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Ing. Heydi Méndez-Vázquez,
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RT_026 marzo 2010

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Abstract. Variations in illumination are one of major limiting factors for face recognition system performance. Here, a new photometric face normalisation method based on the local Discrete Cosine Transform is presented. The proposed method is compared with the best state of the art preprocessing technique producing equally good results. Although the obtained error rates in the tested database are very similar, we show that both methods classify the images different and their fusion improve the results. Based on this, a method which combines both preprocessing techniques is presented and it outperforms the results obtained with the methods working individually in face recognition under varying lighting conditions. Although the performance is degraded on good quality images, on which the best results are obtained when no preprocessing technique is applied. Then, a method to determine if a face image is affected or not by illumination is also presented in this work and it is used in a general framework for face recognition, in which the combination of preprocessing methods is only applied when the image is classified as bad illuminated while is directly classified if not, obtaining in this way very good results for both cases, permitting to apply this framework when the illumination conditions are variable and unknown.

Keywords: Face Recognition, Illumination Variations, Photometric Normalisation, Local DCT.

Resumen: Las variaciones de iluminación es uno de los principales problemas presentes en el reconocimiento automático de rostros. En este trabajo se presenta un nuevo método de normalización fotométrica para imágenes de rostros basado en el uso local de la transformada discreta del coseno. El método propuesto es comparado con en el mejor método de preprocesamiento reportado en la literatura, obteniéndose resultados igualmente buenos. A pesar de que los porcientos de error son muy similares en la base de datos utilizada para pruebas, se muestra que ambos métodos clasifican las imágenes de manera diferente y la fusión de ellos mejora los resultados. Basado en esto, se presenta un nuevo método combinando ambas técnicas de preprocesamiento que mejora los resultados individuales en el reconocimiento de rostros en presencia de variaciones de iluminación. No obstante los resultados empeoran cuando las imágenes no presentan problemas de iluminación, en cuyo caso los mejores resultados son obtenidos cuando no se aplica ninguna técnica de preprocesamiento. Se presenta entonces en este trabajo un método para determinar si una imagen de rostro está afectada o no por la iluminación, el cual es incorporado a un esquema general para el reconocimiento de rostros en el cual, la combinación de los métodos de preprocesamiento sólo es aplicada cuando se determina que una imagen está afectada por la iluminación, mientras que esta es directamente clasificada cuando no presenta afectación, obteniéndose de esta forma los mejores resultados para ambos casos y permitiendo aplicar este esquema cuando las condiciones de iluminación son variables y desconocidas.

Palabras clave: reconocimiento de rostros, variaciones de iluminación, normalización fotométrica, DCT local.

1 Introduction

Face recognition is one of the most used biometric techniques. Although a great number of algorithms have been developed, face recognition is still an open and very challenging problem, especially in real outdoor applications where the imaging conditions are too variable. In different face recognition studies it has been shown that variations in lighting is one of major limiting factors for face recognition system performance [1]. To cope the problem of face recognition under illumination variation, several algorithms have been proposed. They can be divided in three main categories: pre-processing, invariant feature extraction and face modeling.

Pre-processing methods normalise the input face image trying to obtain a stable representation of the face under different lighting conditions. The second approaches attempt to extract facial features invariant to illumination variations. The third ones, also called generative models, try to model the face image under all possible illumination conditions. The pre-processing and face modeling methods are the most popular ones. Nevertheless, the generative models usually require a large number of training images while the first ones are very easy to apply in real scenarios and do not need any comprehensive training data. There are a lot of pre-processing methods proposed in the literature. They include well known approaches like Histogram Equalization, Gamma Intensity Correction, Homomorphic Filtering [2], Multi-scale Retinex [3] and Anisotropic Smoothing proposed by Gross and Brajovic [4]. Most of these kind of methods can be used either in a holistic or local way, however in [5] it is shown that local normalisation methods are more invariant to illumination variations than global ones.

In this work we present a new photometric normalisation method based on the local Discrete Cosine Transform (DCT) in the logarithm domain. The photometric normalised face images are obtained subtracting a compensation term to the original image. The compensation term is estimated smoothing the image constructed using the low-frequency coefficients extracted from the local DCT of the original image in the logarithm domain. The proposed method was tested on the XM2VTS face database and compared with some of the state of the art photometric normalisation methods. Our method (LDCT) and the Processing Sequence(PS) proposed by Tan and Triggs in [6] showing the best performance up to now achieved very similar error rates. Both methods were analysed in depth and differences in their performance were found, so we proposed to use them together to improve the results for face recognition under varying lighting conditions. The combination method improves the results obtained by the individual ones in face images with illumination problems, but the results for images with no illumination affectation were degraded when the preprocessing method is applied. A quality measure for determine when the face images are affected or not by illumination is also presented in this work, which permits to establish a general framework for face recognition with a better overall performance. This framework was presented and evaluated obtaining the best results in both cases: when the images are affected by illumination variations as well as when they not.

This paper is organized as follows. Section 2 explains the experimental setup that was used during this work. Section 3 presents the new photometric normalisation method proposed and describes the experiments conducted in order to select the best parameters for it. Section 4 compares the proposed method with the best state of the art photometric normalisation method and describes how to combine them to obtain a better performance in front of illumination variations. Section 5 presents the method to determine the quality of a face image regards to illumination and describes the experiments conducted in order to select the best parameters for it. Section 6 presents the proposed general framework and reports on the experimental results. Finally, Section 7 concludes the paper.

2 Experimental Setup

The XM2VTS [7] frontal face databases was used to evaluate the performance of the different methods proposed and evaluated in this work. The XM2VTS database contains 2360 images of 295 subjects, captured in 4 different sessions. To conduct the experiments the Lausanne protocol is used. This protocol splits the database into Training set composed of images of 200 subjects as clients, Evaluation set(Eval) with images of the same subjects as clients and of 25 additional subjects as imposters, and Test set with 70 subjects as imposters. Training, Evaluation and Test sets are composed by images under controlled illumination conditions, there is an additional Dark Set which contains images of the same subjects but with varying lighting conditions. There are two configurations of the Lausanne Protocol. Here, we use Configuration I, in which the images for training and evaluation are from the first three sessions of acquisition, for training, 3 images per person are used, and the number of accesses or comparisons in each of the rest subsets can be summarized as:

	Eval	**Test**	**Dark**
Clients accesses	600	400	800
Imposters accesses	40000	112000	56000
Total accesses	40600	112400	56800

The Equal Error Rate (EER) is the point in which the False Rejection Rate (FRR) is equal to the False Acceptance Rate (FAR). The value obtained by the classification method in this point for the Evaluation set is used as a threshold for the decision of accept or reject the face images in the Test and Dark sets. On the other hand, the Total Error Rate (TER) is the sum of the FRR and the FAR, the lower this value, the better the recognition performance.

In our experiments, all face images were closely cropped to include only the face region and the extracted face images were geometric normalised by the centres of the two eyes with the provided positions to be 120×144 (width $\times$ height) pixels in size.

2.1 Face Description and Classification

The Local Binary Pattern (LBP) operator is used for representing and classifying the normalised face images. The original LBP operator, introduced by Ojala *et al.* in [8], labels each pixel of an image with a value called LBP code, which corresponds to a binary number that represents its relation with the $3x3$-local neighbourhood. Different extensions of the original operator have appeared and used for face recognition afterwards [9].

The first and more extended use of the LBP operator for face recognition was presented in [10]. In this case, a neighbourhood of 8 pixels in a radius of 2 $(8, 2)$ is used to compute the LBP codes, but only those binary codes with at most two bitwise transitions from 0 to 1 or vice versa, called *uniform patterns*, are considered. The face image is divided into rectangular regions and histograms of the *uniform* LBP codes are calculated over each of them. The histograms of the regions are concatenated into a single one which represents the face image and the χ^2 dissimilarity measure in a nearest neighbourhood classifier is used to compare the histograms of two different images.

