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Research Article

Comparing Illumination Normalization Methods for Face Recognition

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ABSTRACT

The effects of image illumination changes is one of the major concerns in face recognition because it is significantly degrading recognition accuracy. This work presents a comparative evaluation of eight illumination normalization algorithms (Gamma, DoG, Homomorphic, Gradient faces, SQI, Steerable, Isotropic, and Anisotropic) combined with a unified pipeline of Gabor feature extraction, PCA dimensionality reduction, and four classifiers (Naïve Bayes, SVM, K-NN, and MLP). Practical study is conducted using the Yale B, AR, and CMU-PIE standard image databases. The best recognition rates (RR) were achieved as follows: on AR, DoG and Isotropic filtering reached up to 98.42% (MLP); on CMU-PIE, DoG and Anisotropic filtering achieved 56.84% (K-NN); and on Extended Yale B, SQI, Steerable, and DoG achieved up to 94.21% (MLP). The results demonstrate that local normalization methods consistently outperform global methods under severe illumination. Therefore, DoG and Isotropic filtering are recommended for moderate lighting conditions, while SQI, Steerable filtering, and DoG are more suitable for extreme illumination scenarios.

Keywords: Illumination normalization, Difference of Gaussian, Homomorphic Filtering, Self Quotient Images (SQI), Steerable Gaussian Filtering, Gamma correction, Gradient faces and Isotropic and Anisotropic Filtering

INTRODUCTION

Facial recognition developers are always facing challenges because of the illumination variations. The changes in illumination direction or intensity causing significant effects on the visual representation of the traits and cause to reduce the accuracy of digital image identification [1]. To address this issue, many techniques rely on a pre-processing stage to standardize illumination levels prior to extracting key features. This makes the system less sensitive to visual changes that are not related to the actual identity of the face [1-2]. Illumination normalization is a pivotal and critical step in facial feature classification systems, and its importance lies in the following points: Neutralizing external factors - reducing the effect of shadows and brightness that may alter the true features of the face, highlighting fixed features - making the system to focus on the shape of the main facial parts (eyes, nose, and mouth) instead of the intensity of light, reducing the incorrect recognition rate - ensuring the recognition of the person even if the lighting environment

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differs between the time of capturing and the time of testing, and data uniformity - making all images have similar levels of brightness and contrast, which facilitates the work of machine learning algorithms.

This work is addressing the question of how each specific illumination normalization algorithms is affecting face recognition system’s performance.?

This study compares eight illumination normalization algorithms under the same framework (Gabor feature extraction + PCA + four classifiers) tested on the three standard datasets of AR, CMU-PIE, and Extended Yale B.

The fields of access control, video surveillance, human computer interaction, and law enforcement are some of the main practical applications of face recognition. The process of enhancing illumination normalization for facial image is very essential to enhance the whole system performance [3]. In recent years, modern studies have demonstrated the effectiveness of advanced illumination normalization techniques in improving the performance of facial recognition systems under inconsistent or challenging lighting conditions [2,4-6]. These recent studies show the viability of combining computational illumination processing with statistical or deep methods to address real-world challenges. However, a comprehensive evaluation of various illumination normalization techniques within a standardized experimental framework is still needed to enable comparison of their performance and to draw recommendations regarding their effectiveness in practical applications.

In this work, we investigate techniques for illumination normalization, namely Isotropic, Anisotropic, Histogram, Difference of Gaussian (DoG), Gradient faces, Homomorphic filtering, Self Quotient Image (SQI) and Steerable Filters.

Section 2 of this paper describes the illumination normalization techniques used in this work. Section 3 shows the settings that were used for each of the illumination normalization algorithms to improve the image, as well as extracting the distinctive features of facial images using Gabor filters. In addition to the classification techniques used on the facial databases to which the aforementioned techniques were applied. The experimental results obtained from the aforementioned databases are presented in Section 5. Finally, conclusion is presented in Section 6.

BACKGROUND

The addressed illumination normalization algorithms or methods are presented in this section. Each method is briefly described along with its mathematical formulation.

