Normalization Methods Analysis Applied to Face Recognition

Igor Andrezza, Erick Borges, Iron Almeida, Rajiv Mota, Raphael Marques, Leonardo Batista
Centro de Informática
Universidade Federal da Paraíba
João Pessoa, Brazil

***Abstract*—Biometrics offers a reliable authentication mechanism that identifies the users through their physical and behavioral characteristics. The problem of face recognition is not trivial because there are many factors that affect the face detection and recognition (e.g., lighting, face position, hair, beard, etc). This work proposes to analyze the effects of geometric and illumination normalization on face recognition techniques, aiming to adapt them to unconstrained environments. The results show the use of background information in the normalization process mistakenly increases the face recognition rates as previously seen in many papers of the literature. The illumination and geometric normalization methods, when performed with precise points of the eyes centers, effectively help in face recognition.**

***Keywords*-Geometric Normalization; Illumination Normalization; Face Recognition; Biometrics.**

I. Introduction

Computer Vision allows digital systems to extract information from images. This information can be used for several purposes, among them is the recognition of complex patterns, such as textures, objects, texts or biometric patterns [1]. Biometric recognition systems use unique human characteristics, such as fingerprint, iris, voice, face, to differentiate human beings [2] [3], they are examples of systems that use Computer Vision techniques.

The proliferation of services that require authentication has created a demand for new methods to establish the user identity. Traditional methods include knowledge-based mechanisms (e.g. passwords) and mechanisms based on tokens (e.g. identity cards). However, such mechanisms can be lost, stolen or even manipulated in order to bypass systems. In this context, verification and identification by biometrics arise as alternatives [4].

Face analysis may be divided into several subareas, such as recognition, detection, expression recognition and pose analysis [2]. It is important to distinguish detection from recognition. Face recognition is up to identify an individual through an analysis of his face, comparing it with other pre-labeled faces. Face detection is determining the presence and spatial position of each existing face in an image. Detection is often used as an initial step for recognition [5].

The face recognition problem is not trivial because there are many factors which influence the detection and recognition, as lighting, position, background, facial expressions, presence and variation of beard and hair, skin tone, accessories as piercings, glasses and makeup [2] [6] [5].

Some facial recognition methods have accuracy rates approaching 100% in constrained environments [7] [8] [9], but they have low performance in unconstrained ones. These methods should be investigated and adapted to any environment, whether it is intended to use them in a wider range of applications.

This paper presents a study on how methods of geometric and illumination normalization can help to adapt recognition methods to uncontrolled environments. Six types of illumination normalization, three face crops and two face recognition techniques were evaluated.

The purpose of this study is to research and develop geometric and photometric normalization techniques for facial recognition in controlled environments in order to adapt these methods to uncontrolled ones.

II. Related Works

The following paragraphs briefly describe some works related to this research.

Hafed and Levine [10] developed a holistic facial recognition system based on Discrete Cosine Transform (DCT). The image is preprocessed with a geometrical normalization through the eye position and an illumination normalization by means of Hummel work [11], the DCT is then generated from the normalized image. This work achieved a hit rate of 92.5% in the ORL Database [12] using five training images and five testing images.

In his work, Matos *et al*. [13] uses DCT to perform facial recognition and implement a K-Nearest-Neighbor classifier (KNN) [14] [15] using as similarity measure the first-order Minkowski distance. The shortest distance is used to classify a face. In this work, preliminary steps of normalization are dispensed. To test the algorithm, it was used the cross-validation procedure Leave-One-Out, i.e. all images but one is used for training. The method achieved a hit rate of 99.5% on ORL database using 36 coefficients.

The System for Detection and Recognition of Faces (SDRF) described by Omaia *et al*. [7] selects the low-frequency coefficients of the DCT in an elliptical region, a variation of the work of Matos *et al*. [13]. Also, there is no normalization applied to the images. Using the KNN classifier and the Leave-One-Out procedure, the method achieved a rate of 99.75% accuracy on ORL dataset. Kar *et al*. [16] developed a technique that uses the correlation in grayscale

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and Principal Component Analysis (PCA). In its own database of 109 images of 43 individuals, the algorithm achieves a rate of 89% accuracy.

