# Benchmarking of Pre-Processing Methods Employed in Facial Image Analysis

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***Abstract*—Face images analysis and recognition is one of the most outstanding abilities of human vision. Building an automated system that accomplishes such objective is very challenging. The challenges mainly come from the large variations in the visual stimulus due to illumination conditions, blurring and long distance acquisition. As part of an ongoing project tackling the detection and handling of those three problems, we present in this paper a review and a comparative analysis of the state-of-the-art approaches to enhance the contrast and equalize the illumination of facial images. The comparative performance measure – based on appropriate metrics – is accomplished among available methods, using two publicly available facial datasets with a total of about 500 images.**

***Index Terms*—digital image processing, comparative study, facial image analysis, face detection, face recognition, biometrics, contrast enhancement, illumination equalization**

## I. Introduction

Digital image and video processing plays a vital role in the analysis and interpretation of visual huge data. It has been developed rapidly as an important research field at present, since demanded by various and numerous areas of applications such as in biology, archaeology, medicine, spaceflight, and display industry. Acquiring clear images in bad visibility scenes plays an important role in many fields, which pushes forward the development of enhancement algorithms. The most important field in this aspect is human face. Image face analysis is one of the most challenging problems for human face recognition. The difficulty in face recognition arises mainly from facial appearance variations caused by many factors, such as expression, illumination, partial face occlusion, and long-distance data capture.

We already have numerous processing algorithms and modules to enhance images. For all that, these algorithms or modules are usually imperfect and dependent on the application. This short paper presents partial and preliminary results of a project that intends to introduce an image processing solution for three types of turbid facial images, that is, focusing on three main problems, illumination variation, blurring and long-distance images acquired. The technical goal of the project is to develop a robust software infrastructure to enhance turbid human face images.

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## II. Literature Review

Digital Image Processing consists of many aspects, such as image enhancement, image restoration, image acquisition, compression etc. [1]. The main purpose of image enhancement is to allow human being to obtain image of high quality, or descriptive characteristics of original image. In addition, unlike the human visual system which can adapt itself to various circumstances, imaging machines or sensors are not capable of automatically capturing meaningful characteristics. The image of a scene captured by imaging equipment is affected by the environments between the imaging equipment and the scene [2]. For example, if the environment is a low-light environment, image features can be lost due to low contrast and low lightness as shown in Fig. 1. Illumination variation is a challenging problem in face recognition research area; the same person can appear differently under varying lighting conditions.

Figure 1. The images of an individual in different lighting conditions [2].

Blur is a key factor leading to the degradation of image quality. Most of the blurring effect occurs when the camera or the subject moves while the shutter is open, or when the camera is out-of-focus. In such conditions, most face identification algorithms are not sufficiently robust leading to a very low recognition rate. Fig. 2 shows the original images of two individuals with different blurring degree [3].

Unconstrained face recognition from remotely acquired images is also a compelling issue that needs to be tackled. The main factors that make this problem challenging are image degradation due to blur and the appearance variations due to illumination and pose. Fig. 3 shows face images captured by a distant camera in unconstrained settings. The main challenges in recognizing such faces are variations due to blur, pose and illumination [4], [5].


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Figure 2. Original images of two individuals with varying degrees of blurring [3].

Moreover, to improve the quality of an image from a low-resolution sample, a source of difficulties when processing outdoor images is the presence of haze, fog or smokes which fades the colours and reduces the contrast of the observed objects. Overall, images may suffer from so many factor degradations:

- Poor contrast due to poor illumination or finite sensitivity of the imaging device.
- Electronic sensor noise or atmospheric disturbances leading to broad band noise.
- Aliasing effects due to inadequate sampling.
- Remotely acquired images.
- Moving camera or moving subject.

Figure 3. Face images captured by a distant camera in unconstrained settings [3].

The aim of image pre-processing is that the images would have better visual quality, by enhancing the brightness, contrast, and resolution of image. Various processing techniques including high-frequency emphasis filtering, histogram equalization, adaptive thresholding and intensity-level slicing can be used to achieve a better quality.

## III. Methodologies for Pre-Processing Facial Images

The principal objective of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application. It accentuates or sharpens image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis. Image enhancement techniques can be divided into two broad categories:

- **Spatial domain methods,** which operate directly on pixels, and
- **Frequency domain methods,** which operate on the Fourier transform of an image.