DIFFERENCE OF GAUSSIANS (DOG)

The Difference of Gaussians (DoG) [7] method enhances facial details by suppressing low-frequency illumination components while preserving high-frequency structural features such as edges. This technique improves robustness to lighting variations without effecting the important facial characteristics.

$$DoGIMG(x,y) = IMG_{(x,y)} * (G_{\sigma1(x,y)} - G_{\sigma2(x,y)})$$

(1)

The *IMG* is the original image, and $G_{\sigma1}$, $G_{\sigma2}$ are two-dimension Gaussian filters. The equation shows the outcome of the convolution process.

GRADIENT FACES

The gradient faces is the representation of facial features using spatial gradients instead of the direct intensity values which is less sensitive to illumination changes. This approach enhances feature stability under varying lighting conditions [8].

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$$\text{GRDIMG}(I_p) = \arctan\left(\frac{\text{IMG}_{p+\Delta p} - \text{IMG}_p}{\text{IMG}_p}\right) \quad (2)$$

where, IMG_p is the original image, $\text{IMG}_{p+\Delta p}$ is the intensity of the neighboring pixel, and Δp is the change in parameter p which refers to the normalization control parameter.

HOMOMORPHIC FILTERING

Homomorphic filtering separates illumination and reflectance components in the frequency domain using a logarithmic transformation. It enhances image contrast by suppressing low-frequency illumination variations while preserving high-frequency details [9].

Equation (3) is used to represent this technique:

$$\text{IMGH}_{(u,v)} = (\gamma_{Hi} - \gamma_{Lo}) \left[1 - \exp\left(-c \frac{D_{(u,v)}^2}{D_o^2}\right) \right] + \gamma_L \quad (3)$$

where, γ_{Hi} and γ_{Lo} represent High and Low pass filters; Typically set to >1 and <1 , respectively. D_o is the cutoff frequency determining the boundary between illumination and reflectance. $D_{(u,v)}$ represents the distance on the frequency plane. Noting that c is the constant that decides the slope of the filter.

Converting the image from the spatial domain to the frequency domains carried using the above equation of the Inverse Fourier Transform (f^{-1}) and the exponential function:

$$\text{GIMG}_{(x,y)} = \exp(f^{-1}\{\text{HIMG}_{(u,v)} \cdot \text{ZIMG}_{(u,v)}\}) \quad (4)$$

where, $\text{HIMG}_{(u,v)}$ is the transformed image and $\text{ZIMG}_{(u,v)}$ is the Fourier transform of the log-transformed input image.

SELF QUOTIENT IMAGE (SQI)

The SQI techniques is useful in converting the image into a smoothed copy to reduce the effect of low-frequency illumination [10].

The equation of SQI technique is:

$$\text{SQIMG}_{(x,y)} = \frac{\text{IMG}_{(x,y)}}{\text{SIMG}_{(x,y)}} \quad (5)$$

where, $\text{IMG}_{(x,y)}$ is the original input image and $\text{SIMG}_{(x,y)}$ is the smoothed image - $\text{SIMG}_{(x,y)} = \text{IMG}_{(x,y)} * G_\sigma$; in which G_σ represent the Gaussian kernel. $\text{SIMG}_{(x,y)}$ is the ambient illumination component.

STEERABLE GAUSSIANS

Steerable Gaussian filters capture directional features by analyzing the image at multiple orientations. This allows effective preservation of structural facial details while reducing the impact of shadows and illumination variations [11].

Equation (6) is used to represent this technique:

$$I^\theta(x, y) = \text{IMG}_{(x,y)} \sum_{j=1}^m K_j(\theta) * F^{\theta_j}(x, y) \quad (6)$$

where, IMG is the original image, $K_j(\theta)$ is the interpolation function (steering coefficients) dependent on the angle (θ), and $F^{\theta_j}(x, y)$ is a set of m fixed basis filters which represent the rotated version of the original filter at pre-selected angles θ_j .

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ISOTROPIC FILTERING

Isotropic filtering smooths the image uniformly in all directions, reducing low-frequency illumination variations. It improves overall image consistency but may blur fine details under strong directional lighting [12].

