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Image Quality-based Adaptive Face Recognition

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***Abstract*—The accuracy of automated face recognition systems is greatly affected by intra-class variations between enrollment and identification stages. In particular, changes in lighting conditions is a major contributor to these variations. Common approaches to address the effects of varying lighting conditions include pre-processing face images to normalize intra-class variations and the use of illumination invariant face descriptors. Histogram equalization is a widely used technique in face recognition to normalize variations in illumination. However, normalising well-lit face images could lead to a decrease in recognition accuracy. The multiresolution property of wavelet transforms is used in face recognition to extract facial feature descriptors at different scales and frequencies. The high-frequency wavelet subbands have shown to provide illumination invariant face descriptors. However, the approximation wavelet subbands have shown to be a better feature representation for well-lit face images. Fusion of match scores from low- and high-frequency based face representations have shown to improve recognition accuracy under varying lighting conditions. However, the selection of fusion parameters for different lighting conditions remains unsolved. Motivated by these observations, this paper presents adaptive approaches to face recognition to overcome the adverse effects of varying lighting conditions. Image quality, measured in terms of luminance distortion in comparison to a known reference image, will be used as the base for adapting the application of global and region illumination normalisation procedures. Image quality is also used to adaptively select fusion parameters for wavelet-based, multi-stream face recognition.**

***Index Terms*—Quality Measures, Biometrics, Face Recognition, Illumination, Wavelet Transforms.**

I. Introduction

AUTOMATIC face image analysis has received a considerable amount of attention by the computer vision research community. Much progress has been made in developing robust algorithms and technology to transfer face image analysis from theory to successful automated identification systems for various applications. Continued research in this field is motivated by the need for convenient, reliable, efficient, pervasive and universal person identification methods as proof of entitlement to services, to counter identity theft, crime and international terrorism and as a tool in forensic investigations. The unobtrusive nature and the relative ease of obtaining face biometric samples from a distance, make face recognition systems very desirable. The availability of low-cost devices have enabled face identification systems to move from centralised control rooms to portable, handheld person identification systems. Such *fieldable* biometric systems are an ideal person identification tool for street/city policing, crowed control at large venues and border control.

However, automatic face recognition remains a challenging task when presented with uncooperative users as well as in uncontrolled environments. Intra-class variations due to changes in lighting condition, facial expressions and pose, occlusion and poor sensor quality cause identification errors. In the literature, there is a tendency to associate these variations as distortions from "standard" reference images, giving rise to measures of image quality [1], [2]. This paper is concerned with face recognition under varying illumination.

Discrete wavelet transforms (DWT); multiresolution image analysis tools that decompose an image into low- and high-frequencies at different scales, have been successfully used in a variety of face recognition schemes as a dimension reduction technique and/or as a tool to extract a multiresolution feature representation of a given face image [3], [4], [5], [6], [7], [8]. The multiresolution property of DWT enables one to efficiently compute a small-sized feature representation that is especially desirable for face recognition on constrained devices such as mobile phones.

The Authors [7], [9] have shown that the low-frequency approximation subband is a suitable face descriptor for recognition under controlled illumination but it is significantly affected by varying illumination. On the other hand, the detail subbands (e.g. horizontal and vertical face features) are reasonably robust against varying lighting conditions, but they are affected by geometrical changes such as varying facial expressions and pose. Accurate identification of faces, imaged under poor and uncontrolled lighting conditions, is still a challenge for both subband representations. This is commonly addressed by normalizing the illumination of both enrolled and test images. However, a recent study [9] shows that normalizing well-lit face images could lead to a decrease in identification accuracy and suggests that an adaptive approach to illumination normalisation could improve the identification accuracy of face recognition systems.

In [8], the Authors combine the use of low- and high-frequency subbands in face recognition by means of score level fusion. The identification accuracy of the fused, *multi-stream* approach is higher than that achieved by any of the individual subbands. However, the effective selection of fusion parameters remains unresolved.

Here we propose a quality-based adaptive approach to face recognition. The contribution of this paper is threefold: 1) an objective measure of illumination quality of a given face image is used to decide if the image should be pre-processed in order to normalize its illumination; 2) the *global* quality-based normalisation scheme is extended to a *region* quality-based approach to adaptive illumination normalisation; 3), the illumination quality measure is used as a means to adaptively select the weighting parameters of the fused, wavelet-based, multi-stream face recognition scheme.

The rest of the paper is organised as follows. Section. II presents a review of approaches to face recognition in the presence of varying lighting conditions. The illumination quality measure used in this study and the proposed adaptive approach to face recognition is presented in Sec. III. Section IV evaluates the suitability of the illumination quality measure for the proposed adaptive face recognition scheme. Recognition experiments are presented and discussed in Sec. V. Conclusions and future work are presented in Sec. VI.

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II. Literature Review

Changes in lighting conditions during enrollment and identification stages contribute significantly to intra-class variations of face images. Typical methods employed to address varying illumination conditions could be categorised as: *feature-based methods*, *generative methods* and *holistic 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 [10], [11]. Feature-based methods are known to be robust against varying illumination conditions. However, they rely on accurate face and facial feature point detection, which is a challenging task on its own right.

Generative methods [12], [13], [14], [15] have been proposed to address the problem of varying illumination based on the assumption of the Lambertian model. It has been 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 [16], [17]. Belhumeur and Kriegman [18] 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 (called the illumination cone) in the image space and that this illumination cone can be approximated by a low-dimensional subspace. Experimental results show that these generative methods perform well under varying illumination conditions. However, they require a number of training samples that represent extreme illumination conditions. It may be possible to acquire such images for certain applications (e.g. ID cards and physical access control systems), where individuals are cooperative, but not so for surveillance and counter terrorism related applications where only one or few images of an individual are available for training.