The selection of an appropriate approach for the enhancement process is mainly dependant on a quality evaluation of the images that would measure its degradation [6], [7]. This measured degradation, which quantifies the variability within the captured data, has also to be defined in relevance to a final application (e.g. face recognition, fingerprints analysis ...etc.) [7]. In addition, the quality evaluation might also ensure the existence of genuine features rather than fake/synthetic traits [8]. As mentioned above, one of the main components of our proposed system is the enhancement of blurred images. This step traditionally starts by the detection of the blurred images which usually are the result from excessive light intensity, motion-based distortion, lenses' imperfections, and out-of-focus objects as shown in Fig. 4. Recent literature reviews of those detection approaches (for instance [9]) include edge-sharpness analysis, image segmentation and/or de-convolution, wavelet-based histogram – and so forth – that can be coupled with statistical approaches such as support vector machine and Bayes discriminant functions. In addition to the blur detection, the quality evaluation step would include recognising and characterising – and therefore modelling – any variations and unevenness in the illumination conditions of an image. This objective can be approached using methodologies such as image-gradient comparisons and/or illumination cones [10].

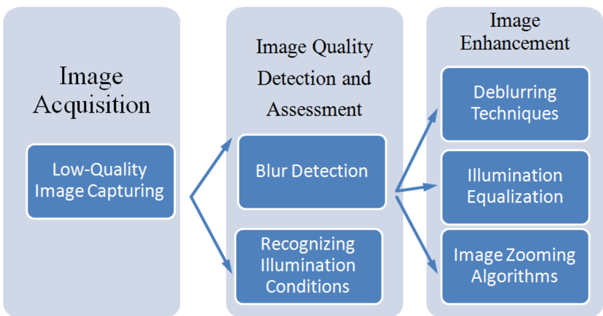



Figure 4. The proposed system flow diagram.

Based on outcome of the image assessment component, a set of key modules (individually or collectively) will carry on the necessary enhancement(s). Deblurring techniques – such as the approaches reviewed in [11] – can be employed to effectively sharpen the image (for example; blur estimation algorithms, image statistics, and subspace analysis). As well, varying techniques for colour normalization [12], illumination equalization and contrast enhancement [13] can be employed resulting in images of acceptable quality that can be efficiently used for face recognition.

This section continues with descriptions for the selected group of methodologies that were selected and implemented. A brief description of the approaches in this section is followed by the results of the comparative analysis in sections 5 and 6.

### A. Homomorphic Filtering

Homomorphic filtering technique is one of the important ways used for digital image enhancement, especially when the input image suffers from poor illumination conditions. This technique uses illumination-reflectance model in its operation. This model considers the image as being characterized by two primary components. The first component is the amount of source illumination incident on the scene being viewed. The second component is the reflectance component of the objects on the scene so that an image can be modelled mathematically in terms of illumination and reflectance [14]. The illumination component of an image is generally characterized by slow spatial variation while the reflectance component of an image tends to vary abruptly. These characteristics lead to associating the low frequencies of the Fourier transform of the natural log of an image with illumination and high frequencies with reflectance.

### B. Single Scale Retinex

Retinex [15]-[20] is an image enhancement algorithm that is used to improve the contrast, brightness and sharpness of an image primarily through dynamic range compression. The algorithm also simultaneously provides colour constant output and thus it removes the effects caused by different illuminants on a scene. The Single Scale Retinex (SSR) is defined for a point (x, y) in an image as:

$R_i(x,y) = \log I_i\ (\mathrm{x,y}) - \log[\mathrm{F(x,y)} * I_i\ (\mathrm{x,y})]$ ,
i=1,…,S

where the sub-index i represents the ith spectral band, S is the number of spectral bands (S =1 for grey scale images, and S =3 for typical colour images), Ri(x,y) is the Retinex output and $I_i(x,y)$ is the input image distribution in the ith spectral band. The symbol "*" denotes the convolution operation. F(x, y) is the normalized surround function.

### C. Multi-Scale Retinex

Multi-Scale Retinex algorithm (MSR) [20] is an extended SSR with multiple kernel windows of different sizes. Its output is a weighted sum of several different SSR outputs.

$$R_i(x,y) = \sum_{n=1}^{N} W_n\, R_m \quad i = 1, \dots, S$$

where $R_m(x,y) = \log I_i\ (\mathrm{x,y}) - \log[\mathrm{F(x,y)} * I_i\ (\mathrm{x,y})]$ , $i = 1, \dots, S$

### D. DoG Filtering – Based Normalization Technique

The DoG [21] is a band-pass filter, which removes high frequency components representing noise, and some low frequency components representing the homogeneous areas in the image. The frequency components in the passing band are assumed to be associated to the edges in the images.

### E. Wavelet-Based Normalization (WAV)

Discrete wavelet transform [16] is used to decompose the facial image into approximation, horizontal, vertical and diagonal components. The approximation components represent low level image components. Next equalizes the histogram of the approximation coefficients matrix. As a final step, it performs an inverse wavelet transform to recover the normalized image.

### F. Discrete Cosine Transform (DCT)

This technique [19] is since illumination can be considered as a low frequency component. Initially an image is transformed into the frequency domain using discrete cosine transform (DCT) and then several DCT coefficients are set to zero. This removes some of the low frequency information contained in the images and reduces illumination influence. The target image is obtained after applying inverse discrete cosine transform (IDCT).