In this work, the traditional LBP using the *uniform patterns* and a $(8, 2)$ neighbourhood with the χ^2 dissimilarity measure **(LBP+χ^2)** is used, but the work can be extended and improved using more recent LBP extensions like the Multi-Scale Local Binary Pattern(MLBP) representation with the Linear Discriminant Analysis(LDA) proposed in [11].

3 New Photometric Normalisation Algorithm based on the Local DCT

The DCT has been used in some face recognition works, either in a holistic appearance-based [12] or local appearance-based sense [13], obtaining promising results. The general idea is to extract the DCT coefficients. Once they are obtained, the top-left one is removed since it corresponds to the average value of pixel intensities. Of the remaining coefficients, the ones containing the highest information, usually associated to the low-frequency band, are extracted via zig-zag scan to form the feature vector which is used by a classifier.

In [14], a different way of using DCT to compensate for illumination variations is presented. They show that illumination variations can be well compensated by adding or subtracting a compensation term to a given image in the logarithm domain. Considering that illumination variations mainly lie in the low-frequency band, they used the low-frequency DCT coefficients of an image in the logarithm domain as an approximation of the compensation term, setting them to zero and reconstructing a normalised image in that way. This method outperformed most of the existing methods dealing with illumination variations. An example of a photometric normalised face image using this method is shown in Fig.1(b).

When the different methods are analyzed it can be deduced that illumination variations and facial features are not perfectly separated with respect to frequency components. Some illumination variations and facial features lie in the same frequency bands, so when using low-frequency components to compensate for illumination variations, some facial information is lost. However, taking into account that illumination variation affect less in a region than in the complete image, if this process is realized in a local way instead of using the frequency information of the complete face image, less frequency components are using in each region to estimate the illumination and less facial information is sacrificed.

In [15], a method discarding low-frequency DCT coefficients in the logarithm domain in a local way was presented and it improves the results obtained using the global DCT. In this method, the face image is divided in regular regions and low-frequency DCT coefficients of each region are discarded, then, uniform Local Binary Pattern (LBP) histograms [10] are computed for each region and used for classification. Note that the same region division is used for the normalisation with the DCT and for the classification step using the LBP, so in this case, the photometric normalisation is very related with the feature extraction and the classification method. If only the illumination compensation with the local DCT in the logarithm domain is applied, a photometric normalised image with a block effect is obtained as can be appreciated in Fig.1(c).

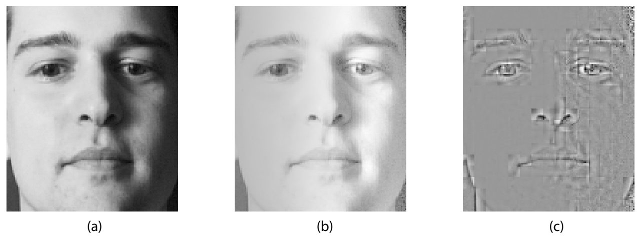


Fig. 1. An example of (a) a face image photometric normalised using (b) the global DCT and (c) the local DCT methods

In this work, only the pre-processing part using the local DCT is taking into account, in a way that the photometric normalised image could be used with any features descriptor or classifier regardless the region division. Then, a modification of the previous work is needed, in order to pre-process the face images eliminating the block effect.

Our method is based on the hypothesis proved in [14] that illumination variations can be well compensated by adding or subtracting a compensation term to a given image in the logarithm domain, as well on the idea that is better to front the illumination problems with local methods than with global ones [5].

Basis on this, and expressing the intensity of a pixel which represents a point on an object surface, $I(x, y)$, as the product of the reflectance $r(x, y)$ and the incident illumination $s(x, y)$, i.e.:

$$I(x, y) = r(x, y) \cdot s(x, y), \tag{1}$$

the first step of the photometric normalisation method is to transform the image to the logarithm domain:

$$\log I(x, y) = \log r(x, y) + \log s(x, y). \tag{2}$$

This is a nonlinear transformation which enhances the local dynamic range of the image in dark regions, compressing it in bright regions, while at the same time, permits to separate the reflectance from the incident illumination.

The seconds step is to obtain the compensation term, which was defined as:

$$\epsilon(x, y) = \log s(x, y) - \log s', \tag{3}$$

representing in the logarithm domain, the difference between the estimated original illumination and the normalised illumination, s', which must be unique for every pixel of the image.

The pixel intensity under desired uniform illumination s' in the logarithm domain, can be expressed as:

$$\log I'(x, y) = \log r(x, y) + \log s', \tag{4}$$

From (3) and (4) can be deduced the final step to obtain a normalised image, consisting in to subtract the compensation term to the original image in the logarithm domain. For a given pixel this can be written as:

$$\log I'(x,y) = \log I(x,y) - \epsilon(x,y). \tag{5}$$

As can be appreciated, the second step consisting in to obtain the compensation term, is the fundamental one to deal with the illumination variations. Consequently is in this step when we have to make use of the local information of the face image. This step will be detailed for its importance in the photometric normalisation algorithm.

3.1 Obtaining the compensation term

From equation (3), the compensation term can be seen as the spare lighting in the face image, then to obtain the compensation term, it is necessary to estimate the incident illumination. Most of the incident illumination represented in an image change slowly, that is why illumination variations are usually associated to the low-frequency components.

There are different filtering methods in the frequency domain. In [14] it was explained the advantages of the use of the DCT to separate the low-frequency components from the high ones and to estimate illumination variations.

The DCT-II of an $M \times N$ image, is defined as:

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x,y) \cos\left[\frac{\pi(2x+1)u}{2M}\right] \cos\left[\frac{\pi(2y+1)v}{2N}\right] \tag{6}$$

where,

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{M}}, & u = 0 \\ \sqrt{\frac{2}{M}}, & u = 1, \dots, M-1, \end{cases} \tag{7}$$

and

$$\alpha(v) = \begin{cases} \frac{1}{\sqrt{N}}, & v = 0 \\ \sqrt{\frac{2}{N}}, & v = 1, \dots, N-1 \end{cases} \tag{8}$$

Since we want to make use of the local information instead of the global one, the face image is divided into rectangular regions and the DCT is computed over them. Afterward, using only the low-frequency coefficients of each block -the ones associated to the illumination variations- and setting to zero the remaining ones, a new image, which must represents the illumination, is obtained by applying the inverse DCT. However, as was told before, it is not so easy to separate the illumination from the facial features in the frequency domain, so the obtained reconstructed image still have facial features information. In this work we analyse how to modify the low frequency components of each block before applying the inverse DCT, to obtain an image that better represents the compensation term.

Specially, for the first DCT coefficient it is easy to detect that contains information about the illumination as well as the facial features. From (6),(7) and (8), this coefficient can be expressed as:

$$C(0,0) = \frac{1}{\sqrt{M}\sqrt{N}} \cdot \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x,y), \tag{9}$$

From equation (9) can be deduced that the first DCT coefficient of each block it is related to the mean intensity values of the region. In a photometric normalised face image all the regions have the same incident illumination, so the difference between the mean intensity values of different regions should be small. We have observed, experimentally, that in an image with a constant or normalised illumination, the first DCT coefficients of each block show a little dispersion in their values, meanwhile and image with variations in lighting has great differences in its first DCT coefficients. In Fig.2 can be appreciated the effect of the light in the first DCT coefficients of a face image, changing as the incident illumination changes over the face surface.

