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Choice of Illumination Normalization Algorithm for Preprocessing Efficiency of Discrete Cosine Transform

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Abstract
Several improvements on recognition system were made, yet there was no benchmark strategy for recognition system in existence. To build a verification or identification system, the commonest natural phenomenon that has not been dealt with is illumination variations. This is considered a great challenge in face recognition. However, regardless of a number of normalization approaches in the literature, the choice of an illumination algorithm that solves a particular problemno matter how littleis very essential. This paper evaluated the existing illumination normalization techniques that minimize poor illumination of imagesfor performing recognition using Discrete Cosine Transform (DCT). We applied JPEG compression on uncontrolled illumination images from Extended Yale-B face database,and evaluated the benchmark using these error metrics; Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) . The results show thatanisotropic diffusion (AS) is the best of the 22 illumination normalization (IN)techniques in the literature that best fit recognition using the DCT. Therefore, the faces were used to test the proposed concept, but the result is also applicable to all physiological biometric recognitions using DCT.

Keywords: Illumination normalization (IN); DCT; Face; JPEG compression; Extended Yale-B.

1. Introduction
Preprocessing is the heart of image processing, being the most valuable stage of any recognition or classification system. It includes image enhancements (i.e. noise removal or illumination normalization), segmentation, geometry normalization, scaling and alignment. Therefore, these techniques are easily achievable even with unconstrained dataset except illumination normalization. Illumination normalization is a preprocessing technique that compensates for the different lighting conditions [1].

Recognition under uncontrolled illumination conditions is a major concern and a great challenge for recognition of real life applications. However, illumination appearsin image as noiseand causes false-accept or false-reject. It is natural that human beings fail to recognize one another in darkness. This is similar to recognition with computer; the algorithms are like human visual system and require an identifiable input to work best. The researchers'efforts in dealing with this aspect have been quite extensive, but at certain period we need to evaluate the existing techniques to allow improvement upon the best techniques under certain defined conditions. The well-known22 illumination normalization techniques are : (1) the single scale retinex (SSR) [2], (2) the multi scale retinex (MSR) [3], (3) the adaptive single scale retinex (ASR) [4], (4) the homomorphic filtering (HOMO) [5], (5) the single scale self quotient image (SSQ) [6], (6) the multi scale self quotient image (MSQ) [6], (7) the discrete cosine transform (DCT)[7], (8) the retina modeling (RET) [8], (9) the wavelet (WA) [9], (10) the wavelet denoising (WD)[10], (11) the isotropic diffusion (IS) [5], (12) the anisotropic diffusion (AS)[11], (13) the steering filter (SF)[12], (14) the non-local means (NLM)[13], (15) the adaptive non-local means (ANL) [13], (16) the modified anisotropic diffusion (MAS) [12], (17) the gradientfaces (GRF) [14], (18) the single scale weberfaces (WEB) [15], (19) the multiscaleweberfaces (MSW) [15], (20) the large and small scale features (LSSF) [16], (21) the tan and triggs (TT) [17], and (22) the difference of gaussian filtering (DOG) [12]. The algorithms are developed periodically to improve the preprocessing stage, but the choice of any one of them depends on the type of feature extraction.

Many researchers worked towards improving face recognition under uncontrolled lighting conditions, through the choice of various techniques for illumination compensation and preprocessing enhancement. They used a set of designed criteria to normalize the illuminations under such constraintsin order to restore a face image back toits normal lighting condition[1],[18],[19],[20],[21],[22]. To the best of the authors' knowledge, only [1]tested the 22 illumination normalization techniques using one metric and discovered thatmulti-scale retinex (MSR) is the best in terms of illumination compensation with the highest PSNR. The present study uses four metrics to evaluate the performance of these techniques, and only in DCT domain. The DCT is a well-known feature extraction technique for image compression that is largely affected by illumination variations.

For this reason, we presented a study on a solution to the choice of illumination normalization algorithm for DCT preprocessing efficiency under uncontrolled illumination conditions. The present study identifies the most suitable illumination compensator for texture-based recognition using DCT feature extractor. The choice enables justification over the widely used illumination normalization techniques in the literature.The best algorithm will promote efficiency of data compaction of DCT andincrease recognition of features using the DCT. The choice of IN technique that will be subjected to compressionequivalent to that of DCT and be reconstructed with least error is our goal. The justifiable reason of carrying out the study is; some feature extraction algorithms are more sensitive to illumination than others, and no algorithm is however insensitive to illumination variations. Furthermore, each of the IN techniquescan work better with some feature extractorsthan others. With this research, we hope the problem of illumination when using DCT as feature extractor will be minimized.The samples of images in this database are shown in figure 1.