### G. Histogram Equalization

Histogram equalization [22] aims at transforming the distribution of the pixel intensity values of the input image I(x,y) into a uniform distribution and consequently at improving the image's global contrast [1], [15]. Formally, histogram equalization can be defined as follows: given the probability p(i)=ni/N of an occurrence of a pixel with the grey level of i, where $n_i$ denotes the number of pixels with the grey-level of i in the image, the mapping from the original intensity value i to the new transformed one $i_{new}$ is given by Heusch et al. (2005).

### H. Self-Quotient Image

The self-quotient image, proposed and presented by Wang et al. [15], [23], is based on an illumination-reflectance model. This model considers that the image has been characterized by two primary components. The first component is the amount of source illumination incident on the scene being viewed $i(x,y)$. The second component is the reflectance component of the objects on the scene $r(x,y)$ so that an image $f(x,y)$ can be modelled mathematically in terms of illumination $i(x,y)$ and reflectance $r(x,y)$ as follow:

$$f(x,y) = i(x,y).r(x,y)$$

### I. Multi-Scale Self-Quotient Image

The multi scale form of the self-quotient image [1], [23] is obtained by a simple summation of self-quotient images derived with different filter scales.

### J. Contrast Stretching

The idea behind contrast stretching [21] is to increase the dynamic range of the grey levels in the image being processed. The contrast enhanced image is given by the following equation:

$$g = \frac{1}{1 + \left(\frac{m}{f}\right)^{r}}$$

where, g is the contrast enhanced image, m is the mean of the input image, f is the input image, and r is a constant.

### K. Log Transformation

The general form of the log transformation [21] is:

$$s = c\log\left(1 + 256^{*} r\right)$$

where, r is the input image and it is assumed that $r \geq 0$, s is the enhanced image and c is a constant which is equal to 1. The log transformation maps a narrow range of low grey level values in the input image into a wider range of output values. The opposite is true of higher values of input levels. This log transformation could be used if we want to expand the valued of dark pixels in an image while compressing the higher-level values.

### L. Power-Law Transformation

Power-law transformations [21] have the basic form of:

$$S = cr^{\gamma}$$

where, c and $\gamma$ are positive constants. As in the case of the log transformation, power-law curves with fractional values of $\gamma$ map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input pixels. A family of possible transformations curves obtained simply by varying $\gamma$. Curves with values of $\gamma > 1$ have exactly the opposite effect as those generated with values of $\gamma < 1$.

### M. Adaptive Histogram Equalization

This is an extension to the traditional Histogram Equalization technique [22], [24]. It enhances the contrast of images by transforming the values in the intensity image I. Unlike the standard equalization, it operates on small data regions (tiles), rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the specified histogram. The neighbouring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying the noise which might be present in the image.

### N. Tan and Triggs Normalization (TT)

The Tan and Trigg's normalization technique (TT) proposed by Tan and Triggs [25] to enhance (normalize) face images which are captured under uncontrolled lighting conditions based on robust pre-processing and an extension of the Local Binary Pattern (LBP) local texture descriptor. Tan and Trigg's normalization technique uses a simple, efficient image pre-processing chain which Applies gamma correction to the input image, then DoG filtering is used to remove the influence of overall intensity gradients such as shading effects, and finally employs a robust post-processor to produce the final result [25].

### O. Large-and-Small Scale Features Normalization

The large-and small-scale features normalization technique [26] is based on normalizing both the Small-and-Large scale (S&L) features of a face image. In this method, a single face image is first decomposed into large-and-small scale features. After that, illumination normalization is mainly performed on the large-scale features, and only a minor correction is made on the small-scale features. Finally, a normalized face image is generated by combining the processed large-and-small scale features [26].

### P. Illumination Normalization Based on Weber's Law with Application to Face Recognition

Weber- face [27] is an illumination normalization which uses Weber's Law to Weber-reduce the effect of illumination, while saving the details of faces' features. An input image is smoothed by a Gaussian filter and then processed by a Weber Local Descriptor (WLD) [27].

### Q. Face Recognition Under Varying Illumination Using Gradient-faces

Gradient-faces [28] is an image pre-processing technique to enhance an image under varying lighting conditions. To apply Gradient-faces to an image, it is transformed into the gradient domain and then Gradient-faces are extracted for face recognition.

### R. Grey World Normalization

Grey-World Normalization [29], [30] removes the effect of the colours illumination per the following equation:

$$\mathrm{r}^{new} = \frac{r}{R_{Avg}},\ \mathrm{g}^{new} = \frac{g}{G_{Avg}},\ \mathrm{b}^{new} = \frac{b}{B_{Avg}}$$

where $r_{new}$, $g_{new}$, $b_{new}$ are new values for any pixel (r, g, b), and $R_{Avg}$, $G_{Avg}$, and $B_{Avg}$ are the average of all pixels in R, G, and B bands of the image.

