HASAN KALYONCU UNIVERSITY
GRADUATE SCHOOL OF
NATURAL & APPLIED SCIENCES

A SURVEY ON IMAGE ILLUMINATION ENHANCEMENT TECHNIQUES AND A NEW APPROACH TO ASSESS THE IMAGE ILLUMINATION QUALITY

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IN
ELECTRONICS AND COMPUTER ENGINEERING

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FATIH ALISINANOGLU
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A Survey on Image Illumination Enhancement Techniques and a New Approach to Assess the Image Illumination Quality

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Hasan Kalyoncu University

Supervisor

Assoc. Prof. Gholamreza ANBARJAFARI

By

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Fatih ALISINANOGLU

ABSTRACT

A SURVEY ON IMAGE ILLUMINATION ENHANCEMENT TECHNIQUES AND A NEW APPROACH TO ASSESS THE IMAGE ILLUMINATION QUALITY

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M.Sc. in Electronics and Computer Engineering
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Presently, digital images are used in many parts of the daily life and various fields of academic and scientific researches. These applications depend on the quality of the image obtained.

Illumination enhancement is required for all the applications which are using digital images in some part, to make them work properly, also assessment of the illumination quality is, as important as the illumination enhancement for comparing images and having an idea about the proposed output of the academic research results in the field of digital image processing.

Illumination problems has become a demanding matter in various applications of digital image processing. A relevant argument in the field of illumination enhancement is lack of a quantitative measurement method to assess the illumination of an image. A quantitative measurement that is demonstrating the illumination case (contrast level, brightness etc.) of an image is proposed. Proposed new approach in this thesis, appropriates the input image’s estimated Gaussian distribution and the Kullback-Leibler Divergence of the estimated Gaussian distribution and the expected Gaussian distribution for measurement and the calculations.

In the results part, the experimental works show the influence and the accuracy of the proposed approach for the assessment of image illumination quality.

Keywords: Digital image processing, Illumination enhancement, Illumination quality assessment.

ÖZET

İMGE AYDINLATMA TEKNİKLERİ ÜZERİNE BİR ARAŞTIRMA VE İMGE AYDINLATMA KALİTESİNİN DEĞERLENDİRİLMESİNDE YENİ BİR YÖNTEM

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Ağustos 2017, 53 sayfa

Günümüzde dijital imgeler günlük hayatımızın yanı sıra akademik ve bilimsel araştırmalar da dâhil olmak üzere birçok alanında kullanılmaktadır. Bu işlemlerde elde edilmiş olan imgelerin kalitesi uygulamanın verimini de doğrudan etkilemektedir.

Dijital imgelerin kullanımını barındıran tüm uygulamalarda, dijital imgelerde ki aydınlatmanın geliştirilmesi çok büyük bir öneme sahiptir. İmgelerde ki aydınlatma geliştirme konusunda ki en büyük eksikliklerden bir tanesi de aydınlatma geliştirilmesinin sonuçlarının değerlendirilmesi hususunda sayısal bir değerlendirme yönteminin bulunmamasıdır. Bu tezde imgenin aydınlatma durumunun (kontrast, parlaklık vb.) sayısal bir yöntemle ölçüldüğü bir yaklaşım ortaya konulmuştur. Ortaya koyulan bu yaklaşım giriş imgesinin tahmini Gauss dağılımını ve bu dağılımın Kullback-Leibler Diverjansını ve ayrıca ölçümler ve hesaplamalar sonucu beklenen Gauss dağılımını ele almaktadır.

Sonuçlar bölümünde ise, deneysel çalışmaların çıktıları önerilen yöntemin, imge aydınlatma kalitesinin değerlendirilmesi konusunda ki etkilerini ve doğruluğunu ortaya koymaktadır.

Anahtar kelimeler: Sayısal görüntü işleme, Aydınlatma geliştirme, Aydınlatma kalitesinin değerlendirilmesi

Dedicated to my family…

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LIST OF SYMBOLS/ABBREVATIONS

EM	Electromagnetic
RGB	Red, Green and Blue
CMY	Cyan, Magenta and Yellow
CMYK	Cyan, Magenta, Yellow and Key (black)
f	Function
L	Number of gray levels
B	Number of bits
N	Number of rows
M	Number of columns
Y	Luma
I	In phase
Q	Quadrature
PAL	Phase Alternation Line
NTSC	National Television System Committee
SECAM	Sequential Color with Memory
HSI	Hue, Saturation, Intensity
HSV	Hue, Saturation, Value
GHE	General Histogram Equalization
LHE	Local Histogram Equalization
DHE	Dynamic Histogram Equalization
SVE	Singular Value Based Image Equalization
PDF	Probability Distribution Function
p	Probability function
CDF	Cumulative Distribution Function