Figure 1: Samples of images extractedfrom Extended Yale-B database

2. Methodology

For suitability, extended Yale-B database was used in this study to test and identify the most suitable illumination normalization technique during preprocessing stage of applying DCT for recognition. This database contains gray scale frontal images of 38 subjects under 9 poses and 64 illumination conditions.The entiretest set used in the experiment were manually aligned, cropped, and then re-sized to 168x192 images [23]. In the proposed scheme,several images from the mentioned database wereautomatically normalized one after the other using each of the illumination normalization technique source codes. In addition, Mat lab R2012b version 8.0 was used for simulation. The images werecompressed using principle of JPEG through conducting the DCT according to equation 1. The compression was carried out to test which illumination technique would compensate lighting effect without degrading the quality of images.The compressed features were obtained by run-length encoding. These features were then reconstructed using inverse DCT. The reconstructed features were retrieved to determine the quality variation between the original images of each IN technique and the reconstructed ones. After that, average results of the images were computed. The errormeasurements were calculated using these metrics: PSNR, MSE, RMSE, and MAE. The block diagram of the proposed algorithm is illustrated in figure 2.

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N}, \quad \begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1 \end{matrix} \tag{1}$$

Where $\alpha_p = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le p \le M-1 \end{cases}$ And $\alpha_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{\frac{2}{N}}, & 1 \le q \le N-1 \end{cases}$

The 'M' *and* 'N' are the row and column size of the input image 'A' respectively. Since the DCT tends to concentrate information, making it useful for image compression applications [24], [25], therefore choosing the best IN technique that supports compression and increases the compaction of data is highly recommended.

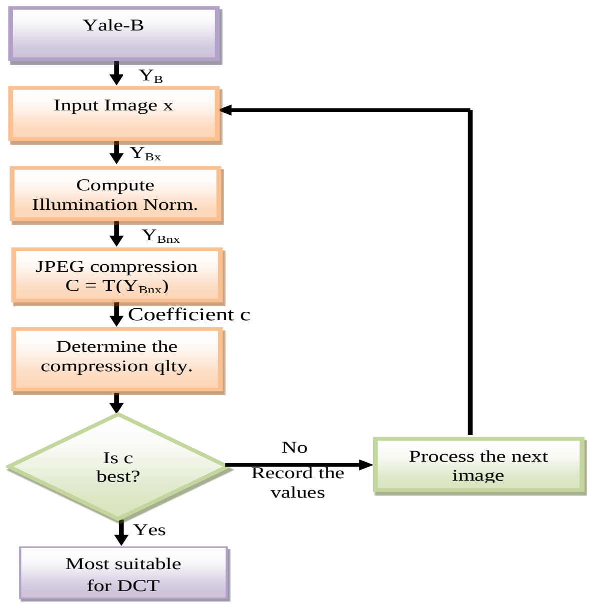

Figure 2: Block diagram of the performance evaluation

3. Results and Discussion

Figure 3 describes the results of different IN techniques applied on the extended Yale-B. The effect of each technique depends on the type of its function. On the other hand, the DCT compression is largely affected by increasing the coefficient magnitude at the top left corner of the matrix, and reducing the values of this coefficient diminishes the image quality [26]. Thus, normalizing the illumination of the images before extracting the features compensates these coefficients variances and sets the blocks to more equalizedintensity. It is very important to categorize preprocessors according to their suitability on a particular algorithm. This will produce a benchmark strategy for a near perfect recognition system.

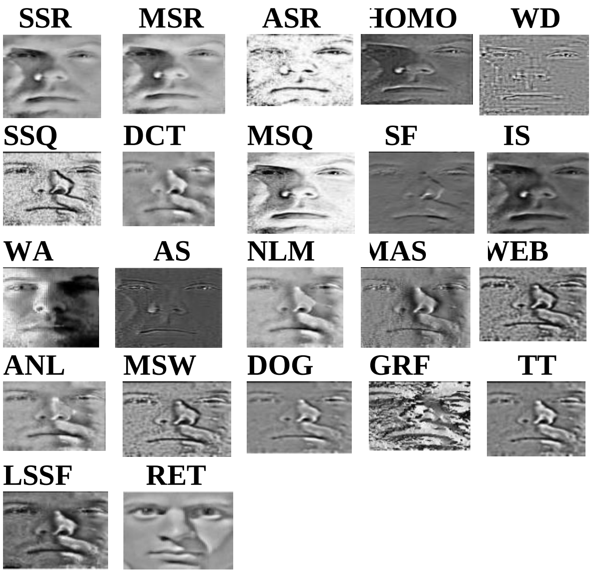

Figure 3: Results showing the effect of 22 IN algorithms applied on the extended Yale-B

The JPEG compression was computed on each normalized image, and the error calculation was carried out between original and compressed images using the four error metrics. Figure 4 and 5 demonstrate the results of original images and corresponding compressed images respectively.