In holistic approaches, the entire face image is considered for face representation without taking into account any specific geometrical features of the face. 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, a face image is first linearly transformed into a low-dimensional subspace before extracting a feature vector. The most commonly used dimension reduction technique in face recognition is the Principal Component Analysis (PCA) [19]. PCA is known to retain intra-class variations due to changes in illumination. It has been demonstrated that leaving out the first 3 eigenfaces that corresponds to the 3 most significant eigenvalues could reduce the effect of variations in illumination [20]. 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, or the Linear Discriminant Analysis (LDA) which is used to maximize the ratio of the determinant of the *inter-class* scatter to that of *intra-class* scatter [20], [21]. Like generative approaches, the downside of the holistic approaches is that a number of training samples from different conditions are required to identify faces in uncontrolled environments.

A more common approach to address the effects of varying lighting conditions is to pre-process face biometric samples to normalize illumination, before extracting facial features for identification. Widely used normalisation techniques include histogram equalization (HE), histogram matching, gamma intensity correction and Quotient Image. These normalisation techniques can be applied to an image either globally or regionally. Shan et al. [22] proposed a region-based approach to illumination normalisation where an image is first partitioned into four regions. The selected normalisation technique (e.g. HE) is applied to each region separately (RHE). the region-based normalisation lead to higher identification accuracy than the traditional global normalisation.

It is commonly accepted that illumination normalisation techniques help to improve recognition accuracy [22], [23]. However, the improvements depend on the extent of variation in illumination present between enrolled and test images and are often not repeatable on different datasets [24], [7]. In a recent study [9], the Authors show that normalizing well-lit face images could lead to a decrease in identification accuracy and highlight the need for a quality-based, adaptive approach to illumination normalisation as an alternative to existing approaches where all images, irrespective of their lighting conditions, are normalized, prior to feature extraction.

This paper focuses on wavelet-based face recognition in the presence of varying illumination. A brief description of WTs and their use in face recognition is given below in Secs. A & B.

A. Wavelet Transforms

A wavelet transform (WT) hierarchically decomposes a signal into low- and high-frequency components, providing a multiresolution analysis of the signal. The Discrete Wavelet Transform (DWT) is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed efficiently [25], [26].

The most commonly used wavelet decomposition of an image, the one adopted here, is the pyramid scheme (also known as the non-standard decomposition). At a resolution level of k, the pyramid scheme decomposes an image I into $3k+1$ subbands (LL_k, HL_k, LH_k, HH_k, $\ldots$, HL_1, LH_1, HH_1), with LL_k, being the lowest-pass subband. The subbands LH_1 and HL_1, contain finest scale wavelet coefficients that get coarser with LL_k being the coarsest. The LL_k subband is considered as the k-level approximation of *I*.

B. Wavelet Transforms in Face Recognition

A subband of a wavelet transformed face image can be used as face feature descriptor [4], [5], [7]. Typically, subband coefficients (i.e. LL_k, HL_k or LH_k) are normalized by Z-score normalisation (ZN) in terms of its mean and standard deviation. The ZN has shown to improve the recognition accuracy, especially under varying illumination [7]. Two feature vectors, from the same stream, are typically compared by calculating a distance score and the subject's identity is classified according to the nearest-neighbour.

In [4], [5], WTs are used to reduce image dimension prior to using statistical dimension reduction techniques such as PCA and LDA. The wavelet-based schemes are computationally efficient and their identification accuracy is comparable, if not better than the PCA and LDA only approaches [5], [24]. The advantage of using only the wavelet coefficients as the feature representation over methods such as PCA and LDA is that the wavelet only approach does not require a training stage to create a low-dimensional subspace.

Different decomposition levels and/or wavelet filters yield different face feature vectors, giving rise to different face recognition schemes and provide opportunities for a multi-stream (multi-channel) identification. In the multi-stream approach [8], [7], a face image is represented by multiple feature vectors at a given scale (e.g. LL- and LH-subbands). Two images are compared by first calculating a distance score for each subband representation, followed by a score fusion which can be performed by calculating a weighted average of the scores. The fused score is then used to classify the identity of the individual. The selection of fusion-weights is an important task as it influences the accuracy of the system. This paper presents an adaptive approach to select fusion-weights based on illumination quality of the given probe image.

III. Image Quality-based Adaptive Face Recognition

Real-time computation of a quantitative, objective image quality measure is an essential tool for biometric-based identification applications. Such measures can be used: as a quality control to accept, reject or reacquire biometric samples; as quality-based processing to select a biometric modality, algorithm and/or system parameters; and as confidence estimators of reliability of decision.

This study investigates the use of an image quality measure as a base for an adaptive approach to face recognition in the presence of varying illumination. Naturally, the illumination quality of a given face image is to be defined in terms of its luminance distortion in comparison to a known reference image. The mathematically defined quality measure proposed by Wand and Bovik [27], called the *universal image quality index* (*Q*) incorporates the necessary ingredients that fits our needs. The Q aims to provide meaningful comparisons across different types of image distortions by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion and contrast distortion. Here, the luminance distortion factor of *Q* is used to measure global or regional illumination quality of images. This will be called the *luminance quality index (LQ)*.

A. Universal Quality Index

Let $x = \{x_i | i = 1, 2, \ldots, N\}$ and $y = \{y_i | i = 1, 2, \ldots, N\}$ be the reference and the test images, respectively. The universal quality index in [27] is defined as

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]}, \tag{1}$$

where

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i,$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N} x_i - \bar{x}^2, \qquad \sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N} y_i - \bar{y}^2,$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})$$

Statistical features in Eq. 1 are measured locally to accommodate space variant nature of image quality and then combine them together to a single quality measure for the entire image. A local quality index Q_j is calculated by sliding a window of size $B \times B$, pixel-by-pixel, from top-left corner until the window reaches the bottom-right corner of the image. For a total of M steps, the overall quality index is given by

$$Q = \frac{1}{M}\sum_{j=1}^{M} Q_j \tag{2}$$

B. Global and Regional Luminance Quality Index

The universal quality index *Q* can be written as a product of three components:

$$Q = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \cdot \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \cdot \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_x^2} \tag{3}$$

The luminance quality index (LQ), which is the luminance distortion factor in *Q* is defined as

$$LQ = \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \tag{4}$$

With a value range [0, 1], the LQ measures how close the mean luminance is between x and y. LQ equals 1, if and only if $\bar{x} = \bar{y}$. The window size used in this paper is the default 8×8 pixels.