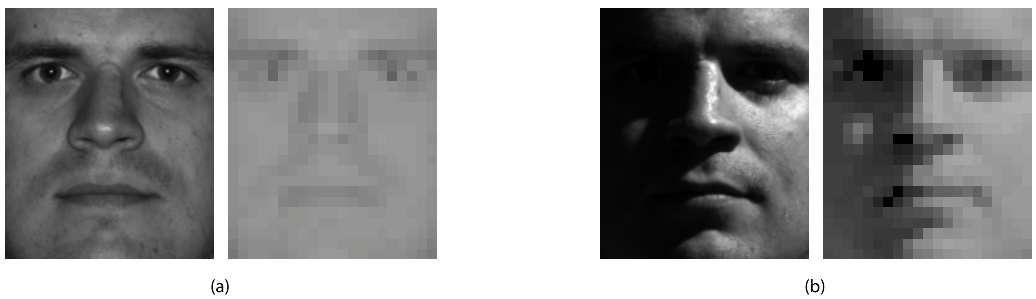


Fig. 2. A representation of the first DCT coefficient of each block for a face image with (a) a frontal and (b) a lateral incident illumination

Since we want to estimate the compensation term or spare lighting for subtracts it to the image for normalise it, it is necessary to modify the first DCT coefficient of each block in a way that represents the difference between its real value -associated to the incident illumination for that region- and a similar value for all the regions of the image. Then, to obtain the image which represents the illumination compensation term, we use the low-frequency DCT coefficients of each block, replacing the first one for its original computed value minus a constant reference value. We decided to use the mean value of all the image pixels in the logarithm domain as the reference constant.

The obtained illumination compensation image still have some block effect produced by the block division. In order to reduce the block effect, we apply a smooth filter to the obtained image before subtracts it to the original image in the logarithm domain.

Fig. 3. An example of the effect of each one of the steps of the pre-processing method: (a) original image, (b) logarithm transformation, (c) illumination compensation image with block effect, (d) smoothed compensation image and (e) result image after subtraction

The proposed procedure can be summarized as: 1) to apply the logarithm transformation to the original face image, 2) to obtain the illumination compensation term using the local DCT low-frequency components and modifying the first coefficients, 3) to smooth the obtained image and 4) to subtract the smoothed compensation term to the original image in the logarithm domain. The effect of each one of these steps in a face image can be appreciated in Fig.3, showing at the end the normalised image with the proposed method.

3.2 Parameters Selection

There are some parameters that can be chosen to optimise the performance of the proposed algorithm. The first parameter is the size of the regions in which the images are divided. If the region is too small more computational effort is needed, on the other hand the larger the regions the more affected by the illumination variations. We chose to divide the image into $k \times k$ equally sized rectangular regions and tested the method for different values of k to select the best one.

Another parameter is the number of low-frequency DCT coefficients used from each region to obtain the illumination compensation term. Taking into account that illumination variations and facial features are not perfectly separated with respect to frequency components, to decide which and how many coefficients are used is an important decision in the proposed methodology. The DCT coefficients usually are scanned in a zig-zag manner to go from the low frequencies to the high ones. Following this zig-zag scan in a rectangular window, we tested three different number of coefficients for the different values of k. In Fig.4 the performance of the proposed method with different k values and using different numbers of DCT coefficients in the three subsets of the XM2VTS database is shown. As was told before, the LBP+χ^2 was used to run the experiments.

As can be appreciated the best performance in all the cases is obtained dividing the images into 8×8 regions, which is also the traditional division for other applications of the DCT. The case of the number of coefficients is more difficult to select as it was expected, however we decided to use 15 low-frequencies DCT coefficients because it shows the most stable performance in the three sets and with the different regions sizes.

As a final parameter we need to select the filter and the size for the smoothing operation that needs to be applied to the estimated illumination. There are a lot of smoothing filters defined for digital image processing, among them we tested an averaging filter -with a square and a circular kernel- and a Gaussian filter, for their simplicity and more extended use. In Fig.5 the TER of the proposed method, using the selected regions size and number of coefficients, for the different smoothing filters in the three subsets of the database is shown. The x axis corresponds to the size of the kernel for the averaging filters and a change of the standard deviation for the Gaussian filter.

Analysing the obtained results, for the Gaussian filter, the errors are very similar for different standard deviations, meanwhile for the averaging filters, as the size of the kernel is increased the classification error decreases, however the larger the size of the kernel the higher the computational cost. In general, the averaging filter with a circular kernel shows a better performance than with a square kernel, and both of them are better than the Gausssian. In the three sets of the database a good performance was obtained using a

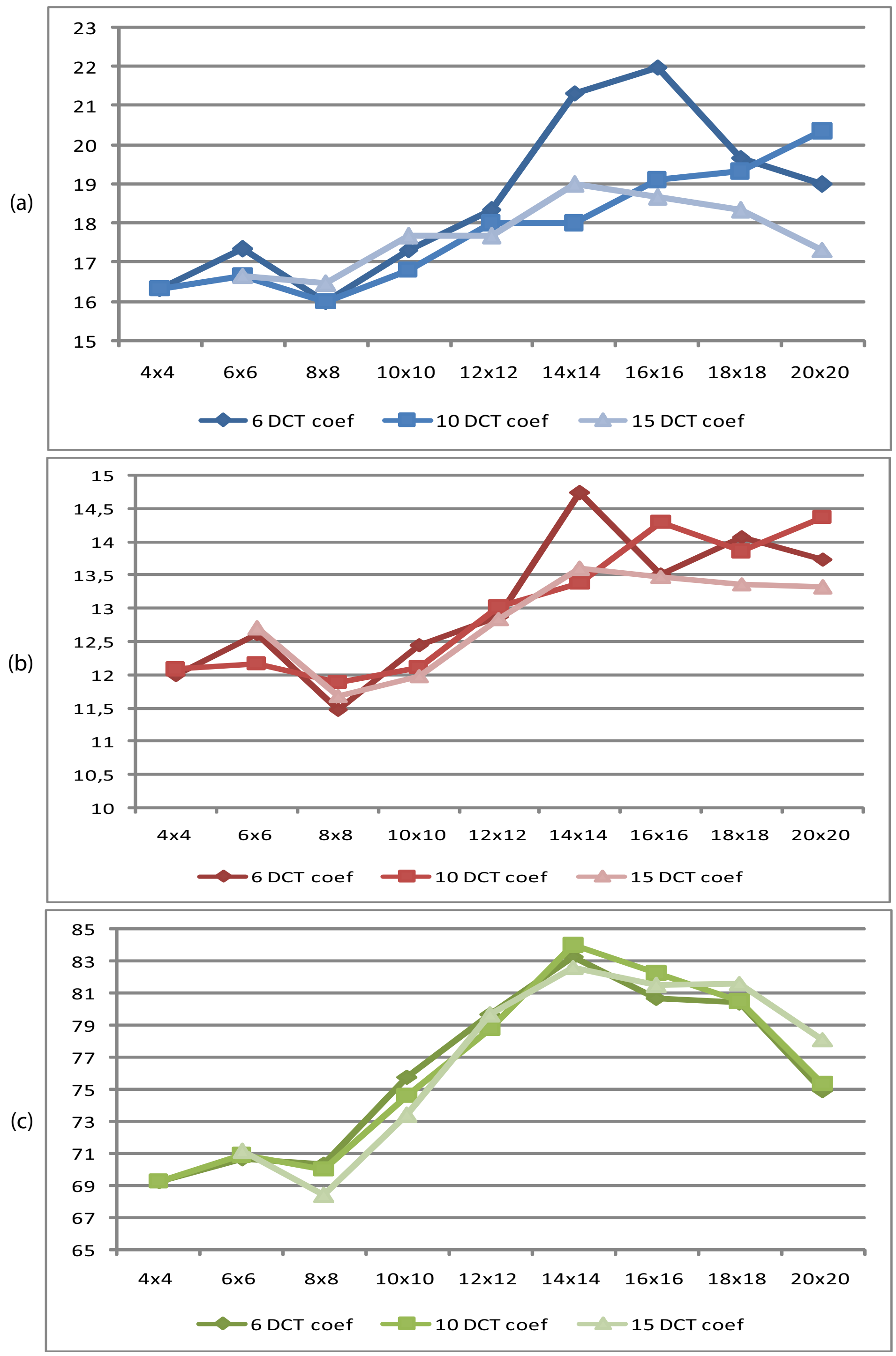


Fig. 4. Performance (TER) of the proposed method with different $k \times k$ regions divisions and number of DCT coefficients in (a) the Evaluation set, (b) the Test set and (c) the Dark set from XM2VTS database