Mendona *et al*. [8] compare three illumination normalization methods, homomorphic filter, wavelet and LogAbout. Using a recognition system that uses PCA and neural network learning by Learning Vector Quantization (LVQ) on the Yale Face Database B, all methods were able to improve hit rates compared to tests without photometric normalization. In his work, Levine *et al*. [17] proposed a normalization method that combines Retinex with histogram equalization, which achieved a hit rate of 99.84% on the Yale Face Database B using the classifier Support Vector Machines (SVM).

Gao *et al*. [18] detects the face using Active Appearance Model (AAM) and, from that information, they normalize the face position, through warping, and crop an oval region of interest. The normalization followed by a recognition system based on DCT and KNN provides an improvement in the hit rate of the system. This improvement resulted from the geometric normalization is also noticed by Chai *et al*. [19].

The use of Local Binary Pattern (LBP) for facial analysis has been one of the most successful applications in recent years. The facial representation by LBP has been widely exploited for different purposes, including face detection, face recognition, facial expression analysis, demographic analysis (gender, race, age, etc.), classification, etc. [20].

III. Materials and Methods

In this section are described the steps used in the work and the dataset used for the evaluations.

A. Yale Face Database A

The face database of Yale University has images of 15 people in 11 different situations to represent each one, counting 165 images. The images have different types of facial expressions and configurations as displaced centers illumination, glasses, happiness, sadness and sleepiness expressions, left-side illumination, right-side illumination, and others. All images are on grayscale and has dimensions 320x243, on BMP format (Figure 1).

Fig. 1. Eleven samples from the same individual.

B. Algorithms

This section describes the steps adopted to analyze the effects of normalization techniques in face recognition systems in unconstrained environments. The work consists in pre-process the image to remove the position and lighting variations and all the information which does not belong to the face, then it can be classified. This pre-processing is made by a geometric normalization, followed by a crop of the face region and then an illumination normalization.

1) Geometric Normalization: The normalization consists in removing the position, rotation and scale variation of the images. The proposed geometric normalization is based on eye position, so, an accurate eye detection is critical for the next steps.

The two most used methods of eye detection were evaluated: the "cascade" eye detection from OpenCV [21] and the Active Shape Model (ASM) [22]. In performed tests, the ASM showed better accuracy on detecting the center of the eyes. Looking for regions similar to the models, it can estimate the location of the eyes even when they are occluded, as the images of people wearing sunglasses. Besides, the ASM provides 57 points (as shown in Figure 2), which are related to the positions of the mouth, eyebrows, nose and face contour, so it is one further advantage compared to the OpenCV method.

Fig. 2. Points provided by ASM

Having the eyes position enables to perform the geometric normalization. It begins with the alignment of the eyes (rotation normalization), that removes the line segment slope that joins the two eyes. This slope is measured from the coordinates of the two eyes, then a rotation is applied to align them.

Next step is normalizing the image scale. This process aims to make all images have the same distance between eyes. It was necessary to choose a default distance between eyes, so, the distances between eyes of all databases were measured, resulting in a histogram of eyes distances. Based on this analysis, the 48 pixels distance was chosen.

In the geometric normalization stage, it is advantageous to discard information does not belong to the face (hair, clothes, neck, background), doing that, the classifier will not be affected, thus it becomes robust to the environment and irrelevant information, like a hair cut and dyeing. It was also defined standard image dimensions, as it is a condition of the holistic methods used in this work.

Three distinct crops were made from the original images. The first one produced 127-pixel width by 147-pixel height images, the eyes were within 38 pixels from the closest side border and from 49 pixels from the top border. The second crop consists in removing the information that does not belong to the face from first crop images, this is accomplished by using the points provided by the ASM corresponding to the contour of the face. The pixels which are not within the area bounded by these points are painted gray. The third crop generated images of 88 pixels wide by 100 pixels high, with eyes 20 pixels away from the closest side and top borders. The results are shown in Figure 3.