Global Luminance Quality (*GLQ*) is calculated similarly to the calculation of a single *Q* value in Eq. 2. *Region Luminance Quality* (*RLQ*) represents the luminance quality of a region of an image that resulting from a 2×2 partitioning of the image. The LQ of a region of an image is calculated by partitioning the local quality index map (resulting from the block-wise calculation of Eq 4) into 4 regions.

C. Image Quality-based Adaptive Normalization

The proposed image quality-based adaptive normalisation works by first calculating the *GLQ* of a given image and normalising only if its *GLQ* is less than a predefined threshold.

Inspired by the work of Shan et al. [22] and the fact that the images tend to exhibit regional variation in image quality as a result of the direction of the light source, the *global* quality-based adaptive normalisation is extended by introducing a *region* quality-based adaptive normalisation. A region of an image is normalized only if the region's luminance quality (RLQ) score is lower than a predefined threshold.

The commonly used histogram equalization (HE) is adopted here for illumination normalisation. Hence, the two proposed approaches to adaptive normalisation will be referred to as global quality-based HE (GQbHE) and region quality-based HE (RQbHE). The threshold can be determined empirically depending on the objectives of the applications under consideration.

D. Image Quality-based Adaptive Fusion

The idea is to select fusion weight parameters to adaptively suit the condition of probe images. The quality-based fusion (QbF) works by first calculating LQ of the input image and if its LQ score is higher than a predefined fusion threshold, then the approximation subband is given a higher weight than the detail subbands during score fusion. If the LQ score is less than the threshold, the approximation subband gets a very low weight (to indicate that the face descriptor is unreliable for the given image).

IV. Evaluation of Luminance Quality Index

A. Evaluation Data

A.1 Extended Yale Face Database B

The Extended Yale Face Database B (Extended YaleB) [13], [15] consists of 38 subjects, each imaged under 64 illumination conditions in frontal pose, capturing a total of 2414 images. These images can be divided into 5 illumination subsets according to the angle θ of the light-source with respect to the optical axis of the camera. The number of images, the range of the angle θ and an example image of each subset are shown in Fig. 1. The 168×192 pixel cropped images in the database are resampled to a fixed size of 128×128 pixels for the experiments reported in this paper.

[Fig. 1 about here.]

A.2 AT&T (ORL) Face Database

The AT&T (formerly ORL) [28] database consists of 40 subjects, each with 10 face images captured against a dark homogeneous background. Images of some subjects were captured at different times. Variations in pose (frontal images, with tolerance to some side movements), facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses) are captured in this collection of face images. Sample images of the database are shown in Fig. 2. The original 92×112 pixel images are resampled to 128×128 pixels for the experiments in this paper. The AT&T database is used to find an suitable threshold for the adaptive normalisation as well as to demonstrate, that the reference image used to calculate the illumination quality of a face image can be selected independently of the gallery images of a face recognition system.

[Fig. 2 about here.]

A.3 The Reference Image

The calculation of the LQ index for a given face image relies on the use of a reference image, preferably one that is independent of subject and gallery face images. The reference image used the evaluation of LQ index as well as for face recognition experiments is the average face image of the 38 individual faces, each one captured in frontal pose and under direct illumination (i.e. the average image of the P00A+000E+00 image of each subject). The same 38 images are commonly used as gallery images for face recognition experiments using the Extended Yale B database. The yale reference image and a sample of individual faces are shown in Fig. 3a.

[Fig. 3 about here.]

B. Evaluation

The illumination condition of each image and of each subset of the Extended Yale B database is well-defined. In order to demonstrate the appropriateness of LQ index for our purposes, we determined the distribution of *GLQ* values in different subsets of this database. The subject-independent reference image (see Fig 3a) based on Extended YaleB data is used to calculate luminance quality scores. The P00A+000E+00 image of each subject was excluded in the evaluation since these are used to calculate the reference image. The distribution of *GLQ* scores of the images in each illumination subset is shown in Fig. 4a.

A close examination of the distributions reveals that 60% of the 225 images in subset-1 have a *GLQ* score of 0.95 or higher, compared to only 19% of the images of subset-2 with such high illumination quality. 91% and 73% of the images of subsets-1&2 respectively, have a *GLQ* score of 0.9 or higher. This demonstrates that the *GLQ* measure correctly quantifies the illumination quality of images in subsets 1&2 to be very near to that of the reference image, while also recognising that the images in subset-1 are nearer to the reference image than the images in subset-2. Only 4% of images in subset-3 have a *GLQ* score of 0.9 or higher, while 33% of its images have a *GLQ* value range of [0.8, 0.9]. This indicates a noticeable variation in illumination of subset-3 images. Nearly 82% of the images of subset-4 have a *GLQ* value less than 0.6, while the highest *GLQ* score of its images is only 0.76. Nearly 45% of the images in subset-5 scored a quality value less than 0.3, while its highest *GLQ* score is only 0.59. This reflects the poor illumination quality of the images in subsets 4&5 due to the extreme changes in illumination direction (horizontally and/or vertically) with regard to the camera axis (see Fig. 1 for details).

The above evaluation demonstrates that the luminance quality index, LQ is a suitable illumination quality estimator for face image samples. To determine if the choice of the reference image: the average image of the 38 subjects in the database itself; influenced the above evaluation, the experiment was repeated using the reference image based on face images from the AT&T database. The reference image (see Fig. 3c) is the average image of the first image of each of the 40 subjects of the AT&T database (see Fig. 3d for example face images).