The equation formula of this technique is expressed in equation (7):

$$G_{(x,y)} = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\pi^2}} \tag{7}$$

where σ is the standard deviation.

ANISOTROPIC FILTERING

Anisotropic filtering reduces illumination variations through adaptive diffusion while preserving important edges and structural details. It is particularly effective under directional lighting, where maintaining edge information is essential [13-14].

Equation (7) is used to represent this technique:

$$\frac{\partial IMG_{(x,y,t)}}{\partial t} = \nabla \cdot (c(|x,y,t|)\nabla IMG_{(x,y,t)}) \tag{8}$$

This equation shows the evolving of the image intensity represented by (IMG) over time (t) under a diffusion process.

where, IMG is the original intensity function at (x,y) and iteration t, $\frac{\partial IMG}{\partial t}$ represent the rate of change of the pixel intensity over time, ∇ is the gradient operator, $\nabla \cdot$ is the divergence operator, and $c(|x,y,t|)$ is the diffusion coefficient. This diffusion coefficient can be represented by the equation: $c = \exp\left(-\left(\frac{|\nabla I|}{k}\right)^2\right)$, k is a constant parameter.

GAMMA CORRECTION

The gamma correction is a nonlinear transformation technique to treat the image’s non-uniform illumination. The illumination intensity of each pixel is adjusted after normalizing the values to the range [0, 1] according to an exponential relationship controlled by the correction factor γ [15]. Equation (9) represents this technique:

$$GImg_{out}(x,y) = Img_{in}(x,y)^\gamma \tag{9}$$

Were, Img_{in} and $GImg_{out}$ represent the intensity values before and after correction, respectively. When $\gamma < 1$, it leads to enhance the dark area, while $\gamma > 1$ reduces the intensity of the bright data, thereby improving light distribution and minimizing shadows.

METHODOLOGY SET UP

This section describes the complete experimental pipeline, including preprocessing, illumination normalization, feature extraction, dimensionality reduction, classification, and datasets.

PREPROCESSING

The accuracy of any facial recognition systems is always depending on the quality of the initial face image under test, especially when there are significant variations in illumination. A series of preprocessing steps are usually implemented before applying the illumination normalization algorithm. First, face cropping was performed to remove backgrounds and unrelated elements, reducing noise and increasing the system’s focus on the face area only. Subsequently, the image dimensions were standardized to 128×128 pixels to ensure

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consistent feature representation across samples and prevent structural variations in subsequent processing. Color images were also converted to grayscale, as most illumination normalization and feature extraction algorithms are most effective on images with only intensity values, resulting in more stable representations against changes in lighting [16-17]. Images in the AR and CMU-PIE databases were converted from color to grayscale, while images in the Extended Yale B database are originally grayscale and do not require conversion. Figure 1 shows the effect of applying preprocessing steps.

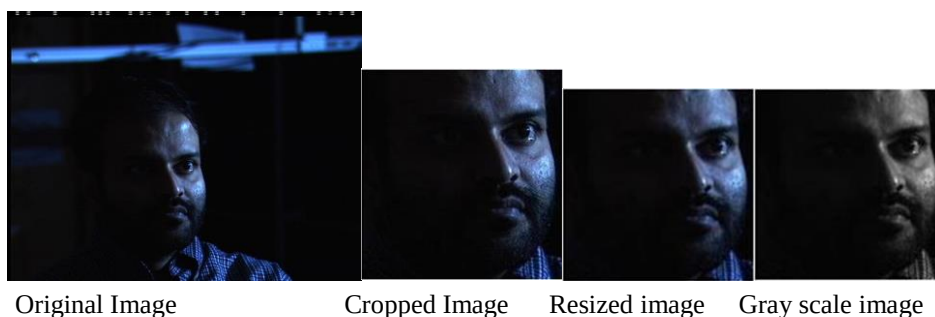


Figure 1: Applying preprocessing steps.