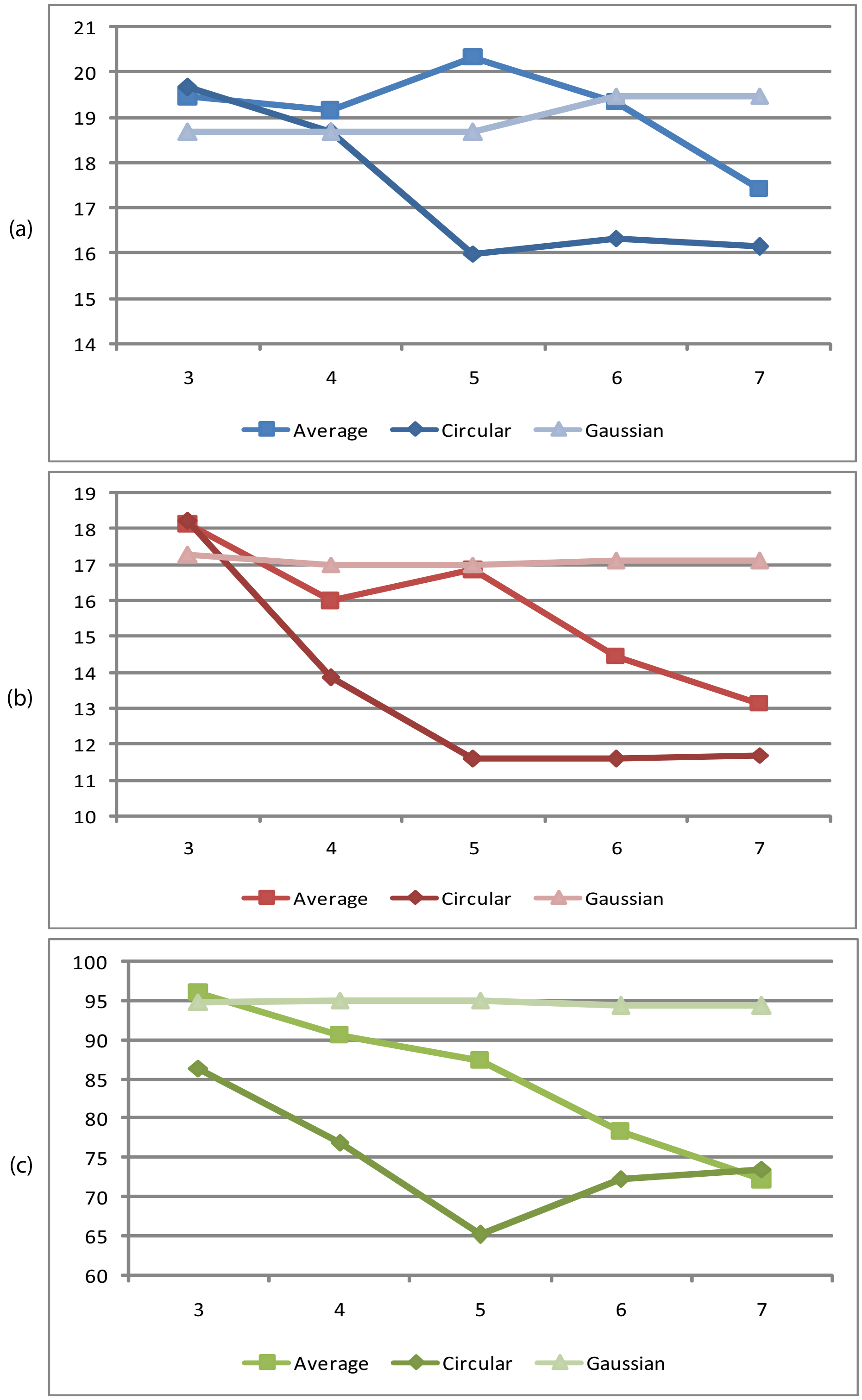


Fig. 5. Performance (TER) of the proposed method with different smoothing filters of different sizes in (a) the Evaluation set, (b) the Test set and (c) the Dark set from XM2VTS database

circular averaging of radius 5, which is also a good value for the trade-off of the size of the kernel, so we select this filter to smooth the illumination images.

4 Combining preprocessing methods

The proposed photometric normalisation method (LDCT) was compared with the Preprocessing Sequence (PS) method [6] which showed to be superior than all the existing preprocessing methods up to the moment. In Table 1 it is shown the TER in each subset of the database for both methods and for the original images (OI) without applying any preprocessing step.

Table 1. Comparison of different photometric normalisation methods in the XM2VTS database

	Eval	**Test**	**Dark**
OI	10.33	7.12	95.75
PS	15.33	12.9	62.35
LDCT	16.0	11.8	65.29

As can be appreciated, the PS shows the best results in the Dark set -the one containing the illumination variations- follows very short by our LDCT method. However, in the Test set, where the images do not present large illumination variations, the PS shows a worst performance but also with a little difference regards our method, in this case it is important to notice the very good performance obtained in this set without applying any preprocessing images which means that the preprocessing methods degrades on good quality images.

Since the performance of the PS is very close to the performance of the LDCT method, we should compare them in more detail. The PS method was proposed by Tan and Triggs [6]. It is composed by a series of steps aiming to reduce the effects of illumination variations, local shadowing and highlights, while still keep the essential visual appearance information for use in recognition. The first step is to apply a gamma correction, which is a nonlinear gray level transformation replacing the pixel value in I with I^γ where $\gamma > 0$. The second step is a Difference of Gaussian (DoG) filtering, a band-pass filter which not only suppresses low frequency information caused by illumination gradient, but also reduces the high frequency noise. The final step is a global contrast equalization which re-normalises the image intensities to standardise a robust measure of the overall contrast, where the large values are truncated and their influence is reduced. After this step, the image is well scaled but it can still contain extreme values, so a nonlinear function that compresses over-large values is optionally applied.

If the PS and our method are compared, it can be found that the most important difference between them is in the frequency information that is retained and suppressed in the main step of each algorithm. The first step for both methods, gamma correction and logarithm transformation, works in the same way, enhancing the dark image intensity values, while compressing the bright ones. For both methods the second step is the fundamental one. In the PS, the DoG filtering attenuates the lower and higher frequencies retaining the ones in the middle, while our method uses the low frequencies DCT coefficients to construct the compensation term which is subtracted to the images, so mainly low frequency information is suppressed. The high frequencies attenuation in the PS could be the cause for a worst result when the images are not affected by illumination variations, since the important facial features mainly lie in the high frequency bands. The subsequent steps in each method have different purposes, in the PS case, the filtered image is re-normalised to improve its overall contrast, while in the LDCT the image constructed with the low frequencies is filtered for smoothing and subtracted from the original image, so basically they work different and different outputs are obtained in each case.