The distribution of *GLQ* scores of images in Extended YaleB database, based on AT&T reference image is shown in Fig. 4b, and it is similar to that of the reference image calculated from Extended YaleB database. This shows that the reference image used to calculate illumination quality is independent of enrolled images and subjects.

The LQ index is further evaluated using images from the AT&T, which consists of well-lit face images. However, variations in pose and face size are a characteristic of the images in this database. The distribution of *GLQ* scores for 360 images of the AT&T database is presented in Fig. 4c and it confirms that all images of the AT&T database have a very high illumination quality and shows that the LQ measure is unaffected by the pose and size variations present in the database.

The global luminance quality of nearly all the images from subset 1&2 is higher than 0.8, while it is less than 0.8 for all the images from subset 4&5. Taking these factors into account, a sensible threshold that could distinguish between images with good illumination and images with poor illumination is an LQ score of approximately 0.8.

[Fig. 4 about here.]

B.1 Global Vs. Region Luminance Quality

The previous section demonstrated the suitability of using the global luminance quality index as an objective measure of illumination quality of face images. However, in real-life scenarios, variations in illumination between enrolled and test images could be confined to a region of the face image due to the changes in the direction of the light source or pose. Therefore, it is sensible to measure the illumination quality on a region-by-region basis.

The distribution of *GLQ* , and *RLQ* scores are shown in Fig. 5. The analysis demonstrates that the *RLQ* measure is a better representation of the illumination quality of a face image than the *GLQ* as it identifies individual regions that have either good or poor illumination quality. This is especially reflected in the differences of the distribution of *GLQ* and *RLQ* scores of subsets 3,4&5.

[Fig. 5 about here.]

C. Effect of Illumination Normalization on Image Quality

In order to determine the effect of illumination normalisation by HE on image quality, the evaluation in Sec. B is repeated for the Extended YaleB database, after normalizing all the images by the conventional HE as well as the proposed global- and region-based adaptive normalisation. Two example images, their global and region luminance quality scores, before and after normalisation, are shown in Fig. 6. The distribution of *GLQ* scores, before and after normalizing all the evaluation images in Extended YaleB are shown in Fig. 7.

The distribution of quality scores for subset 1&2 shows that HE has an adverse effect on well-lit face images. This could be a result of the noise that HE process adds to images. The quality scores demonstrate that HE is still a useful illumination normalisation tool when there is a significant variation in lighting between the enrolled and test images (i.e. subsets-4&5 and to some extent, subset-3) as it improves illumination quality of these images. However, the most improvement is achieved by the region quality-based adaptive HE (RQbHE).

[Fig. 6 about here.]

[Fig. 7 about here.]

V. Experiments and Discussions

The accuracy of the proposed illumination quality-based face recognition scheme is tested using the Extended YaleB database. Firstly, the effect of adaptive normalisation on recognition accuracy is investigated. This is followed by an evaluation of the proposed adaptive multi-stream fusion scheme for wavelet-based face recognition.

The identification experiment setting adopted here is the same as in [9]. Only the P00A+000E+00 image of each of 38 subject is used for the gallery and the remaining 2376 images are used as probes to test the accuracy of the identification system. The Haar wavelet filter is used for the DWT and all subband coefficients are normalised by ZN. The CityBlock distance is used to calculate a distance score between a probe and a gallery image.

A. Illumination Quality-based Adaptive Normalization

Based on the earlier analysis of the distributions of LQ scores for each illumination subset (see Sec. B), an LQ score threshold of 0.8 is selected for the global and regional quality-based HE. Identification error of different wavelet-based feature representations, with different approaches to illumination normalisation are shown for each illumination subset in Tab I.

[Table 1 about here.]

Compared to the traditional use of HE, the proposed GQbHE further decreased the overall identification error by a further 1-2%, across different feature representations. More significantly, unlike HE, the use of GQbHE did not result in a noticable increase in identification error that is achieved by original images. The proposed RQbHE further reduced the identification error, with LH_2 representation being the best overall feature descriptor, briging the identification error down to almost 10%. As these results indicate, the lowest overall recognition error rate, as well as the lowest error rate of majority of the illumination subsets are achieved by using the proposed region quality-based adaptive normalisation.

The experiments confirms the findings in [9] that the LL-subband is the most robust feature representation for face recognition under controlled lighting conditions, while LH and HL-subbands are the better option for face recognition in the presence of varying illumination. Hence the motivation for an image quality-based adaptive approach to multi-stream face recognition, where during recognition, the selection of weighting parameters of subband scores is to be determined by the illumination quality of the given probe image. Sec. B evaluates the proposed image quality-based adaptive fusion approach for wavelet-based multi-stream face recognition.

B. Quality-based Adaptive Fusion for Face Recognition

The multi-stream approach to face recognition [8] is tested on the Extended Yale Database B with the same gallery and probe images as in the previous experiments. Illumination of the face images is normalised by the proposed region quality-based HE with a luminance quality threshold of 0.8. The identification error rates based on the fusion of LL_2 with LH_2 subband and LH_2 with HL_2 subband using fixed weights are given in Tabs. II and III respectively, followed by the error rates for the proposed illumination quality-based adaptive fusion approach in Tab. IV. For the adaptive fusion, if the LQ of a probe image is greater than 0.9, the weight given to its LL_2 subband score, W_{LL}, is 0.7. Else, W_{LL} is set to 0. The last row of Tab. IV represents the fusion of distance scores from 3 subbands (i.e. LL, LH and HL). In this case, LH_2 and HL_2 scores were fused by giving an equal weight to both scores. The resulting score is then fused with the LL-subband score according to the proposed quality-based fusion.