ILLUMINATION NORMALIZATION

In many applications, it is very important to apply the illumination normalization step to mitigate the impact of these light variations prior to the stages of feature extraction and classification. These algorithms are categorized according to their areas of operation as follows:

GAMMA CORRECTION

It is used for non-linear illumination transformation, which helps to regulate the distribution of intensity values in the image and improve the clarity of details in dark and bright areas. A gamma coefficient of $\gamma = 0.8$, within the values commonly found in the literature, was adopted to achieve a balance between compression and expansion of intensity.

DIFFERENCE OF GAUSSIAN (DOG)

A high-pass filter is used to highlight fine details and reduce low-frequency components associated with general lighting. Default values for standard deviations are: $G_{\sigma 1} = 1.0$, $G_{\sigma 2} = 2.0$

HOMOMORPHIC FILTERING

It separates the illumination components from the reflection in the logarithmic and frequency domains, with the application of a high-frequency pass filter with a value of $D_o = 30$ and the coefficients of $\gamma_{HI} = 2.0$ and $\gamma_{LO} = 0.5$ to separate the illumination components and reduce the irregular contrast.

ISOTROPIC FILTERING

It is used to improve the uniformity of light intensity across the image, with a coefficient of $\sigma = 1$.

ANISOTROPIC FILTERING

It preserves important edges and reduces variations in illumination in homogeneous regions, with the values of coefficients: $T = 15$, and a sensitivity coefficient $\kappa = 20$ to adjust the diffusion sensitivity.

GRADIENT FACES

The gradient direction is represented rather than the intensity of the light, with a 3×3 window size used to calculate the gradients, which reduces sensitivity to strong light changes [8]. The value of the normalization control coefficient used $P = 0.2$.

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STEERABLE GAUSSIANS

The multi-scale directional features are analyzed, with 4 levels and 8 directions identified for each level to accurately represent structural details.

SELF QUOTIENT IMAGE (SQI)

The (SQI) technique is usually used to mitigate the effect of uneven illumination in facial images. This technique relies on splitting the original image using Gaussian filter into a smoothed version. A Gaussian filter with a standard deviation of $\sigma=1$ and a window size of 5×5 is used in this study.

The aforementioned techniques have been adopted for illumination normalization and contrast treatment, including: Gamma Correction, DoG, Homomorphic Filtering, in addition to diffusion models (Isotropic and Anisotropic Diffusion), Gradient Faces, Steerable Gaussians, and SQI, in order to improve the stability of the visual representation and reduce the effect of lighting changes. Figure 2 bellow will show the effect of applying these techniques to the face image.

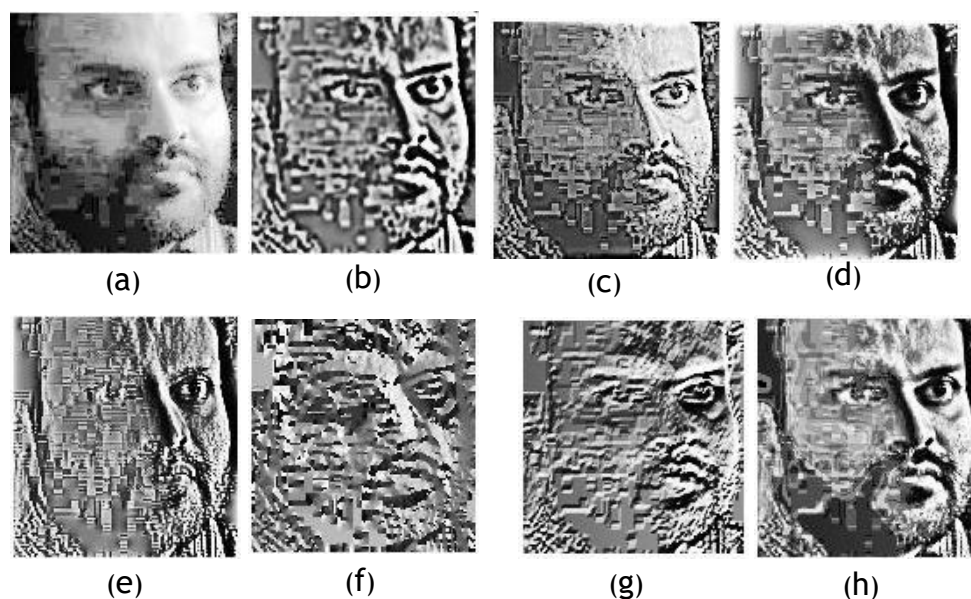


Fig. 2. The effect of applying different illumination algorithms (a) Gamma correction, (b) DoG, (c) Homomorphic Filtering, (d) Isotropic Diffusion, (e) Anisotropic Diffusion, (f) Gradient Faces, (g) Steerable Gaussians, and (h) SQI.