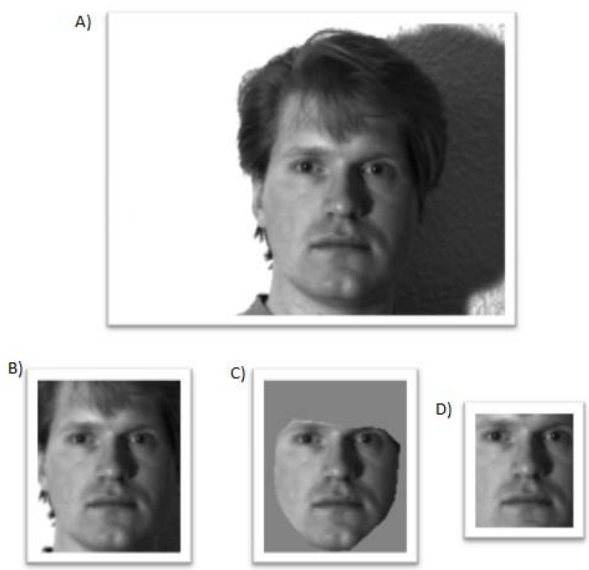

Fig. 3. Crop results. A) Original image. B) Crop 1. C) Crop 2. D) Crop 3.

2) Illumination Normalization: The illumination normalization, or photometric normalization, aims to exclude the variation of lighting conditions. This is used in order to make a robust recognition system to changes in lighting in the scene.

Six illumination normalization methods were developed and tested: histogram equalization, local histogram equalization, logarithm filter, LogAbout filter, Retinex, and Retinex followed by histogram expansion. These algorithms were chosen because they have been used in the literature and they have shown good results.

The illumination normalization methods were applied in both the original images and the geometric normalized images, including the results of the two crops referred above. Figure 4 shows this process applied to the images.

IV. Experiments and Results

The 1-to-1 approach is evaluated by assigning a score for each comparison between two faces and establish a threshold if the score is greater than the threshold the faces belong to the same individual, otherwise, the faces are classified as different individuals. Varying the threshold, two curves can be plotted, the False Rejection Rate (FRR), which shows the rejected samples rate that should be accepted, and the False Acceptance Rate (FAR), which shows the accepted samples rate that should be rejected. The meeting point of these curves

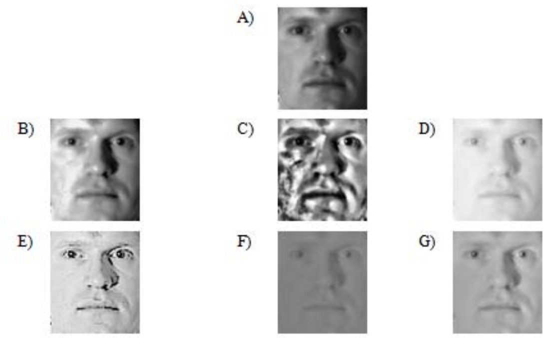

Fig. 4. Illumination normalization methods applied to original images. A) Original image. B) Histogram equalization. C) Local histogram equalization. D) Log filter. E) LogAbout filter. F) Retinex. G) Retinex followed by histogram expansion.

is called Equal Error Rate (EER), often used to compare the performance of different biometric systems [23].

To evaluate these methods were used two holistic classifiers for face recognition, one based on DCT [5] and other based on LBP [24]. It was not possible to perform tests on geometry-based classifiers because the method used to detecting face landmarks (eyes, mouth, nose, eyebrows, etc.) is not sufficiently accurate to be able to distinguish two individuals.

