15.56	5.26	64.18	93.54	88.66	62.12
LH_2	None	14.67	0.00	35.60	66.35	89.64	49.83
	HE	16.00	0.00	34.29	60.27	42.02	34.05
	ZN	13.33	0.00	22.64	36.12	69.75	34.55
	HE, ZN	13.33	0.00	24.84	28.33	18.35	17.80
HH_2	None	34.22	8.11	58.24	80.61	96.22	62.71
	HE	28.44	3.73	55.60	82.13	76.75	55.30
	ZN	28.44	2.41	37.14	48.48	85.01	46.55
	He, ZN	23.56	2.85	36.26	45.44	51.26	35.19

We used the no-glasses image of each subject for the enrolment and the remaining 10 images for testing. The identification error rates (%) of each category as well as the total error rates for different feature representations are shown in Table IV. The results show that the approximation subband is robust against the presence of facial expressions as well as eye glasses because anomalies due to facial expressions or eyeglasses in the face image are attenuated in the approximation band. However, the LH subband, which captures high-frequency horizontal features of the face, performed poorly under varying facial expressions. This indicates that the choice of the feature representation should be adaptive by taking into account the facial expression captured in the live face image sample. In [22], Martinez used the optical flow concept between the enrolled and the test images, to assign weights to the image areas in a manner which is inversely proportional to the amount of change (due to facial expressions) in that area. However, this may also affect facial features important for accurate person identification. Also, variations in facial expressions is only one obstacle to accurate face recognition.

Previous work [17], [18] has shown that the fusion of match scores resulting from diffrent wavelet-based feature representations (e.g. LL-score and LH-score) could increase the recognition accuracy under varying conditions.

V. Toward Sample Quality-based, Adaptive Fusion

A. Multi-stream Face Recognition

Recognition systems that are based on multiple biometric traits (e.g. fusion of handgeometry and face or voice and face modalities) are known to be more robust than systems that use a signal biometric trait [23], [24] in verifying or identifying an individual. Information from multiple biometric sources/traits can be fused at different stages/levels of the recognition process:

1) Feature level fusion: Extracted features of each biometric modality is combined into one feature set to represent the individual.
2) Score level fusion: Match scores obtained from each biometric system for the same verification/identification attempt is combined into a single *fused score* and the claimed identity is accepted if this fused score falls within a predefined decision threshold.
3) Decision level fusion: Final decision (i.e. accept/reject or the class label) of each biometric recognition system is combined to a single decision (e.g by majority voting).

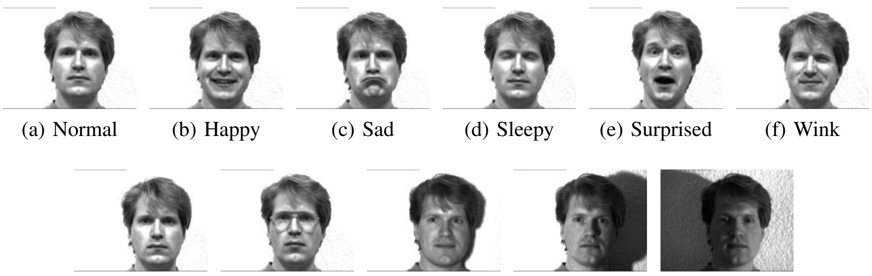
The wavelet-based mutli-stream face recognition approach [18], [17] is describe below.

Each class T_i in the identity database contains multiple feature representations at a given scale k (i.e. $LL_{k,i,j}$, $HL_{k,i,j}$ and $LH_{k,i,j}$ features) of a number of images, $T_{i,j}$ (where j = 1,..., m). For a given unkown test image, the identification system calculates scores $S^{LL}_{i,j}$, $S^{HL}_{i,j}$ and $S^{LH}_{k,i,j}$ using a NN classifier. The fused score $S_{i,j}$ for the enrolled image j of identity i is;

$$S_{i,j} = \left(S^{LL}_{i,j} \times w^{LL}\right) + \left(S^{HL}_{i,j} \times w^{HL}\right) + \left(S^{LH}_{i,j} \times w^{LH}\right)$$

where w^{LL}, w^{HL}, w^{LH} are the weights given to respective subband. The fused score S_i for the identity i is:

$$S_i = \min\left(S_{i,j},\, j = 1, \ldots, m\right)$$



(a) Normal (b) Happy (c) Sad (d) Sleepy (e) Surprised (f) Wink

(g) No glasses (h) Glasses (i) Center-light (j) Left-light (k) Right-light

Fig. 2: Example images of Yale Face Database [4].

TABLE IV: Yale Face Database: Identification error rates (%) for different facial expressions and lighting conditions. Only the *noglasses* image of each subject was used for enrolment.