EXTRACTING FEATURE USING GABOR FILTERS

Gabor filters are among the most effective methods for obtaining distinct facial features since they can simultaneously represent both spatial and frequency information. This makes them capable of capturing local structural features of the face, such as edges, textures, and directional patterns. A Gabor filter is based on a composite sine wave function enclosed in a Gaussian envelope, enabling it to detect structural variations in multiple directions and frequencies. Recent studies have shown that these properties significantly enhance the performance of facial recognition systems [18-19].

The below equation is representing the two-dimensional filter:

$$\omega_{(u,v)}(P) = \frac{\|K_{(u,v)}\|^2}{\sigma^2} \exp\left(-\frac{\|K_{(u,v)}\| \|P\|^2}{2\sigma^2}\right) \left[\exp(iK_{(u,v)} P^{\exp(-\frac{\sigma^2}{2})}) \right] \quad (9)$$

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The variable P is representing the intensity pixel value at $(x, \text{horizontal})$ and $(y, \text{vertical})$ coordinates. $K_{(u,v)} = K_v \exp(i\phi_u)$ is a wave vector with magnitude of $(K_v = \frac{K_{max}}{\mathcal{F}^v})$, where $\mathcal{F}$ is the scaling factor or can be also described as the frequency ratio between the kernel filters. The K_{max} is a reference to the maximum frequency, $\phi_u = \frac{\pi}{8} * u$ and $\|\cdot\|$ is the norm vector. Below is the convolution of the image with Gabor filters:

$$GI = IM * \omega_{(u,v)}(P) \quad (10)$$

In this work, a Gabor filter bank with five scales and eight orientations is designed to carry out the practical experiments. Each filter is applied to a face image to generate response maps that reflect the image's structural and frequency characteristics. Given that the face images used were 128×128 pixels, applying the Gabor filter bank with eight orientations and five scales yielded 655,360 initial features for each face image. Down sampling factor of 64 is then applied. So, the final number of features per image became 10,240, a structurally rich representation with a significant reduction in computational data size.

As a result of extracting frequency features, a large number of high-dimensional features are produced, which may expose the system to the problem of high dimensionality. The principal component analysis (PCA) [20] is applied to reduce these dimensions to 100 principal components to reduce the computational complexity and increase the performance of the classifiers.

CLASSIFICATION

The classification stage represents the final and crucial stage in the facial recognition system, in which the extracted feature vector is assigned to the correct category that represents the person's identity. The effectiveness of this stage depends largely on the classification algorithm's ability to differentiate between various categories based on available features, while achieving a suitable balance between accuracy and generalizability. Four commonly used classification algorithms are used in this work, (K-Nearest Neighbors, Support Vector Machine, Naive Bayes, and Multi-Layer Perceptron) to evaluate the performance of the proposed system under different classification strategies. The K-NN algorithm is based on the principle of measuring the similarity between samples, where the new sample is classified according to the category that best represents the nearest neighbors in the feature space. This algorithm is characterized by its simplicity and direct reliance on data, making it a suitable reference for evaluating the discriminatory nature of extracted feature [21]. The SVM algorithm relies on finding an optimal separation between different classes that achieves the largest possible separation margin. It has proven highly efficient in facial recognition applications, particularly when dealing with feature extracted from spectral transformations. The SVM algorithm has the ability to generalize well and limits the overlearning [22]. The Naive Bayes algorithm is another simple and efficient probability classification technique that is using the conditional probabilities of features, assuming their independence. The use of Naive Bayes is to classify features extracted from images after processed by Gabor or PCA filters. This algorithm provides good and fast performance even with high-dimensional data [23]. The MLP is another classification tool that is using artificial neural network with supervised learning method to discover nonlinear relationships between features and their corresponding categories. The MLP algorithm is usually used to represent complex patterns in the data because it can handle the residual variation in facial features after the processing and extraction stages [24].