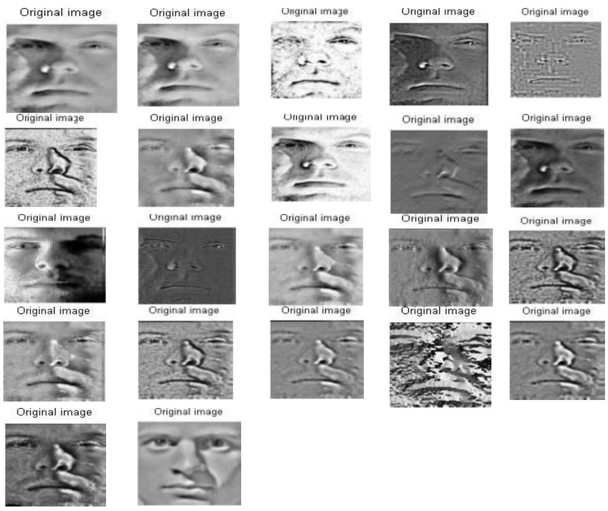

Figure 4: Retrieved original images before JPEG compression

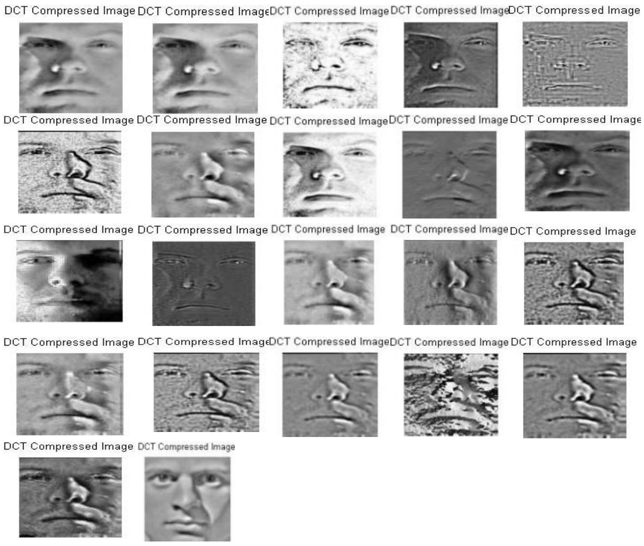

Figure 5:Compressed images after JPEG compression

Therefore, on the basis of evaluation of these techniques, the average results obtained were recorded in table 1, and plotted using line graph as shown in figure 6. The anisotropic diffusion based illumination technique (AS) emerged as the best technique, having the highest PSNR of 58.199, MSE of 0.298, RMSE 0.546 and least MAE of 0.931. The MSE with mathematical relation in '(2)' is the cumulative squared error between compressed and the original images, whereas PSNR in '(3)' is a measure of the peak error.

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y) - I'(x,y)\right]^2 \quad (2)$$

$$PSNR = 20 * \log10\,(255 / \mathrm{sqrt}(MSE)) \quad (3)$$

Table 1: The metrics comparison of the 22illumination normalization techniques

S/N	TECHNIQUES	PSNR(dB)	MSE	RMSE	MAE
1	**WEB**	53.885	0.804	0.897	1.483
2	**WD**	53.003	0.985	0.992	1.687
3	**WA**	53.650	0.849	0.921	1.368
4	**TT**	53.912	0.799	0.894	1.498
5	**SSR**	52.629	1.073	1.036	1.752
6	**SSQ**	51.114	1.521	1.233	2.052
7	**SF**	55.830	0.514	0.717	1.232
8	**RET**	52.425	1.125	1.061	1.800
9	**NLM**	51.760	1.311	1.145	1.946
10	**MSW**	53.060	0.972	0.986	1.650
11	**MSR**	51.990	1.243	1.115	1.876
12	**MSQ**	50.171	1.890	1.375	2.297
13	**MAS**	54.348	0.722	0.850	1.432
14	**LSSF**	54.937	0.631	0.794	1.297
15	**IS**	56.574	0.433	0.658	1.089
16	**HOMO**	56.181	0.474	0.688	1.150
17	**GRF**	52.591	1.082	1.040	1.629
18	**DOG**	53.460	0.886	0.941	1.595
19	**DCT**	52.716	1.052	1.026	1.744
20	**ASR**	49.419	2.248	1.499	2.543
21	**AS**	**58.199**	**0.298**	**0.546**	**0.931**
22	**ANL**	52.418	1.127	1.061	1.802