The results in Tabs. II and III show that the overall identification accuracy of the multi-stream approach is higher than any of the individual subbands representations. However, this depends on the selection of weights as well as the choice of subbands. On the surface, it appears as if the LL_2 subband makes little or no contribution to improve the identification accuracy. However, a closer examination of the results in Tab. II shows that the LL_2 subband is the most suitable feature representation for probe images of subset-1.

The results for the proposed approach (in Tab. IV) shows an improvement in recognition accuracy when LL- and LH-subband scores are fused using adaptive weights selected by measuring the probe image quality. The highest identification accuracy is achieved by fusing the similarity scores of LH- and HL-subbands by giving an equal weight to both subbands and by combining LL-subband score with the adaptive weights. With a single gallery image per enrolled subject, these results are comparable to or if not better than most other face recognition schemes reported in the literature for the Extended Yale Database B [13], [22], [15].

Overall, the experimental results demonstrate the viability of using the luminance quality index to objectively select the weighting parameters for the wavelet-based multi-stream face recognition scheme. The adaptive fusion strategy could be further improved by incorporating other aspects of face biometric sample quality (e.g. changes in expression and pose).

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

VI. Conclusions and Future Work

This paper is the first part of a project to develop image quality-based adaptive approaches to face recognition. We investigated the challenges of face recognition in the presence of extreme variation in lighting conditions. The luminance component of the already known Universal Quality Index, is used to associate a quantitative quality value to an image that measures its luminance distortion in comparison to predefined reference image. This measure is called the Luminance Quality Index (LQ), and was used to develop global and region quality-based adaptive illumination normalisation procedures. Using the well know Extended Yale Database B, we demonstrated the effectiveness of the proposed image quality-based illumination normalisation schemes in face recognition compared to the traditional approach to illumination normalisation.

Finally, the observation that the wavelet-based multi-stream recognition scheme, developed previously, has no objective means of selecting fusion parameters and that it performed differently for face images captured with different lighting conditions has led to developing of a new adaptive approach to face recognition. The illumination quality-based adaptive fusion approach works by adapting the weights given to each subband according to the LQ values of the probe image, and again this led to significantly improved identification accuracy rates.

Our future work will investigate other aspects of face image quality such as facial expression, pose and occlusion. Such objective quality measures are to be used in a fully adaptive face recognition system, which will be able to select the most suitable gallery images, an appropriate face feature representation (or a combination of them), a classification algorithm for a given probe image and then be able to predict the confidence of the system's decision.

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List of Figures

Extended Yale Database B				
Subset-1	Subset-2	Subset-3	Subset-4	Subset-5
263	456	455	526	714
$\theta < 12^\circ$	$20^\circ < \theta < 25^\circ$	$35^\circ < \theta < 50^\circ$	$60^\circ < \theta < 77^\circ$	$85^\circ < \theta < 128^\circ$