FACIAL DATABASES USED

The impact of illumination normalization algorithms on the performance of facial recognition systems will be tested using all of the three listed standard databases. The same experimental setup was adopted when using all types of databases, for 38 individuals and 10 facial images per each (totaling 380 images per database). These different databases are providing diverse illumination conditions to ensure a suitable framework for assessing the efficiency of the considered illumination normalization algorithms.

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- For AR and CMU-PIE datasets, 5 images per subject were used for training and 5 for testing (same as Extended Yale B for consistency).
- K-NN: $k = 3$ (or your actual value — adjust if needed).
- SVM: RBF kernel was used due to its effectiveness in nonlinear classification.
- MLP: A feedforward neural network with one hidden layer was used.
- Naïve Bayes: Gaussian assumption applied to feature distribution.

AR DATABASE

One of the widely used databases for designing facial recognition systems is the standard AR database. It is a collection of diverse images that are captured under different conditions, including changes in illumination. . Images in this database were captured in a controlled environment with varying illumination intensity and direction, making it suitable for evaluating illumination normalization algorithms under relatively realistic imaging conditions. The AR database is used in this work to assess the ability of considered illumination normalization algorithms to mitigate the effects of illumination variations. The improvements of the feature's stability is also studied, before applying the feature extraction and classification stages.

CMU-PIE DATABASE

The CMU-PIE database is another standard database used to design and evaluate the performance of facial recognition system. it is selected due to its controlled variation in illumination conditions and facial rotation angles for different facial expressions. The database includes several subsets, such as one for expression variations, one for capturing individuals when talking, and two subsets dedicated to illumination variation. with moderate and sever illumination. The subset used in this research is characterized by sever illumination. The illumination level for some images is ranging from nearly total darkness to very illuminated with different facial rotation angles. The ability of the suggested normalization technique is well tested under such images database, especially for images with sever illumination variations. The enhancement of the extracted features before applying feature extraction and classification stages is also considered. This provides a rigorous benchmark for evaluating the effectiveness of preprocessing methods in realistic and complex capturing conditions.

EXTENDED YALE B DATABASE

The Extended Yale B database is one of the most challenging standard databases for facial recognition research. The images of these databases reflecting extreme variations in illumination conditions, including very low light and uneven facial angles. The database contains a wide range of images for each individual that are captured under varying illumination intensities and directions. This database is also suitable for testing the effectiveness of illumination normalization algorithms in harsh and complex photographic conditions. 10 images for each individual are selected from this database. The selected images are divided into two groups, the first is used for training (five images) and the second is used for testing phase (another five images). This varying illumination environment provides a good examining for the ability of the normalization algorithms to improve the stability of extracted features. Also, it will mitigate the effects of clear, moderate, and bad illumination before the feature extraction and classification stages.

EXPERIMENTAL WORK AND RESULTS

This section presents the experimental work and analyses the collected results after the selected mages from the above mentioned three datasets. The collected results are tested to are used to compare the performance of normalization methods and classifiers.

The three data bases are all used together to evaluate the effect of each method on improving recognition accuracy. The resulted performance's differences have reflected the ability of each algorithm to reduce the effects of illumination while preserving the distinctive features of the face.

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The Recognition Rate (RR) measure is adopted as a key performance indicator to evaluate the efficiency of the system. All programming steps related to image processing and extraction of distinctive facial features were implemented using the MATLAB R2021b programming language. The classification and evaluation results were obtained using Weka 3.8.6 machine learning software.

RESULTS WHEN APPLYING AR DATABASE

When using images from the AR database, the results show that illumination normalization algorithms improved the performance of face recognition system compared to the unnormalized state. The results show the importance of illumination normalization process in reducing the variability caused by changes in light intensity and shadows. The below table 1 presents the measured accuracy of recognizing faces. The best performance is achieved by DoG and Isotropic filtering methods.