GL	Gray Level
μ	Mean Value
σ	Standard Deviation
SVD	Singular Value Decomposition
DWT	Discrete Wavelet Transform
LL	Low-Low
LH	Low-High
HH	High-High
HL	High-Low
SVDWT	Singular Value and Discrete Wavelet Transform
IDWT	Inverse Discrete Wavelet Transform
I	Image Intensity
ζ	Correction Coefficient
$\mathbf{H}$	Information of the image
MOS	Mean Opinion Score
PSNR	Peak to Signal Noise Ratio
$\boldsymbol{N}$	Normal Distribution
$\boldsymbol{G}$	Gaussian Distribution
KLD	Kullback-Leibler Divergence
ξ	Proposed Illumination Metric

1 INTRODUCTION

Evolution of the digital image processing from a historical perspective belongs to improvement of the computers. Image processing needs powerful processing units and high-capacity memory devices, therefore using the computers and the technology is an avoidable necessity.

Rapid development in digital computation, frequently allows us to hear an announcement of new technological advancements. Due to this technological enhancements, digital image processing became an important field of study, furthermore, producing new methods for efficiently enhancement and compression of this visual data are intensified among the academic studies.

To accelerate the learning process and to lead the absolute beginners, presenting understandable materials which, explains the application of the techniques and algorithms used in digital image processing.

1.1 MOTIVATION

Image processing is such an interesting topic of study that has astonishing variety of applications. In our current world all kinds of information are digitalized, as expected, the images cannot break away from this process. Billions of images are digitalized and stored on physical memories all over the galaxy.

Digital image processing is a progress with goal of decreasing the size or enrichment of the quality of the digital images according to purpose of the applied methods. From the academic point of view digital image processing is considered as subfield of digital signal processing. Considering all the reasons mentioned above, a research study or writing a thesis in the field of digital image processing has become an intriguing and attractive topic which is quite motivating for a researcher or academician.

2 DIGITAL IMAGE PROCESSING

2.1 HISTORICAL OVERVIEW OF DIGITAL IMAGE

The Bartlane Transmission System (Figure 1) was invited in 1920, is one of the first picture transmission system in the matter of digital images. Name of the system “Bartlane” came from two inventors of the system, Mr. Bartholomew and Captain McFarlane.

Publication of the pictures in a foreign newspaper had been taking at least one week before the 1922, however published news texts in newspapers had appeared in intercontinental newspapers the day after they had taken place. This lapse of time between publishing pictures and texts encouraged the inventors of the Bartlane transatlantic picture service.

Figure 1. The Bartlane Transmitter

Captain McFarlane had worked alone two years on elementary models of the system and later he discovered that Mr. Bartholomew who was a director of London Daily Mirror was working on the similar subject. The inventors met and understood that they had something on their studies which were the complementary subjects of each other. Thereupon, they began an intensive research program which resulted in the creation of the Bartlane picture transmission system. Early on, the pictures transmitted from London to

Glasgow, Berlin and Halifax, but there were no receiver systems in these cities, for this reason, pictures traveled the twice of the distance between the cities and came back to the transmission system.

By the following year, due to this encouraging experiment results, Captain McFarlane made a decision on installing the picture transmission system in New York. Transatlantic submarine link between New York and London were used for the transmission of the pictures.

Telegraphic typewriters were used by the system for converting picture values into the forms of transmission. Baudot Tape (Figure 2) was one of the elementary components of the Bartlane System. Different hole combinations on Baudot Tape transmits specific signals to the receiving station and activates the keys of typewriter.

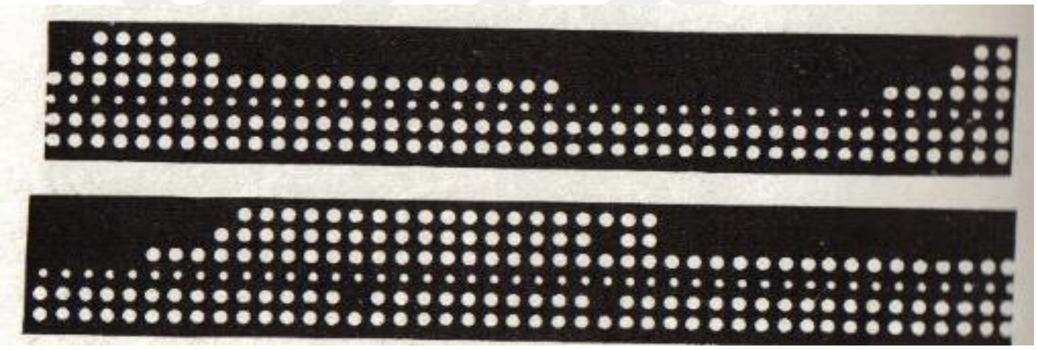


Figure 2. The Baudot Tape used to transmit pictures by the Bartlane System

When transmitting a picture by the Bartlane transmission system, firstly a regular picture of the subject was taken and five tint plates were made that had five different exposure periods (Figure 3), which means 5 gray levels, this method had been developed until 1929 and reached to 15 gray levels (Figure 4)