### S. Comprehensive Normalization

Comprehensive normalization [29] eliminates the colour illumination effect using a chromaticity normalization followed by the grey-world normalization. Where the chromaticity values (r, g, b) are defined as:

$$\mathrm{r} = \frac{R}{\mathrm{R+G+B}},\ \mathrm{g} = \frac{G}{R+G+B},\ \mathrm{b} = \frac{B}{\mathrm{R+G+B}}$$

where any colour is represented only by two chromaticity values, so that r + g + b = 1.

### T. Adaptive Local Contrast Enhancement

Adaptive Local Contrast Enhancement [31] is applied to local areas depending on its mean, variance, and it does not depend on the global statistics of the image. Assume W is a window of size M × M and centred at pixel(i, j), then the pixel is changed according to the following equation (where $f_{min}$ and $f_{max}$ are the minimum and maximum intensities in the whole image):

$$\mathrm{f}(\mathrm{i}, \mathrm{j}) = 255 * \left[\frac{\left[\Psi_{W}(f) - \Psi_{W}(f_{min})\right]}{\left[\Psi_{W}(f_{max}) - \Psi_{W}(f_{min})\right]}\right]$$

and the sigmoidal function Ψw(f) is (where $<f>_W$ and $\sigma_W$ are the mean and variance of the pixel values within W):

$$\Psi_W(f) = \left[ 1 + \exp\left( \frac{<f>_W - f}{\sigma_W} \right) \right]^{-1}$$

### *U. Division by an Over-Smoothed Version*

Division by an Over-Smoothed version [32] simply divides the image by an over-smoothed version of itself using a spatially large median filter to correct the non-uniform illumination in the image.

### *V. Desired Average Intensity*

Desired Average Intensity [33] reduces the effect of non-uniform illumination by equalizing each pixel in the image using the following equation:

$$I_{eq}(r,c) = I(r,c) + m - I_W(r,c)$$

where m is the desired average intensity (128 in an 8-bit grayscale image) and:

$$\bar{I}_W(r,c)$$

is the mean intensity value of the pixels within a window W of size N×N.

### *W. Estimation of Background Luminosity & Contrast Variability*

The Estimation of Background Luminosity & Contrast Variability has been proposed to normalize the illumination and contrast in retinal images. foreground-background model, in which the background pixels are extracted using the mean and standard deviation calculated in the neighbourhood N of each pixel, followed by the Mahalanobis distance (from the mean) to mark pixels as background (threshold value set to 1). Them, luminosity and contrast drifts are estimated by calculating the mean and standard deviation for the background pixels in N.

### *X. Adaptive Local Contrast Enhancement Applied to the Illumination Equalized Image Obtained Using Division by an Over-smoothed Version*

This hybrid method has been also proposed normalize the illumination and contrast in retinal images [12]. It simply consists of the applying the approach above-mentioned in 3.21 [32] followed by the approach in 3.20 [31]. This approach was found superior to others in a comparative study that considered publicly available retinal data-sets [12].

## IV. Material Employed: Publicly Available Dataset

This research relied on the publicly available Frontal face dataset (collected by Markus Weber at California Institute of Technology). It consists of 450 face images (2 samples are shown in Fig. 5(a) & 6(a)), with a size of 896 x 592 pixels, and in Jpeg format. The dataset is for about 27 unique people under/with different lighting-conditions / facial-expressions / environments-backgrounds. In this work, the entire dataset is termed as Data-Set #2. A portion of the dataset with basic/common approaches of pre-processing applied to them is termed in this research as Data-Set # 1, and is employed to investigate the performance of consecutive application of varying pre-processing techniques. The total face images in the later dataset is 75.

## V. Experimental Setup and Results

To compare the performance of the twenty-four-automated pre-processing literature approaches aforementioned and surveyed in section 3, we used the abovementioned datasets. We applied the 24 methods as described in literature.

### *A. Benchmarking of the Computational Effort Required by Every Approach*

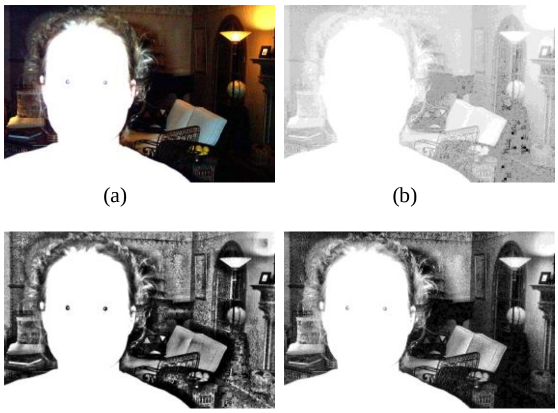
Tables I and II presents the average computational effort (in terms of seconds) required for applying each pre-processing techniques. Every data-set was run on a different platform to produce to comparisons.