Table 1. RR % on the AR database under moderate illumination conditions.

Illumination Normalization	Classifier			
	Naïve Bayes	SVM	K-NN	MLP
without normalization	49.4737	92.1053	92.1053	94.2105
Gamma	55.2632	92.1053	91.5789	94.2105
DoG	60	95.2632	95.7895	97.8947
Homomorphic	59.4737	94.7368	93.6842	96.3158
Isotropic	57.3684	93.6842	93.1579	98.4211
Anisotropic	61.5789	94.7368	94.7368	95.7895
Gradientfaces	63.1579	94.7368	93.6842	97.3684
SQI	52.1053	94.7368	93.6842	96.8421
Steerable	67.3684	94.7368	93.6842	96.8421

The results indicate that DoG (97.89%) and Isotropic filtering (98.42%) combined with the MLP classifier achieved the highest recognition rates. SVM and MLP demonstrated the most stable performance across different normalization methods. The Naïve Bayes showed comparatively lower accuracy. These results suggest that under moderate illumination conditions, effective normalization combined with strong classifiers significantly enhances recognition performance.

The results show that the best recognition rates in the AR Face database were achieved using the Isotropic Filtering and Difference of Gaussians (DoG) algorithms. This is attributed to the nature of the database, which includes significant variations in light intensity. The isotropic filter smooths the image and reduces noise and unwanted illumination variations in a balanced manner across all directions. It is clear that the DoG algorithm is working good in removing the low-frequency components associated with lighting and enhances the edges and important structural details of the face. Combining the noise reduction and feature enhancement results has led to the extraction of more stable and distinct features, which positively impacts the performance of facial recognition systems.

The advanced classifiers like SVM and MLP exhibited high stability across different normalization algorithms, while NaïveBayes and K-NN were more sensitive to the quality of features resulting from normalization. The results of applying these AR database images confirm that illumination normalization is the most influential factor in improving the overall performance of the system. Classification algorithms play a complementary role in leveraging this improvement and enhancing the effectiveness of integrating spectral preprocessing with appropriate classifiers in face recognition systems.

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CMU-PIE DATABASE RESULTS

The test work on CMU-PIE database has showed a clear impact of illumination normalization algorithms when it is compared to the AR database application results. The reason behind that is the fact of the complex nature of the CMU-PIE database images. This complexity directly impacts system performance in the unnormalized state, and shows the important role of illumination normalization stage in facial recognition systems. The results obtained from applying the illumination normalization algorithms to CMU-PIE database are presented in Table 2 below.

Table 2. The RR % when using CMU-PIE.

Illumination Normalization	Classifier			
	Naïve Bayes	SVM	K-NN	MLP
without normalization	30	48.4211	48.9474	48.9474
Gamma	28.9474	46.8421	48.9474	49.4737
DoG	33.1579	51.5789	56.8421	54.7368
Homomorphic	30.5263	51.5789	52.6316	53.6842
Isotropic	33.6842	52.6316	54.2105	53.6842
Anisotropic	33.1579	51.5789	56.8421	54.7368
Gradientfaces	25.2632	44.7368	46.8421	46.3158
SQI	30.5263	48.4211	49.4737	52.1053
Steerable	34.7368	52.1053	52.1053	53.1579

The results show that the use of DoG and Anisotropic filtering has led to provide the best performance, reaching up to 56.84% using the K-NN classifier. K-NN and MLP classifiers have performed better than SVM and Naïve Bayes which indicating the better method to handle complex variations in facial features under challenging conditions.

The DoG algorithm reduces low-frequency components associated with illumination and enhances facial edges and distinctive details. The anisotropic filtering algorithm smooths homogeneous regions and reduces noise while preserving important structural edges. The combination of DoG, anisotropic filter, and K-NN or MLP has led to improve facial recognition system because it helps to better feature representation, more distinctive features extraction, and increased accuracy in facial recognition systems.