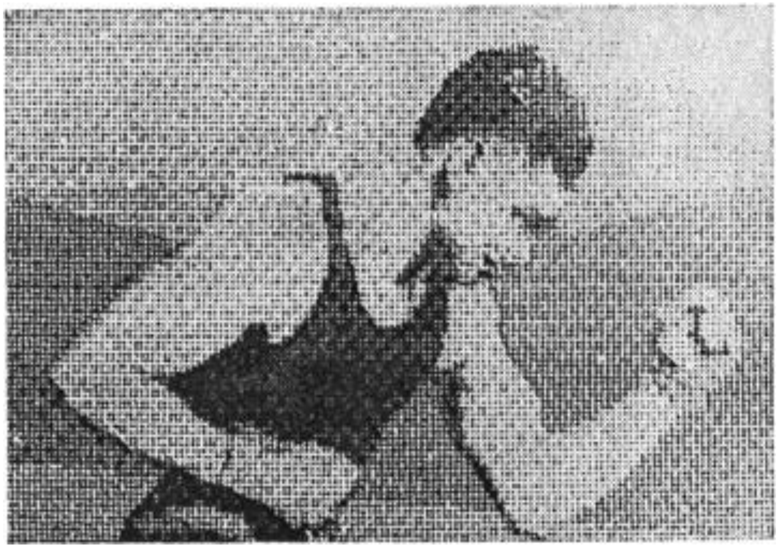


Figure 3. Digital picture produced in 1921 with 5 gray levels

Figure 4. Digital picture of General Pershing and General Foch transmitted in 1929 with 15 gray levels

2.2 GENERAL CONCEPTS

2.2.1 Light and Visible Spectrum

In 1670 Sir Isaac Newton separated the colors by passing sunlight throughout a glass prism. The sunlight is refracted thus white light resolved into its component colors: red, orange, yellow, green, blue and violet. This crucial experiment known as refraction of the light (Figure 5) and explains that white light consists of all the colors.

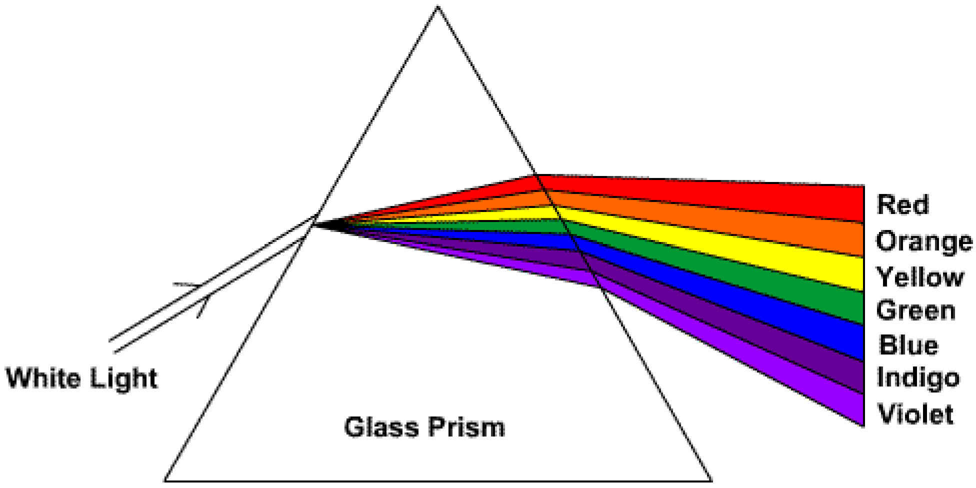


Figure 5. Refraction of the light

Only small part of the electromagnetic spectrum can be seen by human eyes, the band of visible light on electromagnetic spectrum is quite tiny in size of EM spectrum. Human eye can sense the wavelengths between 380nm and 780nm, consequently this part of electromagnetic spectrum is named as "visible spectrum" (Figure 6).