### *B. Benchmarking of the Performance*

Tables III presents the accuracies (in terms of true-positives) when each pre-processing techniques was applied, followed by employing the enhanced images for training and testing a very basic face recognition technique (that is; face recognition using PCA).

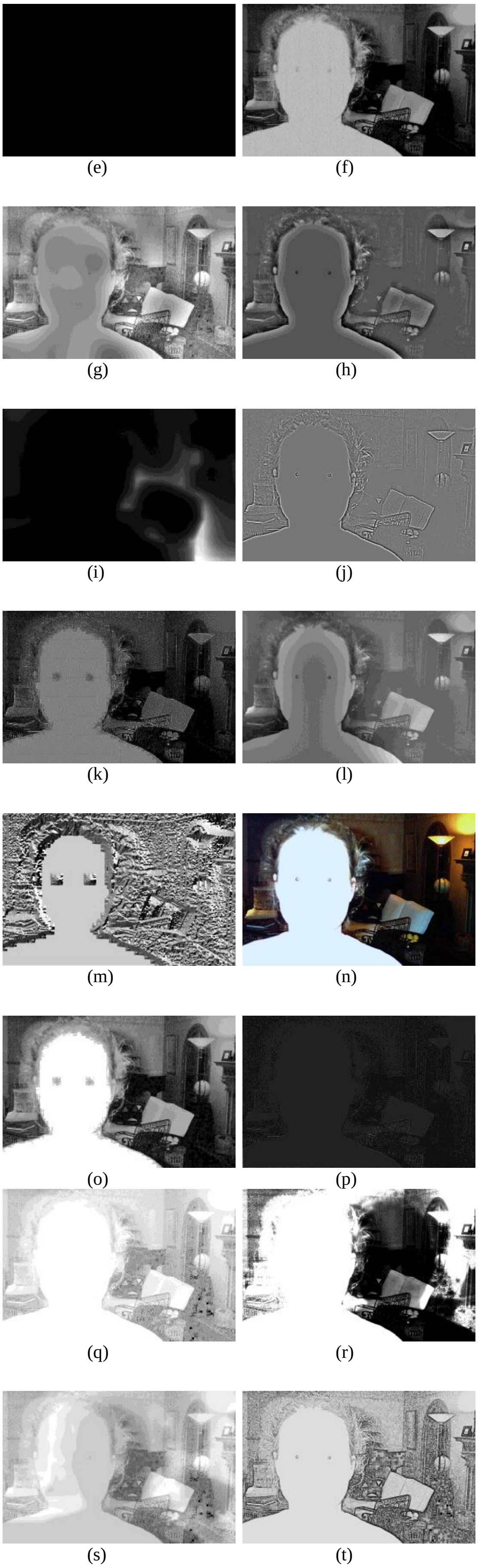
The experiment aims at recognizing a face from a database of human faces using PCA. Principal Component Analysis (PCA) is a statistical approach used for reducing the number of variables in face recognition. One of the simplest and most effective PCA approaches used in face recognition systems is the so-called eigenface approach. The principal components are projected onto the eigen-space to find the eigenfaces (a small set of essential characteristics) and an unknown face is recognized from the minimum Euclidean distance of projection onto all the face classes.

The benefit of this method over other face recognition/detection schemes is in its straightforwardness, speed and insensitivity to any minor or steady variations on the face. However, the main issue with such a basic approach lies in the limitations to the number of images that can be used to recognize a face. That is, the images must be upright frontal views of the human faces.



(a) (b)

(c) (d)