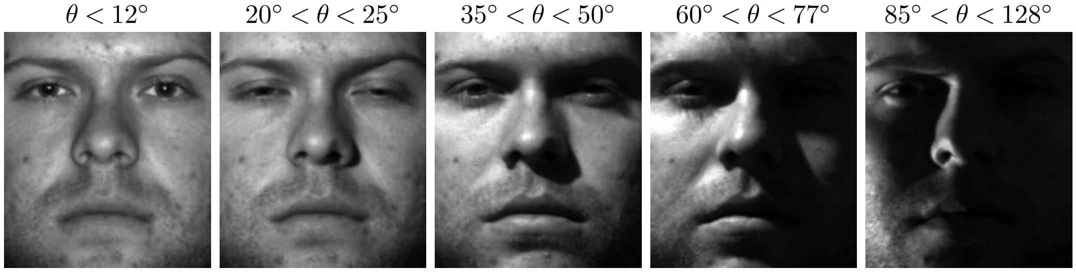


Fig. 1: Illumination subsets of the Extended Yale Face Database B

figure

Fig. 2: Example images of the AT&T Database

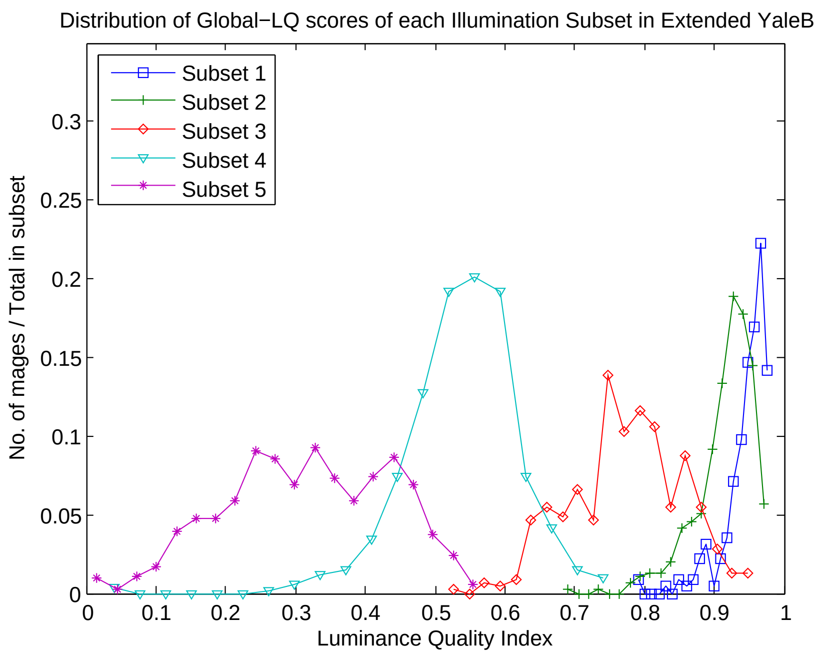
figure

(a) Reference (b) Example gallery images from the Extended Yale B database

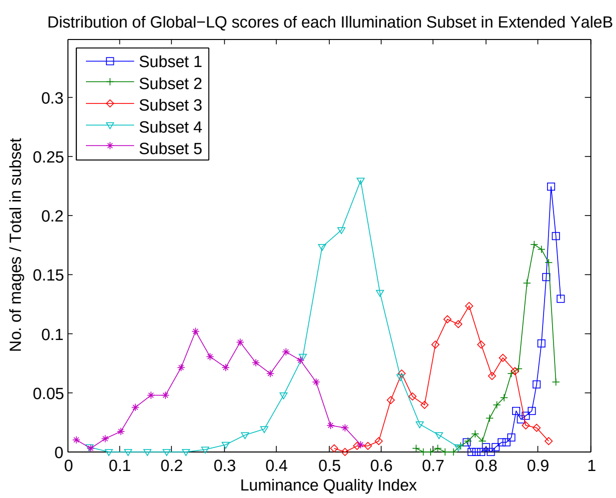
(c) Reference (d) Example gallery images from the AT&T database

Fig. 3: The reference face images used to calculate LQ and a sample of gallery images from each database

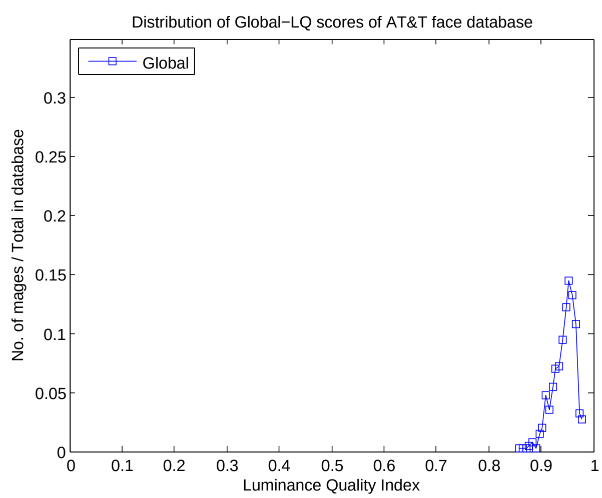
figure



(a) Reference, Evaluation - Extended YaleB



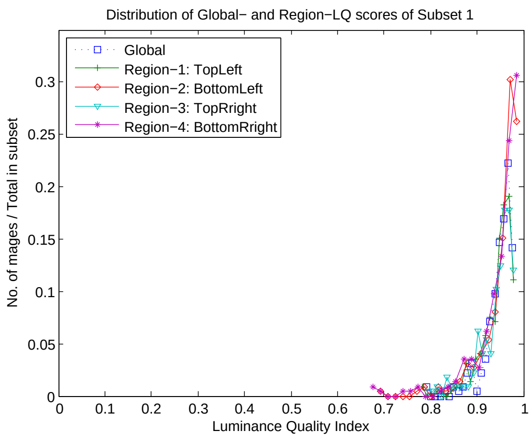
(b) Reference - AT&T; Evaluation - Extend YaleB



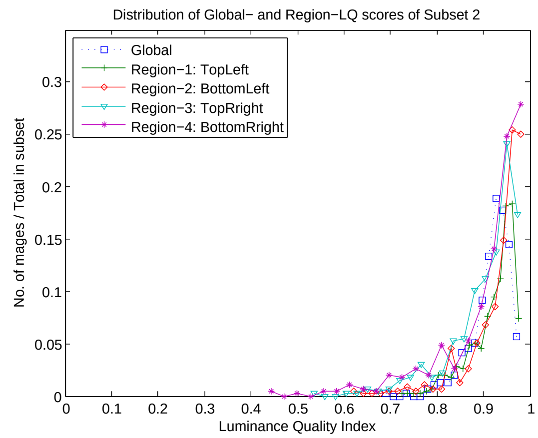
(c) Reference & Evaluation - AT&T

Fig. 4: Distribution of global quality index scores for images in Extended YaleB and AT&T