Taking into account that the PS and the LDCT work different but the total error rates perceived by them in the XM2VTS database are very similar, it was necessary to analysed the specifical misclassifications committed for each method. In [16] a statistical test to determine the probability of incorrectly detecting a difference between classifier performance when no difference exists is described. Using this statistic measure we can probe if the PS and the LDCT methods have or not the same error.

Let:
n_{00} = number of samples misclassified by both PS and LDCT
n_{01} = number of samples misclassified by PS but not by LDCT
n_{10} = number of samples misclassified by LDCT but not by PS
n_{11} = number of samples misclassified by neither PS nor LDCT

From [16], the z statistics is defined as:

$$z = \frac{|n_{01} - n_{10}| - 1}{\sqrt{n_{10} + n_{01}}}$$

and if $|z| > 1.96$ we can say that the two methods do not have the same error (with a 0.05 probability of incorrect decision).

To compare both methods, the number of samples misclassified for each of them can be represented in a confusion matrix for a better understanding, where the first column and row represent the misclassified images by LDCT and PS respectively and the second ones the well classified images:

$$\begin{array}{cc} & \textbf{LDCT} \\ \begin{array}{c}\textbf{P}\\ \textbf{S}\end{array} & \begin{array}{|cc|} n_{00} & n_{01} \\ n_{10} & n_{11} \end{array} \end{array}$$

In Table 2 it is shown the confusion matrix for each set of the XM2VTS database and in Table 3 the z statistic computed using these values.

Table 2. Comparison of the number of images misclassified by PS and LDCT methods in each set of the XM2VTS database

a) Eval

	LDCT		
P	581	1042	1623
S	699	38278	38977
	1280	39320	40600

b) Test

	LDCT		
P	1724	3028	4752
S	1950	105698	107648
	3674	108726	112400

c) Dark

	LDCT		
P	353	640	993
S	968	54839	55807
	1321	55479	56800

Table 3. The z statistics computed in each set of the XM2VTS database

	Eval	**Test**	**Dark**
$\lvert z \rvert$	8.19	15.26	8.15

Considering the statistical test in all cases is higher than 1.96, it can be said that both methods misclassified the images in a different way. Also if the coincidences in the misclassification (n_{00}) are analysed, it is easy to note that for both method they are less than the half of the total of misclassified images. This can be confirmed in Table 4 where the percent that represents the coincidences with respect to the total of images misclassified for each method in each subset of the database is shown.

Table 4. Percent that represents the coincidences with respect to the total of images misclassified for each method

	Eval	**Test**	**Dark**
PS	35.80%	36.28%	35.55%
LDCT	45.39%	46.92%	26.72%

As was told before, it is appreciated a difference in the behaviour of the methods. Although the TER for both methods in the XM2VTS are very similar, in more than the half of the cases, one image which is misclassified with one method is well classified by the other, so this two methods can provide complementary information and their fusion can produce a superior result.

4.1 The proposed method

Taking into account the obtained experimental results, we decided to combine the PS and the LDCT methods aiming to improve the performance of face recognition in front of illumination variations.

Various classifier combination schemes have been proposed. In our case we have the same classifier using two different representations for each pattern or image and we want to combine the outputs of the individual classification as can be appreciated in Fig.6. In [17] it was shown that the sum rule under certain assumptions outperforms other classifier combinations schemes in this scenario.

Let F be a face image that needs to be assigned to one of the m possible classes of faces $\omega_1, ..., \omega_m$, X_{LDCT} and X_{PS} the input vector used by the classifier with the LDCT and PS

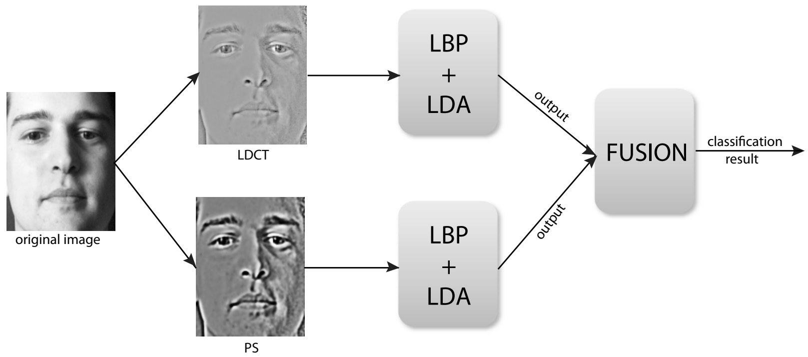


Fig. 6. Proposed combination scheme

representations respectively and assuming all classes have the same a priori probability, F is assigned to ω_j, if

$$P(\omega_j|\mathrm{X}_{LDCT}) + P(\omega_j|\mathrm{X}_{PS}) = \max_{k=1}^{m}[P(\omega_k|\mathrm{X}_{LDCT}) + P(\omega_k|\mathrm{X}_{PS})] \tag{10}$$

Although the restrictive assumptions, it was demonstrated in [17] that the sum rule is most resilient to estimation errors. It is also possible to apply a weight to the classifiers in the sum rule, which could improve the final result of the combination. Here we applied the simple sum rule presented in equation (10) and good results were obtained as can be appreciated in Table 5.

Table 5. Results of the fusion of both methods

		Eval	**Test**	**Dark**
	FAR	7.68	5.4	0.10
PS	**FRR**	7.5	0.5	62.25
	TER	15.33	12.9	62.35
	FAR	8.00	5.15	0.17
LDCT	**FRR**	8.00	6.75	65.12
	TER	16.0	11.8	65.29
	FAR	7.33	6.50	0.11
Combination	**FRR**	7.45	4.72	61.25
	TER	14.78	11.22	61.36

Using the proposed combination an improvement in the results of the individual methods was obtained when the images are affected by illumination variations as well as when they not.

5 Determining illumination affectation in face images

As was concluded in previous section, the preprocessing combination method improves the results of the individual techniques, but if the results are compared with the ones obtained when no preprocessing method is applied shown in Table 1 can be appreciated that although the improve achieved when dealing with illumination problems(Dark set), it is degraded on good quality images(Evaluation and Test sets). A method which can automatically detects if a face image is of good quality or not, regards to illumination, permits to determine if a preprocessing method is needed or not.

Different image quality metrics have been proposed for a number of tasks: to monitor and adjust image quality, to optimize algorithms and parameter settings of image processing systems and to benchmark image processing systems and algorithms [18]. Quality assessment methods can be classified according to the availability of the prior information of what a good image is, into full-reference, reduced-reference and no-reference. Most existing approaches are known as full-reference, meaning that a complete reference image is assumed to be known. In many practical applications however, the reference image is not available, and a no-reference or reduced-reference approach is needed. In biometrics, a reference image with a high quality is usually not available, but the information available from the biometric images or models helps to evaluate the quality of the distorted images in a kind of reduced-reference approach.

For the face recognition case, there are some image quality assessment methods, but most of them measure the distortion present in the face images cause by the image acquisition process, the compression methods and the blur [19][20]. There are other works [21] [22] aiming to evaluate the face images according to ICAO definitions [23]. But to the best of our knowledge no method to determine the illumination affectation in a face image has been reported in the literature.

5.1 The proposed method

First of all, the face image is converted from RGB to HSL color space in order to obtain the luminance $L(x, y)$ of each pixel from the image, using:

$$L(x, y) = \frac{maxcolor + mincolor}{2} \tag{11}$$

where,

$$maxcolor(x, y) = \max[R(x, y), G(x, y), B(x, y)] \tag{12}$$

$$mincolor(x, y) = \min[R(x, y), G(x, y), B(x, y)] \tag{13}$$

and $R(x, y)$,$G(x, y)$,$B(x, y)$ are the Red, Green and Blue values of the (x, y) pixel.