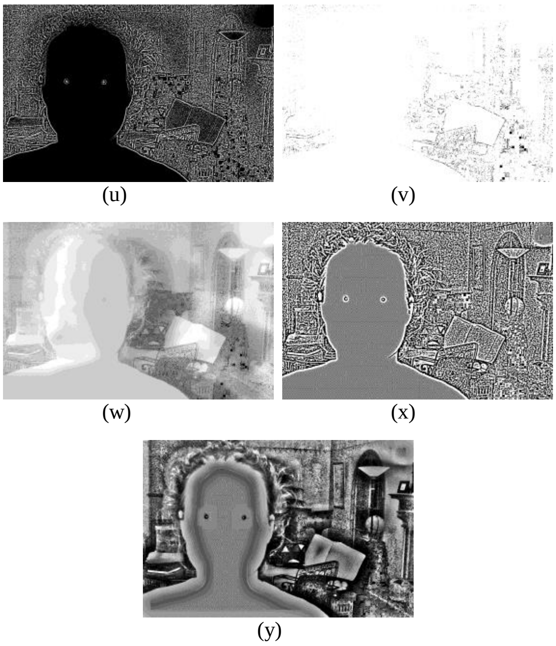
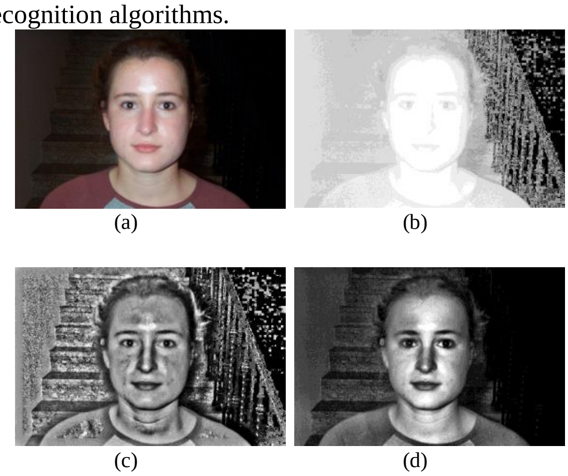
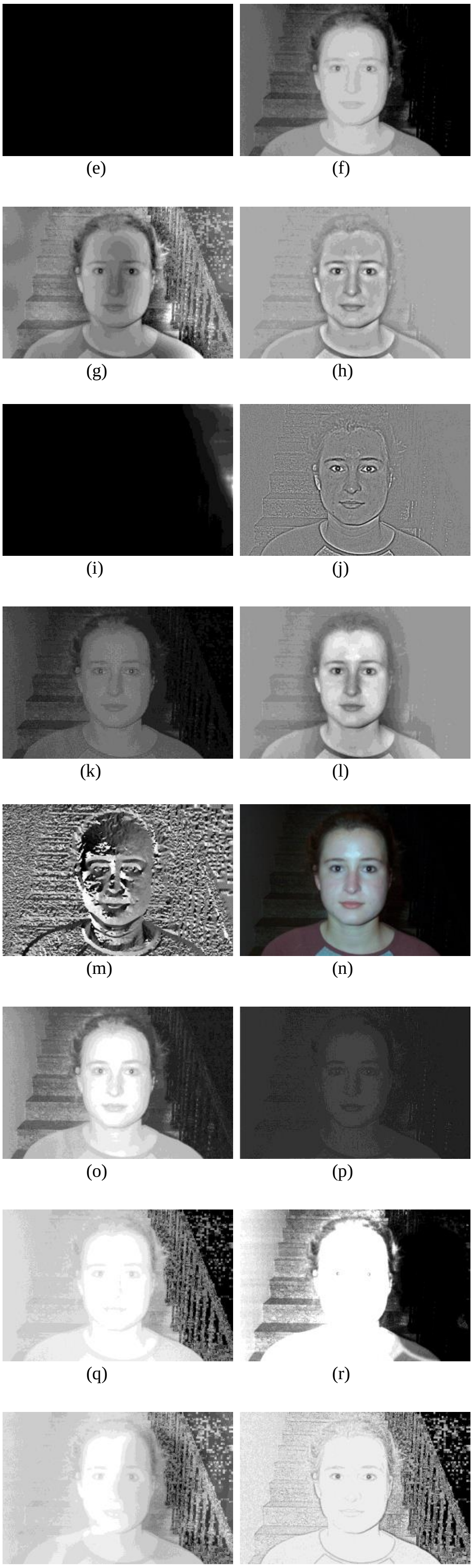




Figure 5. The results on a selected image from Data-Set #1. (a) original image. (b) Power Law. (c) Adaptive Local Contrast Enhancement. (d) Adaptive Histogram Equalization. (e) Comprehensive Normalization. (f) Contrast Stretching. (g) DCT-based Normalization. (h) Desired Average Intensity. (i) Division by Oversmoothed Version. (j) Difference of Gaussians (DoG). (k) Discrete Wavelet Transform. (l) Background Luminosity & Contrast Variability. (m) Gradient faces. (n) Grey World Normalization. (o) Histogram Equalization. (p) Homomorphic. (q) Log Transform. (r) Large and Small-Scale Features Approach. (s) Multi Scale Retinex. (t) Multi Scale Self-Quotient. (u) Multi Scale Weber-faces. (v) Single Quotient. (w) Single Scale Retinex. (x) Tan and Triggs Normalization. (y) Division by Oversmoothed Version followed by Adaptive Local Contrast Enhancement.

## VI. Conclusion and Future Work

The paper presented and compared twenty-four different methods for contrast enhancement and illumination equalization of face images. A publicly available dataset of total 450 images along with a manipulated portion of 75 images from the same dataset were used for the test purpose. An extension for this study could be investigating other pre-processing methods. In addition, more comprehensive results can be achieved by examining the performance of the existing pre-processing approaches using other face detection and recognition algorithms.