Yale Database: Identification Error Rates (%)												
Wavelet subband /Illumin. Norm		Facial Expression							Illumination Direction			Total
		Normal	Happy	Sad	Sleepy	Surprised	Wink	Glasses	Center	Left	Right	
LL_3	None	0.00	6.67	13.33	0.00	26.67	0.00	0.00	53.33	60.00	86.67	24.67
	HE	0.00	6.67	6.67	0.00	40.00	0.00	0.00	6.67	60.00	66.67	18.67
	ZN	0.00	6.67	6.67	0.00	40.00	0.00	0.00	13.33	40.00	73.33	18.00
	HE, ZN	0.00	6.67	13.33	0.00	40.00	0.00	0.00	6.67	60.00	66.67	19.33
HL_3	None	6.67	6.67	6.67	0.00	46.67	26.67	6.67	46.67	60.00	80.00	28.67
	HE	0.00	6.67	6.67	0.00	33.33	26.67	6.67	26.67	60.00	46.67	21.33
	ZN	6.67	6.67	13.33	0.00	40.00	26.67	6.67	33.33	66.67	60.00	26.00
	HE, ZN	6.67	6.67	13.33	0.00	33.33	13.33	6.67	40.00	66.67	53.33	24.00
LH_3	None	6.67	20.00	20.00	13.33	73.33	26.67	6.67	40.00	60.00	66.67	33.33
	HE	6.67	26.67	20.00	0.00	66.67	20.00	6.67	46.67	60.00	46.67	30.00
	ZN	6.67	13.33	20.00	6.67	80.00	20.00	6.67	26.67	53.33	40.00	27.33
	HE, ZN	6.67	13.33	20.00	6.67	80.00	13.33	6.67	26.67	46.67	20.00	24.00
HH_3	None	20.00	33.33	40.00	13.33	80.00	26.67	26.67	60.00	60.00	73.33	43.33
	HE	6.67	33.33	26.67	20.00	80.00	26.67	26.67	53.33	60.00	60.00	39.33
	ZN	13.33	26.67	26.67	13.33	80.00	20.00	20.00	60.00	60.00	53.33	37.33
	HE, ZN	6.67	26.67	26.67	0.00	80.00	20.00	20.00	46.67	53.33	40.00	32.00

We applied the multi-stream approach to the identification experiment on the Extended Yale Face Database B in section III-B using LL_2 and LH_2 scores and compared the identification performance for each of the illumination subset. Two illumination normalisation methods, ZN as well as HE followed by ZN was compared as shown in Fig. 3. The results reiterates that the LL subband is suitable for face recognition under control illumination while the LH subband is robust against significant changes in illumination. However, the fusion of the multiple feature representations could improve the accuracy by using appropriate weighting for the approximation and detail features. Based on these results, we argue for the need to have an adaptive fusion strategy, based on the face image sample quality instead of a using fixed weighting strategy.

VI. Conclusions and Future work

We have investigated the robustness of face recognition schemes that are based on different wavelet subbands against variations in lighting and variation in expression, with the aim of identifying the best fusion parameters for a multi-stream scheme. While the low frequency LL subband is a good feature representation under controlled lighting, the high frequency LH subband is robust against varying illumination conditions.

We have also conducted a limited number of experiments on simple fusion of multi-subbands which revealed that in some cases, fixed fusion parameters does not help in improving robustness in a consistent manner. These results motivate further investigation that should aim at developing an intelligent multi-stream face recognition scheme that is aware of the changes in illumination and would dynamically adapt the fusion parameters. Our future work will involve the investigation of face image sample quality measures that could be used for an adaptive fusion strategy.

VII. Acknowledgments

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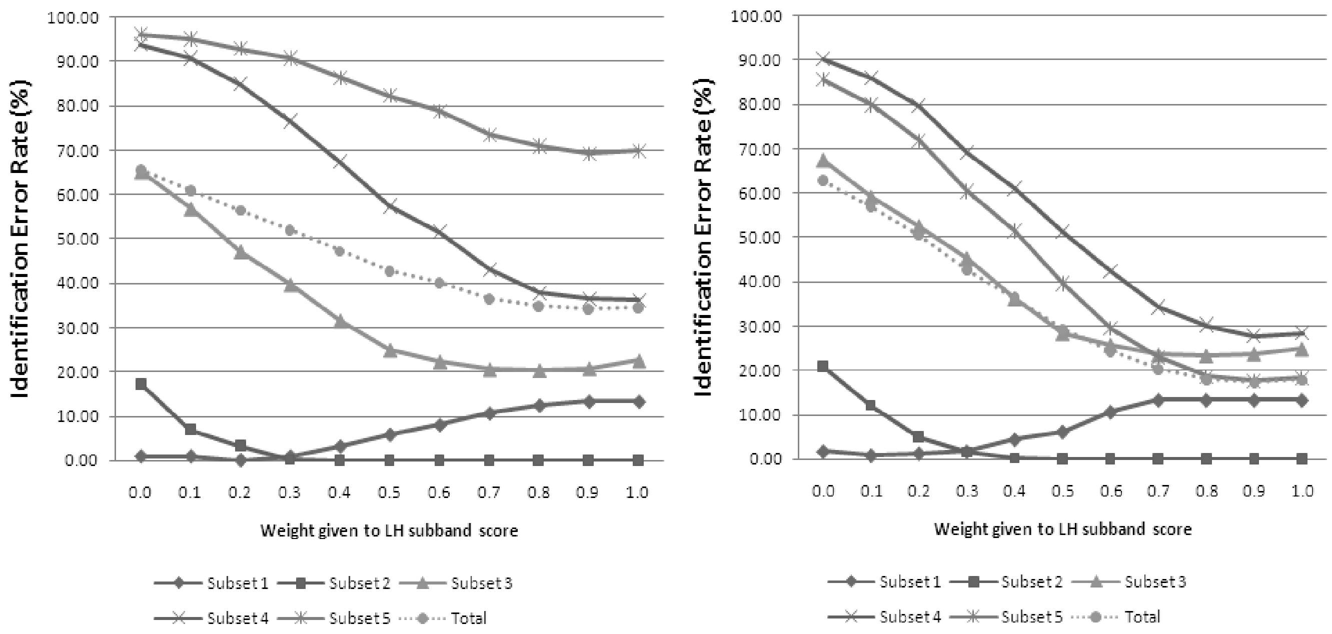

(a) Illumination Normalisation - ZN

(b) Illumination Normalisation - HE, ZN

Fig. 3: Extended Yale Face Database B: Identification error rates of illumination subsets using Multi-stream fusion approach (LL_2 and LH_2).

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