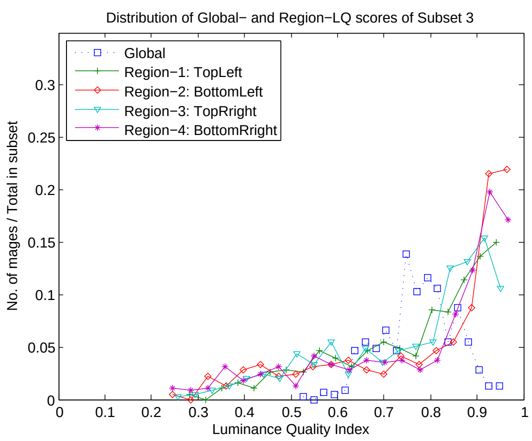
figure



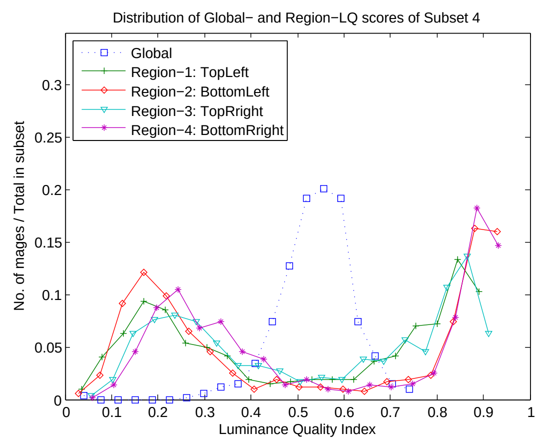
(a) Global Vs. Region LQ: subset-1



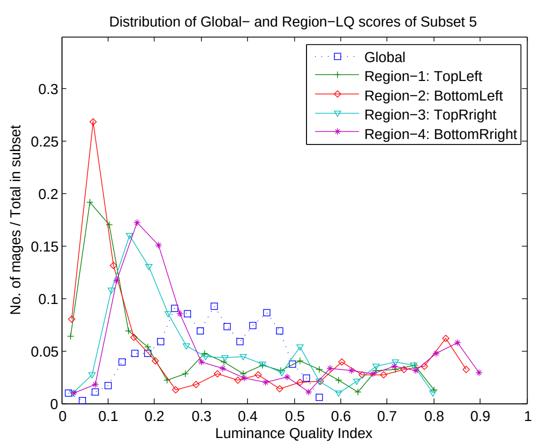
(b) Global Vs. Region LQ: subset-2



(c) Global Vs. Region LQ: subset-3

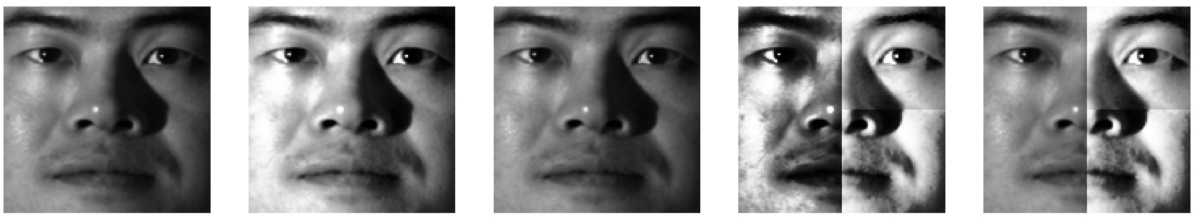


(d) Global Vs. Region LQ: subset-4



(e) Global Vs. Region LQ: - subset-5

Fig. 5: Distribution of global and region luminance quality index scores of the five illumination subsets of the Extended Yale Face Database B
figure



(a) Original (b) HE (c) QbHE (d) RHE (e) RQbHE

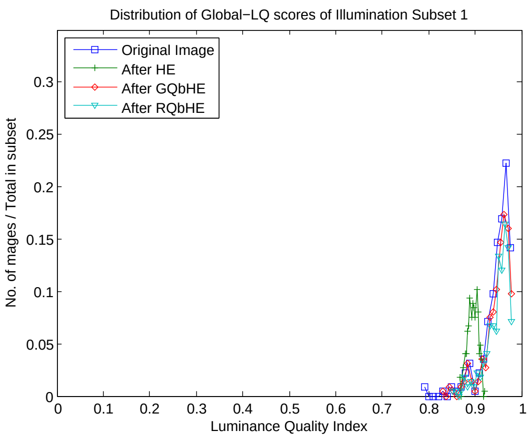
(a) Original		(b) HE		(c) QbHE		(d) RHE		(e) RQbHE	
0.83		0.85		0.83		0.86		0.91	
0.93	0.71	0.86	0.79	0.93	0.71	0.85	0.88	0.93	0.88
0.94	0.73	0.87	0.86	0.94	0.73	0.83	0.88	0.95	0.88

(f) Original (g) HE (h) QbHE (i) RHE (j) RQbHE

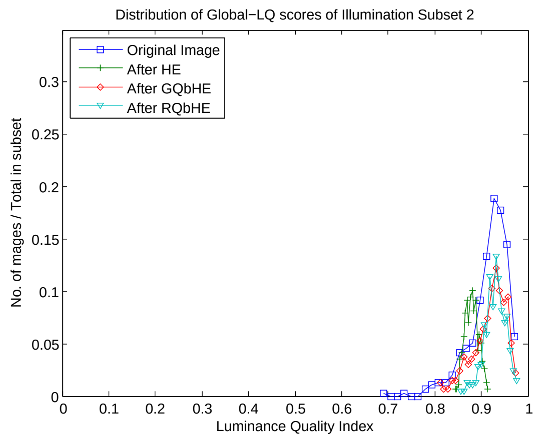
(f) Original		(g) HE		(h) QbHE		(i) RHE		(j) RQbHE	
0.54		0.81		0.81		0.86		0.89	
0.22	0.85	0.82	0.83	0.82	0.83	0.88	0.79	0.88	0.85
0.18	0.91	0.75	0.84	0.75	0.84	0.91	0.85	0.91	0.91

Fig. 6: Global and Regional Luminance Quality scores of original and normalised face images