The results also show that the classification algorithms K-Nearest Neighbors (K-NN) and Multilayer Perceptron (MLP) performed better than both Support Vector Machine (SVM) and Naïve Bayes. This can be explained by K-NN's ability to leverage local similarity between facial features. The MLP's ability to represent complex nonlinear relationships between extracted features. The assumption of independence in Naïve Bayes and the defined separation boundaries in SVM may not be sufficient to represent the high variability in facial data.

RESULTS FROM EXTENDED YALE B DATABASE

The Extended Yale B face database is one of the most challenging databases for facial recognition, due to its near-total opacity. It includes one completely dark image per person, and two extremely opaque images on the right and left sides. This has impacted the system's performance in the unnormalized state, where it recorded the lowest recognition rates compared to AR and CMU-PIE databases. Table (3) shows the accuracy of recognizing faces measured in (RR) obtained from Extended Yale B database. The results demonstrate the superiority of local normalization methods.

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Table 3. RR % on the Extended Yale B database under extreme illumination conditions.

Illumination Normalization	Classifier			
	Naïve Bayes	SVM	K-NN	MLP
with out normalization	34.7368	66.8421	60.5263	68.4211
Gamma Correction	36.3158	66.3158	61.0526	68.9474
DoG	52.1053	89.4737	83.1579	94.2105
Homomorphic	45.2632	86.3158	77.8947	90
isotropic	48.4211	89.4737	81.5789	88.9474
anisotropic	47.8947	86.8421	80	87.8947
Gradientfaces	39.4737	89.4737	78.4211	86.3158
SQI	45.7895	89.4737	78.9474	91.0526
Steerable	51.0526	90.5263	84.7368	89.4737

The results demonstrate that DoG (94.21%), SQI (91.05%), and Steerable filtering achieved the highest recognition rates, particularly when combined with the MLP classifier. In spite of the fact that the use of SVM has led to less performance compared to others but it still proving better performance across most normalization methods. The gathered results confirm that local normalization techniques are more effective in handling extreme illumination conditions by preserving essential facial features.

The effectiveness of the illumination normalization algorithms is clearly evident in improving the recognition results compared to the results obtained without applying illumination normalization algorithms. The results show the superiority of the Self Quotient Image (SQI), Steerable Gaussian filters, and DoG algorithms when applied to images from the Extended Yale B face database. The SQI algorithm normalizes the uneven lighting by reducing the impact of low-frequency components associated with illumination. The integration of good illumination normalization technique with any of the discussed techniques (for all types of databases) has helped to provide better overall system accuracy.

It is also worth noting that using SVM or MLP algorithms on images from Extended Yale B database showed better performance compared to using Naïve Bayes or K-Nearest Neighbors, only for this limited case. The reason behind this is the ability of SVM and MLP to represent the complex nonlinear relationships between features extracted from images.

The Extended Yale B database results confirm that illumination normalization is an essential and indispensable component of facial recognition systems when dealing with extreme opacity. The results confirm enhancing the reliability of the proposed system in real-world applications under uncontrolled illumination.

CONCLUSION

The objective of this work was to practically test the usefulness of different illumination normalization algorithms. A comparison is also carried out among the addressed illumination normalization techniques to find out the best to use for each study case. The filters of Gabor features and PCA are used to build the face recognition system, when trying different types of classifiers. Four different face image databases were used in the test setup for each combination of system design stages (AR, CMU-PIE, and Extended Yale B datasets). The collected results proved that illumination normalization is significantly improving the overall performance of the face recognition system especially under challenging lighting conditions.

The results show that the recognition rates have improved from 94.21% to 98.42% when classifying images from AR database. On images from CMU-PIE, the recognition rate has improved from being 48.94% to 56.84%. The rate has improved from 68.42% to 94.21% when using images from Extended Yale B images database. This improves in recognition rate is due to the application of the selected suitable normalization methods. Another important finding was to confirm that using DoG and Isotropic filtering are recommended

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for moderate illumination conditions. The SQI, Steerable filtering, and DoG are more suitable for severe illumination environments. These findings confirm that selecting an appropriate normalization technique is essential for building robust face recognition systems.

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