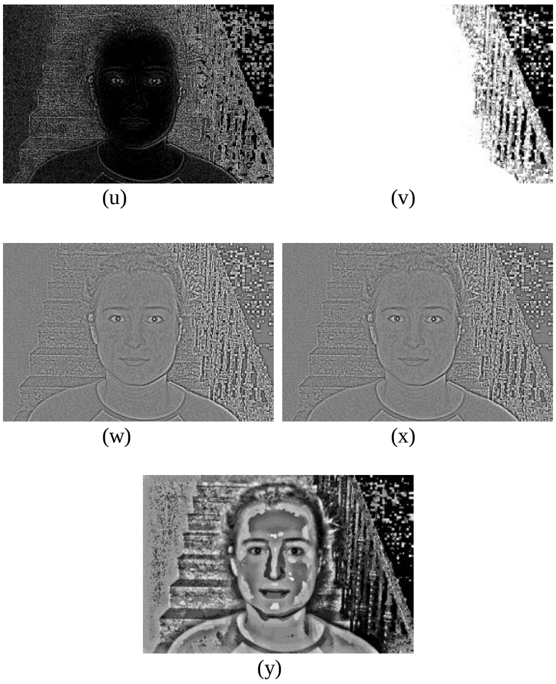




Figure 6. The results on a selected image from Data-Set #2. (a) original image. (b) Power Law. (c) Adaptive Local Contrast Enhancement. (d) Adaptive Histogram Equalization. (e) Comprehensive Normalization. (f) Contrast Stretching. (g) DCT-based Normalization. (h) Desired Average Intensity. (i) Division by Oversmoothed Version. (j) Difference of Gaussians (DoG). (k) Discrete Wavelet Transform.(l) Background Luminosity & Contrast Variability. (m) Gradient faces. (n) Grey World Normalization. (o) Histogram Equalization. (p) Homomorphic. (q) Log Transform. (r) Large and Small-Scale Features Approach. (s) Multi Scale Retinex. (t) Multi Scale Self-Quotient. (u) Multi Scale Weber-faces. (v) Single Quotient. (w) Single Scale Retinex. (x) Tan and Triggs Normalization. (y) Division by Oversmoothed Version followed by Adaptive Local Contrast Enhancement.

TABLE I. COMPARATIVE ANALYSIS OF THE COMPUTATIONAL EFFORT REQUIRED BY EVERY METHODOLOGY

| Approach | | Data-Set # 1 | | Data-Set # 2 | |
|---|---|---|---|---|---|
| | | Mean (in seconds) | Standard Deviation | Mean (in seconds) | Standard Deviation |
| 1 | Power Law | 0.1079 | 0.0198 | 0.0986 | 0.0225 |
| 2 | Adaptive Local Contrast Enhancement | 22.5049 | 0.3525 | 21.9704 | 0.3664 |
| 3 | Adaptive Histogram Equalization | 0.0444 | 0.0147 | 0.0444 | 0.0147 |
| 4 | Comprehensive Normalization | 0.1373 | 0.1730 | 0.3606 | 0.0620 |
| 5 | Contrast Stretching | 0.5000 | 0.0331 | 0.4720 | 0.0184 |
| 6 | DCT-based Normalization | 1.4626 | 0.0882 | 1.5334 | 0.0867 |
| 7 | Desired Average Intensity | 13.5537 | 0.3861 | 13.5537 | 0.3861 |
| 8 | Division by Oversmoothed Vers. | 23.4852 | 0.0812 | 23.9858 | 0.2847 |
| 9 | Difference of Gaussians (DoG) | 0.2946 | 0.0368 | 0.3186 | 0.0405 |
| 10 | Discrete Wavelet Transform | 0.1750 | 0.0604 | 0.1655 | 0.0504 |
| 11 | Background Luminosity & Contrast Variability | 35.6125 | 1.1707 | 41.3988 | 1.6369 |
| 12 | Gradient faces | 0.2930 | 0.0405 | 0.2618 | 0.0358 |
| 13 | Grey World Normalization | 0.0220 | 0.0312 | 0.0618 | 0.0287 |
| 14 | Histogram Equalization | 0.0045 | 0.0071 | 0.0030 | 0.0070 |

| | | | | | |
|---|---|---|---|---|---|
| 15 | Homomorphic | 0.6486 | 0.1138 | 0.6393 | 0.0713 |
| 16 | Log Transform | 0.0317 | 0.0239 | 0.0318 | 0.0241 |
| 17 | Large and Small Scale Features Approach | 9.2235 | 1.8957 | 8.6495 | 1.4457 |
| 18 | Multi Scale Retinex | 9.4521 | 0.2644 | 9.8068 | 0.4218 |
| 19 | Multi Scale Self-Quotient | 415.8723 | 1.5182 | 61.2943 | 0.4836 |
| 20 | Multi Scale Weber-faces | 4.4675 | 0.2168 | 4.4458 | 0.3038 |
| 21 | Single Quotient | 36.5972 | 0.9114 | 37.4744 | 1.0071 |
| 22 | Single Scale Retinex | 3.2340 | 0.0962 | 3.2156 | 0.1122 |
| 23 | Tan and Triggs Normalization | 0.4755 | 0.0481 | 0.7158 | 1.0605 |
| 24 | Division by Oversmoothed Version followed by Adaptive Local Contrast Enhancement | 49.5136 | 0.6942 | 50.0150 | 0.6942 |