Omaia [5] uses the low-frequency coefficients from the DCT as attributes for recognition. This region is defined by an ellipse in which the center is placed on the pixel (0,0) of the image. The ellipse chosen for this work has a horizontal axis of nine pixels length and a vertical axis of ten pixels length. Unlike what was presented by Omaia, which used the KNN with K = 3, it was chosen K = 1 to compare the DCT components. This change was made necessary because the 1-to-1 comparison allows one sample per individual only, what prevents the use of KNN with $K > 1$, and it is not feasible to use different classifiers on comparative tests.

Among the LBP variations used for texture classification, the one presented by Ahonen *et al*. [24] was chosen. This work uses an LBP variation designed specifically for face recognition, based on spatial features. The method *compareHist* from the OpenCV library was used to compare the histograms generated by the LBP. The chosen metric was the Correlation and the parameters for the LBP were four and one, for neighborhood pixels and radius, respectively.

A. One-to-one Algorithms evaluation

In following tables, the mention of any type of cropping will imply the usage of the geometric normalization in the process. Likewise, if it is not mentioned, the process was not performed. Table I refers the EER rates using the DCT based classifier.

Table II represents the EER rates resulted from the usage of the LBP based classifier.

It was shown, by the analysis from 1-to-1 tests and Tables I and II, that the evaluated algorithms have high EER rates. In both tables, the results gotten, from an image that geometric

TABLE I
EER FOR EACH NORMALIZATION TECHNIQUE FOR THE DCT BASED CLASSIFIER.

Illumination Normalization	No Crop	Crop 1	Crop 2
None	23%	37%	40%
Log	13%	32%	39%
LogAbout	13.2%	33%	39%
Equalization	23%	35%	43%
Local Equalization	29.3%	40%	40%
Retinex	21%	37%	41%
Retinex and Expansion	21%	41%	42%

TABLE II
EER FOR EACH NORMALIZATION TECHNIQUE FOR LPB BASED CLASSIFIER.

Illumination Normalization	No Crop	Crop 1	Crop 2
None	26%	36.5%	41.5%
Log	30%	36.4%	43%
LogAbout	35%	36.7%	44%
Equalization	33.5%	37.5%	43.6%
Local Equalization	34%	36.3%	43.6%
Retinex	27%	34%	40.8%
Retinex and Expansion	29%	33.5%	42%

normalization was not performed, have better result than the others geometric normalized. If the tests with same cropping type being analyzed (no crop, Crop 1, Crop 2 or Crop 3), the results from a database without illumination normalization is overtaken in 82% of the cases by one of the results from one or more illumination normalization methods.

B. One-to-many Algorithms evaluation

The second round of recognizing methods evaluation uses 1-to-N tests. In all tests, the cross-validation technique was used.

Tables III and IV show the result from the leave-one-out process, where all samples except one are used for training, the remaining sample is used for the test.

TABLE III
EER FOR RECOGNITION BY LEAVE-ONE-OUT FOR DCT BASED CLASSIFIER.

Illumination Normalization	No Crop	Crop 1	Crop 2
None	9.1%	31.8%	43.5%
Log	3.9%	22.8%	51.3%
LogAbout	2%	19.5%	46.8%
Equalization	16.3%	29.2%	44.8%
Local Equalization	20.8%	33.8%	48.1%
Retinex	3%	28%	42.9%
Retinex and Expansion	2%	33.8%	56.5%

The 1-to-N results were similar to the previous tests (1-to-1), the results from images with Crop 2 were worse than the results with crop 1, and both were outdone by the images without any geometric normalization.

C. ASM Evaluation

To ensure the geometric normalization is well performed, it is necessary to detect whether the center of the eye is

TABLE IV
EER FOR RECOGNITION BY LEAVE-ONE-OUT FOR LPB BASED CLASSIFIER.

Illumination Normalization	No Crop	Crop 1	Crop 2
None	3.3%	18.9%	39%
Log	18.9%	17.5%	44.2%
LogAbout	23.4%	22.1%	59.8%
Equalization	23.4%	20.1%	41.6%
Local Equalization	20.8%	22.1%	52%
Retinex	15%	13%	47.4%
Retinex and Expansion	20.1%	13%	47.4%

reliable. This evaluation is made using automatic detection and handmade detection. Therefore, it was necessary to make the ground truth of an image database, manually identifying the eyes locations in all images. This ground truth was made on Yale Face Database A.