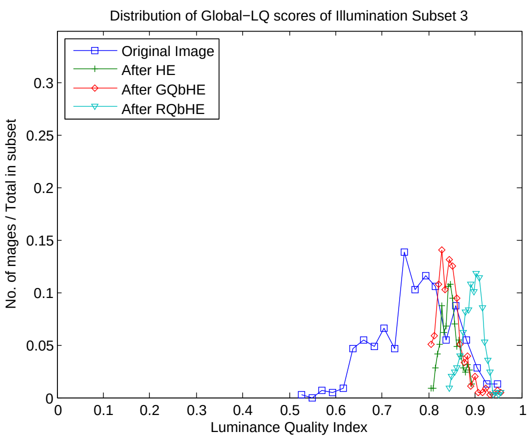
figure



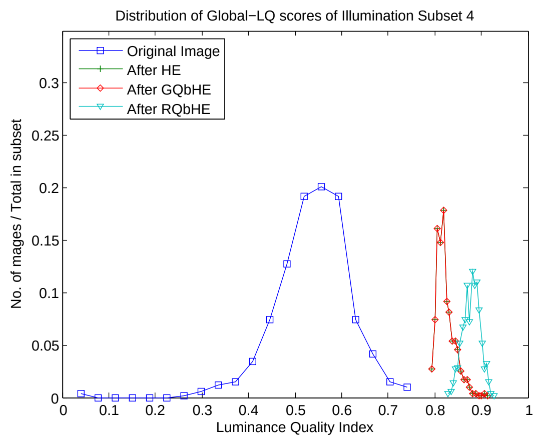
(a) Subset-1



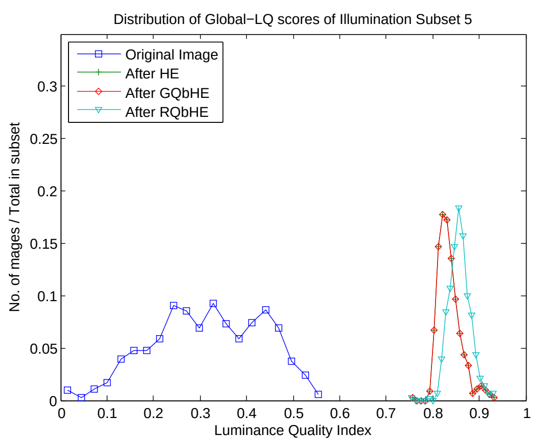
(b) Subset-2



(c) Subset-3



(d) Subset-4



(e) Subset-5

Fig. 7: Distribution of luminance quality index scores of the five illumination subsets of the Extended Yale Face Database B before and after illumination normalisation
figure

List of Tables

TABLE I: Identification error rates for the Extended Yale Database B based on different illumination normalisation techniques table

Extended Yale Database B							
Wavelet subband		Identification Error Rates (%)					
/Pre-process		Set 1	Set 2	Set 3	Set 4	Set 5	Total
LL_1	None	1.33	15.35	61.98	92.40	95.80	64.18
	HE	1.78	17.32	65.27	88.97	82.77	60.56
	QbHE	1.33	15.79	62.64	88.97	81.23	59.26
	RHE	0.00	0.00	22.64	73.00	79.55	44.40
	RQbHE	2.67	13.16	34.51	70.34	73.11	46.93
LL_2	None	1.33	20.18	64.40	92.59	96.22	65.74
	HE	2.67	22.37	67.47	89.92	84.73	62.84
	QbHE	1.33	20.39	64.62	89.92	83.47	61.41
	RHE	0.00	0.00	25.93	77.00	81.09	46.38
	RQbHE	3.56	17.54	38.24	73.57	75.91	50.13
LH_2	None	10.67	0.00	15.16	30.42	68.21	31.14
	HE	11.56	0.00	19.56	17.68	11.06	12.08
	QbHE	10.67	0.00	15.38	14.83	11.90	10.82
	RHE	12.44	0.00	17.80	14.64	10.36	10.94
	RQbHE	10.67	0.00	14.95	14.45	10.36	10.19
HL_2	None	9.33	0.88	15.82	61.41	93.70	45.83
	HE	12.00	0.88	16.70	33.27	54.34	28.20
	QbHE	9.33	0.88	14.51	34.41	56.02	28.28
	RHE	12.44	0.88	16.26	34.41	56.72	29.12
	RQbHE	9.33	0.88	15.16	39.35	61.62	31.19

TABLE II: Identification error rates for the Extended Yale Database B for LL and LH-based multi-stream subband fusion approach table

Extended Yale Database B							
LL_2 + LH_2		Identification Error Rates (%)					
W_{LL}	W_{LH}	Set 1	Set 2	Set 3	Set 4	Set 5	Total
1.0	0.0	3.56	17.54	38.24	73.57	75.91	50.13
0.9	0.1	2.22	7.68	30.11	65.78	70.73	43.27
0.8	0.2	2.22	3.29	22.64	57.03	63.31	36.83
0.7	0.3	1.33	0.44	18.46	46.2	51.26	29.38
0.6	0.4	2.22	0.00	15.16	36.12	38.94	22.81
0.5	0.5	3.56	0.00	14.73	27.95	27.17	17.51
0.4	0.6	4.89	0.00	13.41	19.96	18.91	13.13
0.3	0.7	5.78	0.00	12.97	17.87	14.57	11.36
0.2	0.8	8..00	0.00	14.07	15.59	11.62	10.4
0.1	0.9	8.89	0.00	13.85	13.5	10.36	9.6
0.0	1.0	10.67	0.00	14.95	14.45	10.36	10.19

TABLE III: Identification error rates for the Extended Yale Database B for LH and HL-based multi-stream subband fusion approach table

Extended Yale Database B Identification Error Rates							
LH_2 + HL_2		Identification Error Rates (%)					
W_{LH}	W_{HL}	Set 1	Set 2	Set 3	Set 4	Set 5	Total
1.0	0.0	10.67	0.00	14.95	14.45	10.36	10.19
0.9	0.1	8.44	0.00	14.73	12.55	9.52	9.26
0.8	0.2	7.56	0.00	12.75	12.74	9.38	8.8
0.7	0.3	5.78	0.00	11.65	11.41	9.8	8.25
0.6	0.4	5.33	0.00	9.23	10.65	11.76	8.16
0.5	0.5	4.44	0.00	7.47	10.65	13.17	8.16
0.4	0.6	3.11	0.00	7.47	11.98	18.49	9.93
0.3	0.7	2.22	0.00	8.13	15.78	24.37	12.58
0.2	0.8	5.33	0.00	9.23	19.96	36.97	17.8
0.1	0.9	7.11	0.00	12.75	29.09	51.68	25.08
0.0	1.0	9.33	0.88	15.16	39.35	61.62	31.19

TABLE IV: Identification error rates of the Extended Yale Database B using the proposed image quality-based adaptive fusion approach
table

Extended Yale Database B							
Feature	Subband	Identification Error Rates (%)					
		Set 1	Set 2	Set 3	Set 4	Set 5	Total
Single stream	LL_2	3.56	17.54	38.24	73.57	75.91	50.13
	LH_2	10.67	0.00	14.95	14.45	10.36	10.19
	HL_2	9.33	0.88	15.16	39.35	61.62	31.19
Adaptive Fusion	LL_2+LH_2	2.22	0.00	14.73	14.45	10.36	9.34
	LL_2+LH_2+HL_2	1.78	0.22	7.47	10.65	13.17	7.95