The luminance refers to the amount of visible light that comes from a surface [24], so it is associated with the reflectance of the surface and the amount of incident light. The variations in a face surface are not so great, then if two regions of the face are perceived with a very different luminance is because the incident light in those regions are very different. We then divide the face image in N regular regions and the luminance mean is determined in each of them: L_m^r, where r represents the specific region. A low L_m^r value corresponds to a dark region, while a high value corresponds to a bright region. If there is a markable variation between the different L_m^r values of a face image, it can be classified as a bad illuminated face image. Also if all the L_m^r values are very low means that the complete image is dark, while if all are very high the complete image is bright.

Following the above criterions and being:

$$maxR = \max_{r=1}^{N}[L_m^r]$$

$$minR = \min_{r=1}^{N}[L_m^r]$$

$$dR = maxR - minR$$

a face image is classified as well illuminated if the following expression is satisfied:

$$Q = (maxR > \alpha) \text{ and } (minR < \beta) \text{ and } (dR < \gamma) \tag{14}$$

where α,β and γ are user defined thresholds. The L_m^r values, as well as the parameters are normalized between 0 and 1.

5.2 Parameters selection

To a better performance of the proposed method it is necessary to establish the thresholds values according to the specific application at hand. Besides, it is necessary to determine the size of the regions in which the face image will be divided. In our case, the Extended Yale Face Database B [25] was used to experimentally determine these values. The database is composed by face images under 64 varying, but controlled, illumination conditions. The face images were divided in seven groups according the variation angle of the incident light. In Table 6 sample images from one subject corresponding to each division are shown.

From (14), the β parameter aims to discard those face images which are completely bright. As can be seen in Table 6 we do not have this problem in the database we choose for test, anyway we run an experiment fixing the α and γ parameters and changing the β each time with different divisions of the face image. In Figure 7 the percent of images classified as well illuminated in each case is shown. As was expected, for the Extended Yale Face Database B, this parameter has no influence in the images classified as good or bad illuminated.

Fixing the β parameter, different experiments were run in order to determine the α, γ and the regions division more suitable. In Figures 8, 9 and 10, the percent of images classified as well illuminated is shown for 3×3, 4×4 and 5×5 division respectively, changing α and γ each time.

As can be appreciated, different configurations produce different results, so the parameters need to be chosen in depends on the specific applications at hand. In our case, we want to classify all the images with lighting variations as bad illuminated, then we need to choose a combination of parameters that produce 0% of well illuminated images in subsets 4, 5, 6 and 7. Among the different combinations of parameters that produce 0% of well illuminated images in subsets 4, 5, 6 and 7, we decided to use the 3×3 division with $\alpha = 45$ and $\gamma = 35$ due to is the one which obtains a higher percent of well illuminated images in subset 1.

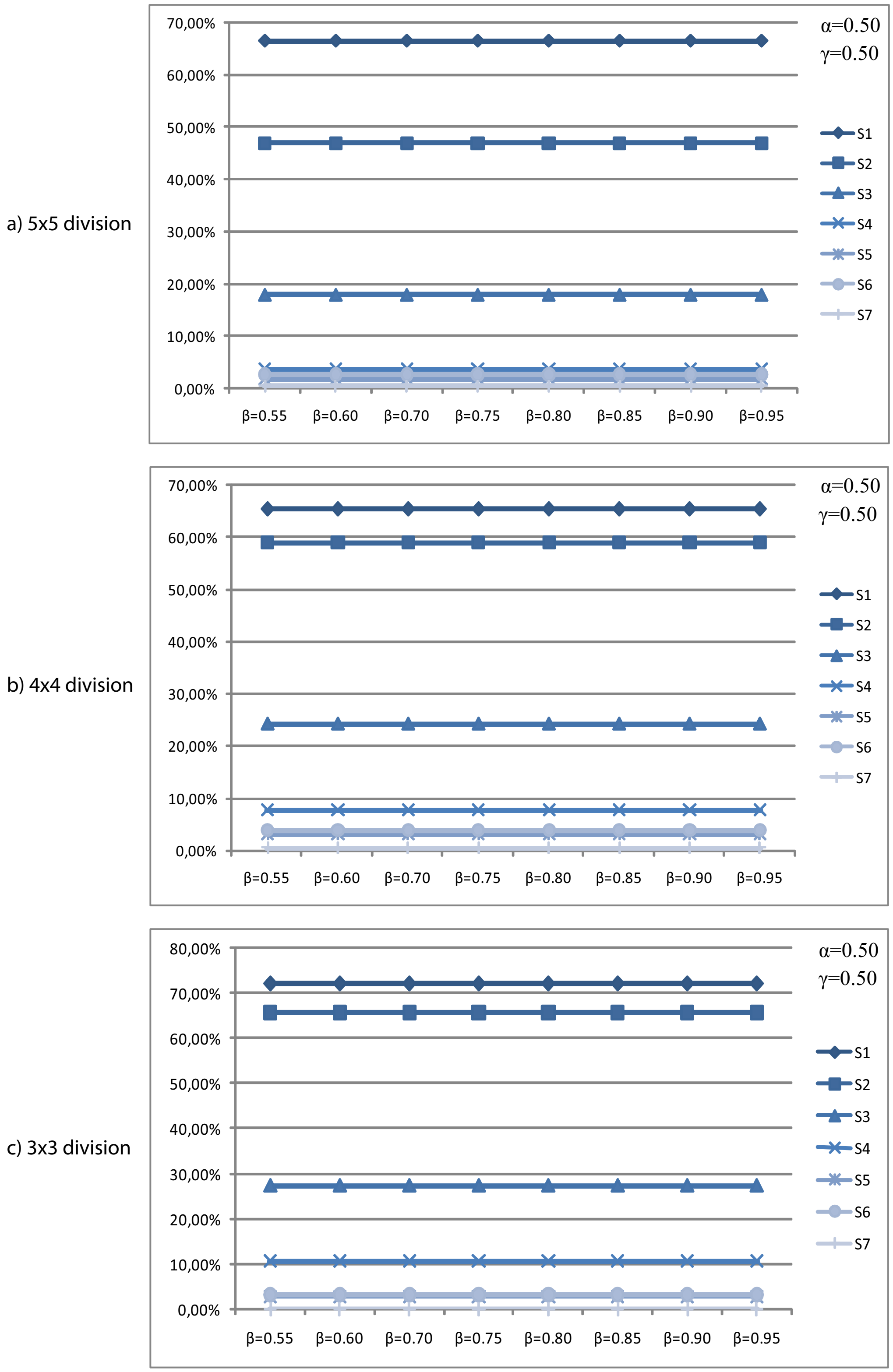
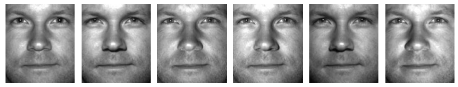
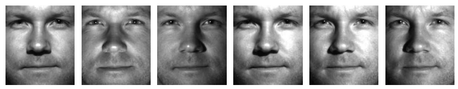


Fig. 7. Percent of images classified as well illuminated changing the β parameter for a)3×3, b)4×4 and c)5×5 regions division

Table 6. Extended Yale Face Database B division according to lighting variations

Lighting Angle	Images Samples
Subset1(0^0-10^0)	
Subset2(15^0-25^0)	
Subset3(35^0-45^0)	
Subset4(50^0-65^0)	
Subset5(70^0-85^0)	
Subset6(90^0-110^0)	
Subset7(115^0-130^0)	