The study consists of computing the Euclidean distance between coordinates provided by ASM and the coordinates detected manually. To ensure if the provided coordinates from ASM is correct, it is necessary to define a distance threshold, i.e. if the distance between two given coordinate is lower than a given value, the result is correct. Thus a plot was generated (Figure 5) from the change of threshold.

The method achieves a success rate of 50%, 80% e 90% using a distance threshold equals to 6,10 and 14, respectively. On average, the difference between the two coordinates is 6.83, with a standard deviation equal to 5.15.

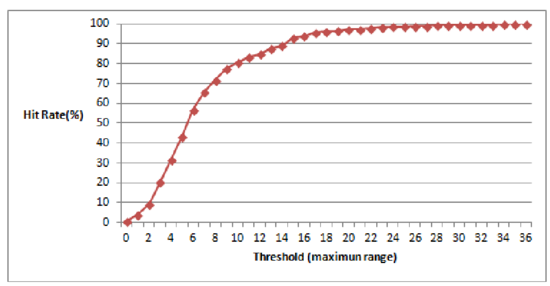

Fig. 5. ASM accuracy study

These error detection rates compared to manual markings are high when considering the dimensions of the images used in the assessment (127-pixel width by 147-pixel height).

D. Handmade Eye Detection Tests

After having obtained the results from the ASM accuracy study, it was decided to repeat the face recognition tests with the manually marked coordinates of the eyes. This was done in order to be aware of the impact caused by the error of geometric normalization on recognition scores, an error caused by the failure to detect the eye center position.

Thus, tests were remade. Evaluating errors in eye points detection (taking that are more accurate than the face contour points detected by ASM) and also from the visual result, a new cut test for removing the non-face information (Crop 3)

TABLE V
EER FROM 1:1 TESTS WITH LBP AND DCT METHODS USING ASM AND HANDMADE EYE DETECTION.

Eye location	Recognition Method	Illumination Normalization	No Crop	Crop 1	Crop 2	Crop 3
ASM	DCT	None	23%	37%	40%	39.5%
		Log	13%	32%	39%	38%
		LogAbout	13.2%	33%	39%	40%
		Equalization	23%	35%	43%	36%
		Local Equalization	29.3%	40%	40%	42%
		Retinex	21%	37%	41%	40.5%
		Retinex and Expansion	21%	41%	42%	41%
	LBP	None	26%	36.5%	41.5%	40%
		Log	30%	36.4%	43%	40%
		LogAbout	35%	36.7%	44%	40%
		Equalization	33.5%	37.5%	43.6%	38%
		Local Equalization	34%	36.3%	43.6%	41%
		Retinex	27%	34%	40.8%	41%
		Retinex and Expansion	29%	33.5%	42%	40.5%
Handmade	DCT	None	23%	30.5%	40%	32%
		Log	13%	18%	31%	29%
		LogAbout	13.2%	18%	32%	29%
		Equalization	23%	27%	37.5%	30%
		Local Equalization	29.3%	21.5%	32.3%	26%
		Retinex	21%	24%	33%	33%
		Retinex and Expansion	21%	24%	30.5%	30%
	LBP	None	26%	20%	31%	27.5%
		Log	30%	18%	32%	22.3%
		LogAbout	35%	24.5%	31.5%	24%
		Equalization	33.5%	20%	30%	25.5%
		Local Equalization	34%	20.5%	30%	23%
		Retinex	27%	13%	31%	19%
		Retinex and Expansion	29%	14%	29%	19.4%

without the needing ASM points. The tables show the same results for the tests with databases without crops because in these ones there is no geometric normalization, so the location of the eyes does not influence the result.

Tables V and VI show EER with ASM and handmade eye detection, using both LBP and DCT based classifiers on 1:1 and 1:N tests respectively.