TABLE II. PERFORMANCE BENCHMARKING AS PART OF A BASIC FACE RECOGNITION ALGORITHM (DATA-SET 1)

| Approach | | Face Detection Accuracies in relation to varying proportions of Training Set to the Entire Data-Set | | |
|---|---|---|---|---|
| | | ~ 81% (62 images) | ~ 63% (48 images) | ~ 45% (34 images) |
| | None (without pre-processing) | 35.71429 | 42.85714 | 35.71429 |
| 1 | Power Law | 78.57143 | 53.57143 | 47.61905 |
| 2 | Adaptive Local Contrast Enhancement | 64.28571 | 67.85714 | 66.66667 |
| 3 | Adaptive Histogram Equalization | 57.14286 | 64.28571 | 61.90476 |
| 5 | Contrast Stretching | 85.71429 | 82.14286 | 66.66667 |
| 6 | DCT-based Normalization | 85.71429 | 89.28571 | 45.2381 |
| 7 | Desired Average Intensity | 92.85714 | 78.57143 | 66.66667 |
| 8 | Division by Oversmoothed Vers. | 57.14286 | 71.42857 | 54.7619 |
| 9 | Difference of Gaussians (DoG) | 78.57143 | 75 | 73.80952 |
| 10 | Discrete Wavelet Transform | 78.57143 | 71.42857 | 59.52381 |
| 11 | Background Luminosity & Contrast Variability | 64.28571 | 71.42857 | 47.61905 |
| 12 | Gradient Faces | 71.42857 | 78.57143 | 80.95238 |
| 14 | Histogram Equalization | 71.42857 | 71.42857 | 73.80952 |
| 15 | Homomorphic | 21.42857 | 28.57143 | 76.19048 |
| 16 | Log Transform | 85.71429 | 75 | 45.2381 |
| 17 | Large and Small Scale Features Approach | 71.42857 | 75 | 80.95238 |
| 18 | Multi Scale Retinex | 57.14286 | 53.57143 | 50 |
| 19 | Multi Scale Self-Quotient | 78.57143 | 92.85714 | 69.04762 |
| 20 | Multi Scale Weber-faces | 85.71429 | 78.57143 | 78.57143 |
| 21 | Single Quotient | 85.71429 | 78.57143 | 66.66667 |
| 22 | Single Scale Retinex | 35.71429 | 78.57143 | 85.71429 |
| 23 | Tan and Triggs Normalization | 71.42857 | 71.42857 | 47.61905 |
| 24 | Division by Oversmoothed Version followed by Adaptive Local Contrast Enhancement | 64.28571 | 57.14286 | 64.28571 |

TABLE III. PERFORMANCE BENCHMARKING AS PART OF A BASIC FACE RECOGNITION ALGORITHM (DATA-SET 2)

| Approach | | Face Detection Accuracies in relation to varying proportions of Training Set to the Entire Data-Set |
|---|---|---|
| | | ~ 88% (400 images) |
| | None (without pre-processing) | 30 |
| 1 | Power Law | 30 |
| 2 | Adaptive Local Contrast Enhancement | 42 |
| 3 | Adapt. Histogram Equalization | 24 |
| 5 | Contrast Stretching | 48 |
| 6 | DCT-based Normalization | 12 |
| 7 | Desired Average Intensity | 6 |
| 8 | Division by Oversmoothed Vers. | 56 |
| 9 | Difference of Gaussians (DoG) | 10 |
| 10 | Discrete Wavelet Transform | 20 |
| 11 | Background Luminosity & Contrast Variability | 30 |
| 12 | Gradient Faces | 74 |
| 14 | Histogram Equalization | 30 |
| 15 | Homomorphic | 14 |
| 16 | Log Transform | 28 |
| 17 | Large and Small Scale Features Approach | 20 |
| 18 | Multi Scale Retinex | 24 |
| 19 | Multi Scale Self-Quotient | 24 |
| 20 | Multi Scale Weber-faces | 18 |
| 21 | Single Quotient | 42 |
| 22 | Single Scale Retinex | 48 |
| 23 | Tan and Triggs Normalization | 38 |
| 24 | Division by Oversmoothed Version followed by Adaptive Local Contrast Enhancement | 4 |

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