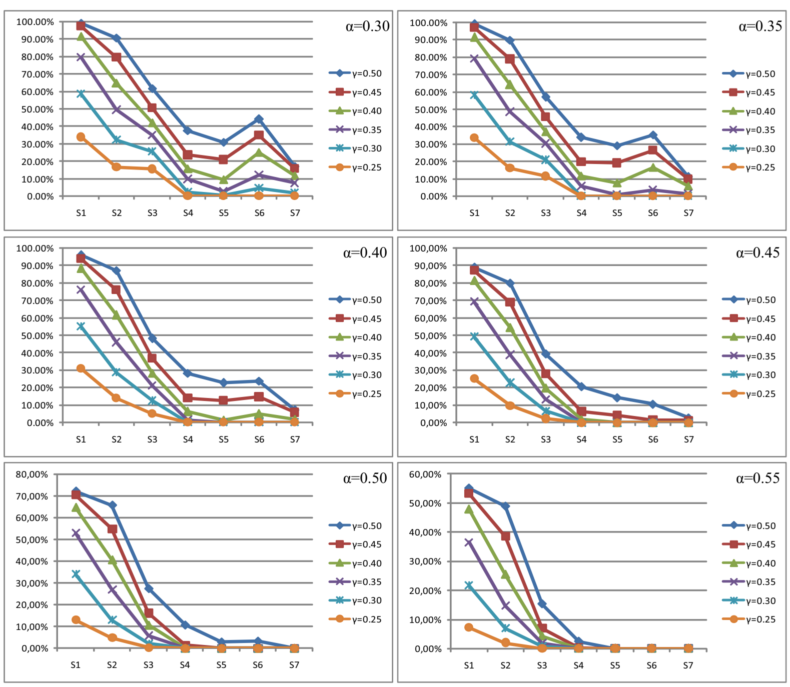


Fig. 8. Percent of images classified as well illuminated for the 3×3 regions division

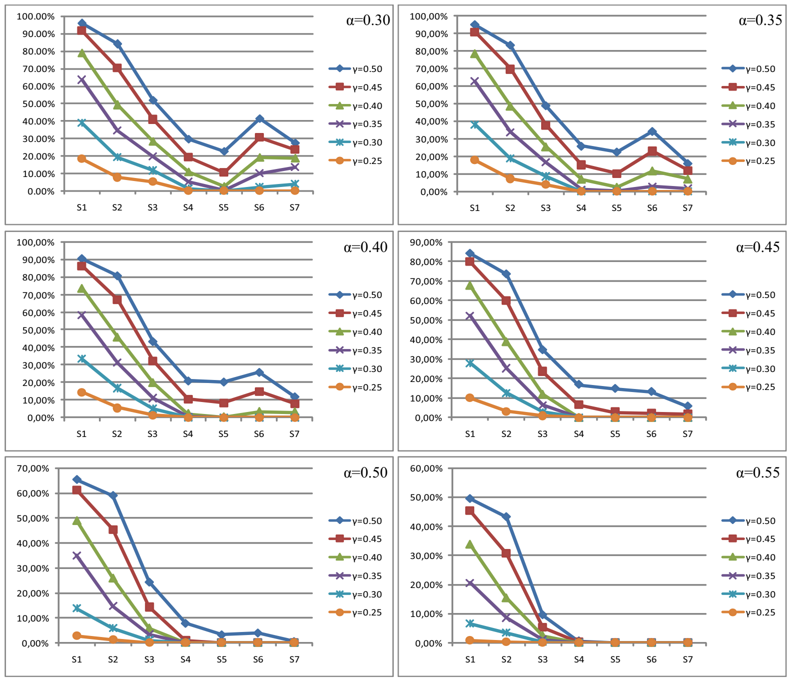


Fig. 9. Percent of images classified as well illuminated for the 4×4 regions division

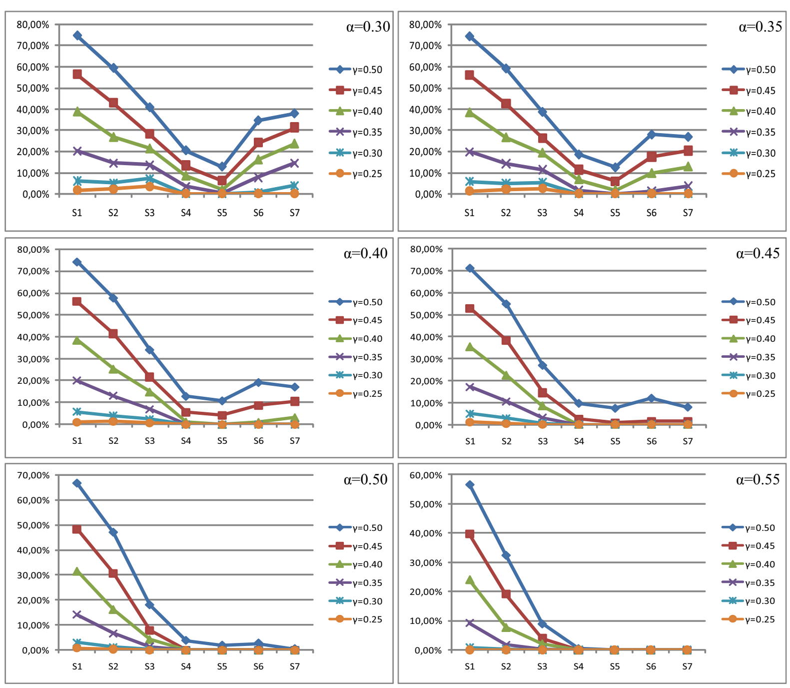


Fig. 10. Percent of images classified as well illuminated for the 5×5 regions division

6 Experimental Evaluation

Based on the methods presented in this work, a general face recognition framework is presented and experimental evaluated. For each face image that will be classified, the illumination quality is determined using the proposed method with the selected parameters; if the image is selected as bad illuminated the combination of LDCT and PS preprocessing methods are applied to it and the representation of the preprocessed training images is used to compare and produce the classification result, while if it is selected as well illuminated the image is directly compared with the training images. The proposed framework is summarized in Fig.11.

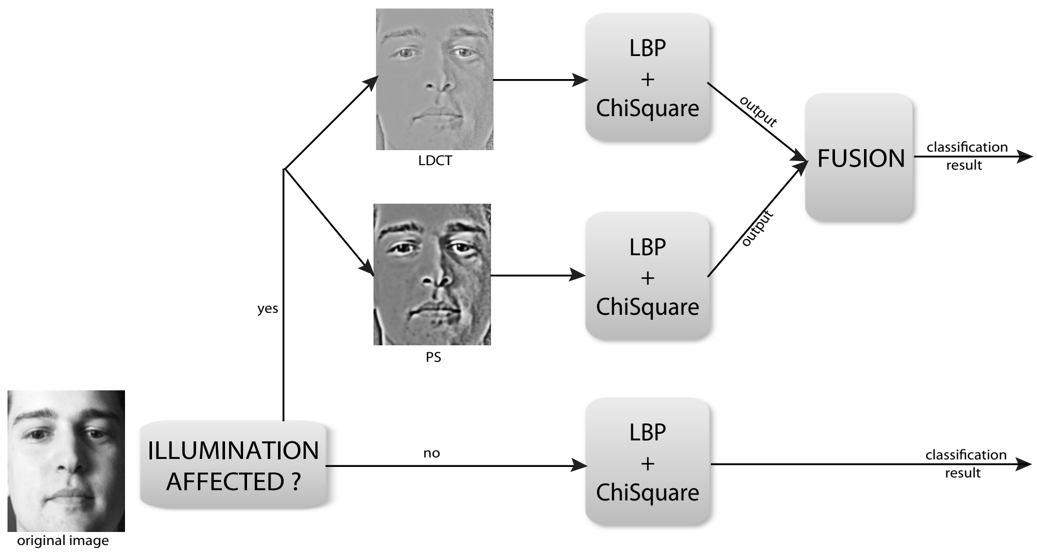


Fig. 11. Proposed general framework

In Table 7 can be appreciated the obtained results with the proposed framework in the XM2VTS database and the TER in each subset can be compared with the results in the same database obtained with the same representation and classification method for the original images without any preprocessing step and for the combination of preprocessing methods applied to all the images.