Using the DCT based classifier, the results from Crop 1 are similar to the results from no crop, getting lower rates compared to the non-preprocessed database (no normalization). The performance of Crop 3 was better than Crop 2 but not as high as the Crop 1 performance.

On tests with the LBP based classifier, the best performance was reached by the Crop 1 in all cases. The Crop 3 got similar rates to Crop 1 in average, although not overtaking the results.

Using handmade eye detection to geometric normalization results in rates improvement, yielding up to 50% EER decrease if compared to the same test using the ASM eye detection. As in previous tests, the illumination normalization produced a performance gain in every case, despite any crop.

The results got from the LBP based classifier are also coherent to the tests. In ascending order, the best recognition rates are from Crop 1, Crop 3, No cropped and Crop 2.

V. CONCLUSIONS

After the study, it comes to the conclusion that this implementation of the ASM, used this way, is not accurate enough to be used, negatively affecting the results. Better eye detection is needed to improve the performance of the methods.

Applying illumination normalization methods has proven its value for the improvement of face recognition rates in unconstrained environments, although it is not possible to identify a method which satisfies every case.

The results have shown that if the image information is restricted to the face, the performance gets worse, what leads to the conclusion that many works [10] [13] [5] [9] which do not crop the face are using background information to perform recognition. As in the dataset, the conditions of different samples are quite similar (background, clothes, size, haircut, beard, camera distance, etc.), the recognition systems end up using this information, improving the final rates.

The obtained results show that the SDRF (based on DCT) is not ready to be used yet, but it is still a system in development, so, it can improve later. One purposed improvement is selecting attributes of the analyzed images, in case of this work, normalized and cropped images, since these procedures remove noisy information.

Improve the eye detection is a future work, being one of the following tests use the illumination normalization before the ASM algorithm, as well as experimenting LBP variations, parameters variation and new methods for histogram comparison.

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TABLE VI
EER FROM 1:N TESTS WITH LBP AND DCT METHODS USING ASM AND HANDMADE EYE DETECTION.

Eye location	Recognition Method	Illumination Normalization	No Crop	Crop 1	Crop 2	Crop 3
ASM	DCT	None	9.1%	31.8%	43.5%	39.6%
		Log	3.9%	22.8%	51.3%	40.2%
		LogAbout	2%	19.5%	46.8%	35%
		Equalization	12.3%	29.2%	44.8%	36.7%
		Local Equalization	20.8%	33.8%	48.1%	44.2%
		Retinex	3%	28%	42.9%	42.2%
		Retinex and Expansion	2%	33.8%	56.5%	52.6%
	LBP	None	3.3%	18.9%	39%	39.6%
		Log	18.9%	17.5%	44.2%	40.2%
		LogAbout	23.4%	22.1%	59.8%	35%
		Equalization	23.4%	20.1%	41.6%	36.4%
		Local Equalization	20.8%	22.1%	52%	44.2%
		Retinex	15%	13%	47.4%	42.2%
		Retinex and Expansion	20.1%	13%	47.4%	52.6%
Handmade	DCT	None	9.1%	12.4%	29.9%	18.2%
		Log	3.9%	2.6%	28.6%	11.7%
		LogAbout	2%	2%	28%	12.4%
		Equalization	16.3%	7.2%	24%	12.4%
		Local Equalization	20.8%	10.4%	21.4%	11.7%
		Retinex	3%	3.3%	22.1%	15%
		Retinex and Expansion	2%	7.2%	33.1%	16.3%
	LBP	None	3.3%	3.9%	39%	8.5%
		Log	18.9%	2%	43.9%	5.2%
		LogAbout	13.4%	7.8%	39.6%	10.4%
		Equalization	13.4%	3.3%	22.8%	6.5%
		Local Equalization	20.8%	4.6%	25.4%	7.2%
		Retinex	15%	0.7%	35.1%	2.6%
		Retinex and Expansion	20.1%	0.7%	19.5%	5.2%

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