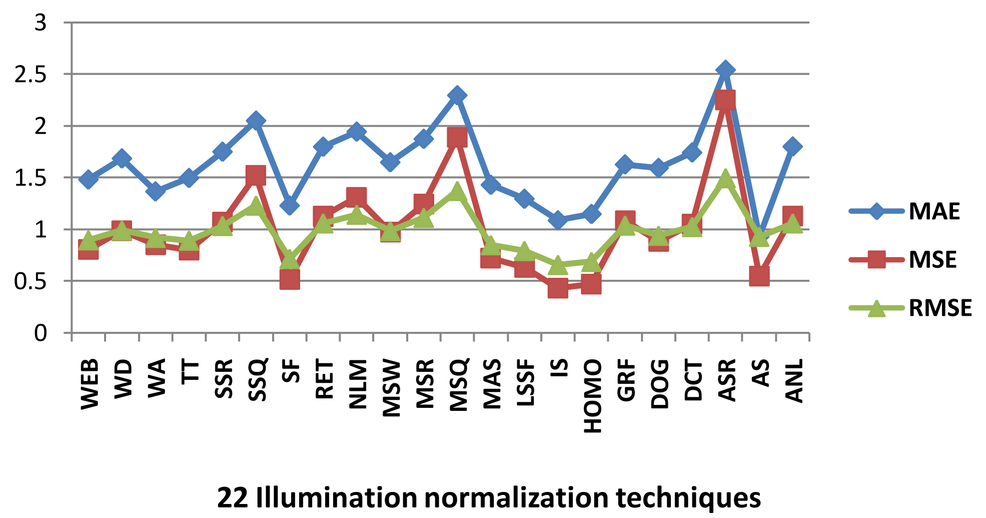

Figure 6:Line graph of comparison of the 22 illumination normalization techniques

The AS estimates the luminance function using anisotropic smoothing. It also supports compression and increases the compaction of the data. Therefore, the design of DCT incorporated with the AS will compensate lighting effects, noise, and preserve object boundary effectively without degrading the quality of images. Additionally, the study proves that the DCT based normalization was outperformed by few others IN techniques. Therefore, employing the AS for any recognition using the DCT will report additional performance over the traditional illumination algorithms. This study is applicable to all physiological biometrics such as palmprint and fingerprint under DCT recognition. Conducting the experiment on uncontrolled illumination images will represent the recognition in real life.

The choice of evaluation using these error metrics is importantsince they compare the various normalized images with the compressed ones. The work of Juefei-Xu and Savvidesin [1], considered only SNR for evaluating those 22 IN techniques. The paper overlooked the performance criterion, which is the goal of every preprocessor, and the measurement was carried out between the normalized images and their corresponding neutral images. However, the paper discovered multi-scale retinex (MSR) as best of the IN techniques with the highest SNR. This basis of evaluation is not efficient for a particular algorithm like DCT.Admirably, the present study discovered anisotropic diffusion (AS) as the most suitable preprocessor for DCT-based recognition.

The major contributions of this paper are: (1) Itevaluated the illumination normalization techniques using JPEG compressionstandard.This is the first work that centers on the DCT illumination enhancement with detailed measurements. (2) The proposed evaluation scheme justifies the target algorithm and suggests the use of anisotropic diffusion based IN technique (AS) for efficient preprocessing of DCTbased recognition. (3) The uncontrolled images were also considered for actual testing of the illumination conditions in real life.

In addition, categorizing a particular compensatorfor a particular algorithm or classifier eases a lot of efforts for the researchers. Thus, subjecting the normalized images into JPEG compression and quality measurement on extended YALE-B can intensively measure the performance of the techniques in accordance with DCTdespite the illumination variations. The limitation of this paper is that, this benchmark reported technique using JPEG compression is only applicable to DCT based recognition.

4. Conclusion and Future Work

This study was conducted to measure the performance of the 22 illumination normalization techniques using JPEG compression standard. Thus, the paper discovered an anisotropic diffusion illumination normalization technique (AS) as the most suitable preprocessor for face recognition using DCT. Hence, the objective is achieved. The best compensator algorithm will promote compaction power of the DCT feature extractor and increase recognition rates.Although the face images were used for conveniences, but the study encompasses all physiological biometric features recognition using the DCT.Gabor-DCT and Histogram Equalization (H.E)-DCT using Yale-B was compared in [27]. The results of Gabor-DCT superseded the use of H.E preprocessor and increased decorrelation power of DCT by 7.35%.Therefore our future work will concentrate on recognition of faces by combining the discovered AS and Gabor-DCT. The choice of this combination will yield a surprising performance since DCT is all about decorrelation and compaction efficiency of the images.Finally, the design of DCT incorporated with the AS will compensate lighting effects, noise filtration, and preserve object boundary effectively without degrading the quality of images.

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