As can be appreciated the performance of the proposed framework in the Evaluation and Test sets, which no present lighting variations, is better than applying the preprocessing method, but also the performance is improved for the case of the Dark set, being the TER

Table 7. Comparison of the results using the proposed framework and only the original images or the preprocessing combination to all the images

	Eval	**Test**	**Dark**
Original Images	10.33	7.12	95.75
LDCT+PS Combination	14.78	11.22	61.36
Proposed framework	9.76	10.76	29.23

lower than both, for the original images and the preprocessing combination, which means that the threshold choose in the Evaluation set is more suitable.

If the results in Table 7 are analyzed, can be appreciated that the performance of the proposed method in the Evaluation set are better even than when the original images are used. This can be motivated by the fact that some of the images in this set present little lighting variations. With the combination of parameters selected, these images are classified as bad illuminated and although the lighting variations are not so great, they are photometric normalized and better classified.

7 Conclusions

In this work, a new photometric normalisation method for face images based on the local DCT in the logarithm domain was proposed. An image which represents a compensation term is subtracted to the original face image in the logarithm domain to compensate for illumination variations. To obtain the illumination compensation image, the local DCT is applied to the original image in the logarithm domain and the low-frequency coefficients modifying the first one are used to reconstruct an image applying the inverse DCT.

The proposed LDCT photometric normalisation process was tested on the XM2VTS face database and compared with the best state of the art preprocessing technique achieving a very similar performance. The images misclassified by the LDCT and the PS methods were analysed in depth, conducing to a new method for classify face images under varying lighting conditions combining both of them. The propose combination strategy improves the results obtained by the individual methods.

Although the good performance of the combination method classifying face images with illumination variations, we showed that the result is not so good on good quality images, where the best results are obtained when no preprocessing method is applied. We then proposed here a method to automatically detects if a face image is affected or not by illumination variations which is inserted in a general framework for face recognition to determine if a face image needs to be photometric normalised or not. The proposed framework was tested in the XM2VTS database and outperformed the previous results in both cases: when the images are affected by illumination variations as well as when they not. With the obtained results we can concluded that the proposed framework can be used when we have a face recognition application with variable and unknown illumination conditions.

References

1. J.P. Phillips, T.W. Scruggs, A.J. O'toole, P.J. Flynn, K.W. Bowyer, C.L. Schott, and M. Sharpe, "Frvt 2006 and ice 2006 large-scale results," Tech. Rep., National Institute of Standards and Technology, March 2007.
2. T.G. Stockham, "Image processing in the context of a visual model," *PIEEE*, vol. 60, no. 7, pp. 828–842, July 1972.
3. Z.U. Rahman, D.J. Jobson, and G.A. Woodell, "Multi-scale retinex for color image enhancement," in *ICIP96*, 1996, vol. III, pp. 1003–1006.

4. R. Gross and V. Brajovic, "An image preprocessing algorithm for illumination invariant face recognition," in *AVBPA03*, 2003, pp. 10–18.
5. M. Villegas and R. Paredes, "Comparison of illumination normalization methods for face recognition," in *Third COST 275 Workshop- Biometric on the Internet*, 2005, pp. 27–30.
6. Xiaoyang Tan and Bill Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," in *AMFG*, 2007, pp. 168–182.
7. K. Messer, J. Matas, J. Kittler, and K. Jonsson, "Xm2vtsdb: The extended m2vts database," in *Second International Conference on Audio and Video-based Biometric Person Authentication*, 1999, pp. 72–77.
8. T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions," *Pattern recognition*, vol. 29, no. 1, pp. 51 – 59, 1996.
9. Sébastien Marcel, Yann Rodriguez, and Guillaume Heusch, "On the recent use of local binary patterns for face authentication," *International Journal on Image and Video Processing Special Issue on Facial Image Processing*, 2007, IDIAP-RR 06-34.
10. T. Ahonen, A. Hadid, and M. Pietikãinen, "Face recognition with local binary patterns," *Lecture Notes in Computer Science : Computer Vision - ECCV 2004*, pp. 469–481, 2004.
11. C.H. Chan, J. Kittler, and K. Messer, "Multi-scale local binary pattern histograms for face recognition," *Advances in Biometrics*, vol. 4642/2007, pp. 809 – 818, 2007.
12. Ziad M. Hafed and Martin D. Levine, "Face recognition using the discrete cosine transform," *Int. J. Comput. Vision*, vol. 43, no. 3, pp. 167–188, 2001.
13. H. K. Ekenel and R. Stiefelhagen, "Local appearance based face recognition using discrete cosine transform," in *13th European Signal Processing Conference (EUSIPCO)*, 2005, pp. 27–30.
14. W. Chen, Meng J. Er, and Shiqian Wu, "Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain," *Systems, Man and Cybernetics, Part B, IEEE Transactions on*, vol. 36, no. 2, pp. 458–466, 2006.
15. H. Mendez-Vazquez, E. Garcia-Reyes, and Y. Condes-Molleda, "A new combination of local appearance based methods for face recognition under varying lighting conditions," in *CIARP08*, 2008, pp. 535–542.
16. A. R. Webb, *Statistical Pattern Recognition*, chapter 8.3, pp. 266 – 271, John Wiley and Sons Ltd, 2dn edition, 2002.
17. Josef Kittler, Mohamad Hatef, Robert P. W. Duin, and Jiri Matas, "On combining classifiers," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, pp. 226–239, 1998.
18. Zhou Wang, Alan C. Bovik, Hamid R. Sheikh, Student Member, Eero P. Simoncelli, and Senior Member, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, pp. 600–612, 2004.
19. H. Fronthaler, K. Kollreider, and J. Bigun, "Automatic image quality assessment with application in biometrics," *Computer Vision and Pattern Recognition Workshop*, vol. 0, 2006.
20. Ahmad Nazri Zamani, Mat Kamil Awang, Nazaruddin Omar, and Shahrin Azuan Nazeer, "Image quality assessments and restoration for face detection and recognition system images," in *AMS '08: Proceedings of the 2008 Second Asia International Conference on Modelling & Simulation (AMS)*, Washington, DC, USA, 2008, pp. 505–510, IEEE Computer Society.
21. M. Subasic, S. Loncaric, T. Petkovic, H. Bogunovic, and V. Krivec, "Face image validation system," in *Proceedings of the 4th International Symposium on Image and Signal Processing and Analysis, 2005 (ISPA 2005)*, Washington, DC, USA, 2005, pp. 30–33, IEEE Computer Society.
22. Markus Storer, Martin Urschler, Horst Bischof, and Josef A. Birchbauer, "Face image normalization and expression/pose validation for the analysis of machine readable travel documents," in *Proceedings 32nd OAGM/AAPR Conference*, Arjan Kuijper, Bettina Heise, and Leila Muresan, Eds., May 2008, vol. 232, pp. 29–39.
23. InterNational Committee for Information Technology Standards (INCITS), *Face Reconition Format Data Interchange, Version 2.0*, INCITS Secretariat, Information Technology Industry Council, 2006.
24. Edward H. Adelson, *Lightness Perception and Lightness Illusions*, chapter 24, pp. 339–351, Cambridge, MA: MIT Press, 2dn edition, 2000.
25. A.S. Georghiades, P.N. Belhumeur, and D.J. Kriegman, "From few to many: Illumination cone models for face recognition under variable lighting and pose," *IEEE Trans. Pattern Anal. Mach. Intelligence*, vol. 23, no. 6, pp. 643–660, 2001.

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