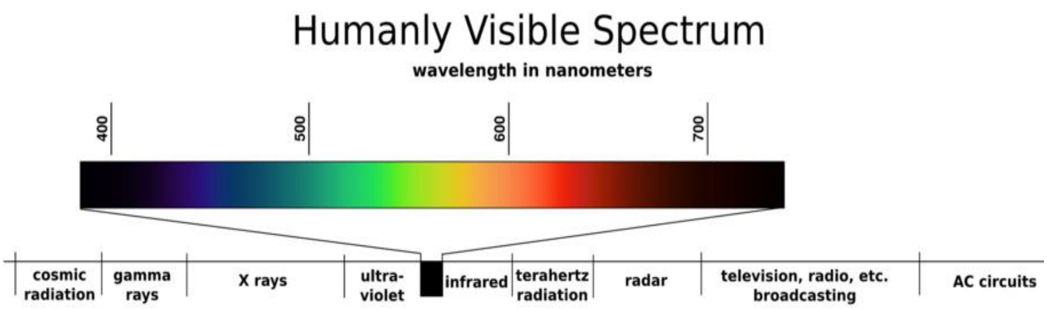


Figure 6. Visible Spectrum

Human eyes includes photoreceptors which are responsive to light and transmits the gathered data to the brain. Photoreceptors do not indicate the colors, only indicate the occupancy of the light in the visual medium.

There are two color models these are called, (Additive) Light Color Primaries and (Subtractive) Pigment Color Primaries (Figure 7).

- (Additive) Light Color Primaries: Red, green and blue (RGB).
- (Subtractive) Pigment Color Primaries: Cyan, magenta and yellow.

Primary additive colors of light are red, green and blue, these colors can be blended to get different colors. For example, when the red and green lights are combined, there will be yellow light occurred.

Primary subtractive colors of light are magenta, yellow and cyan, these colors usually clarified as red, yellow and blue. These colors are used for derivation of new colors from the reflected light by blending paint pigments or using printers. Paints include pigments, when white light gleam on a colored surface, only some parts of wavelengths of the light can be reflected by cause of absorption.

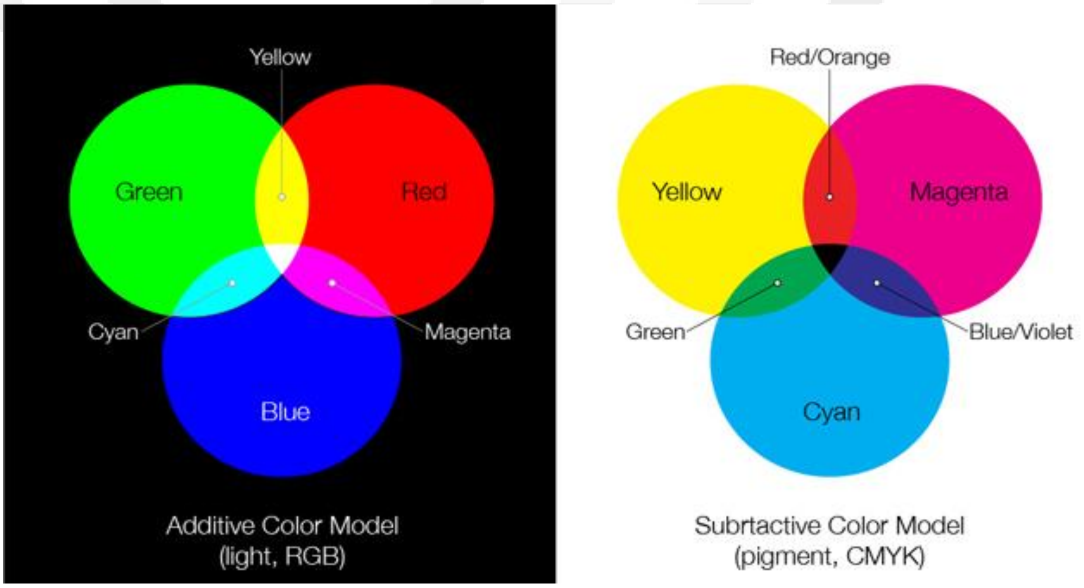


Figure 7. Primary Color Models

2.2.2 Digital Image

Digital image is, accordingly a picture that has been converted into binary format which is including 0s and 1s consistently, contrary to a video, an image means a fixed picture does not alter with the time. An image can be explained as two-dimensional function $f(x, y)$, where x and y indicates the (spatial) image plane coordinates, amplitude of the given f at an unspecified match of coordinates is referred to gray level or intensity of the image and though if the values of x and y and the amplitude of the f are finite and discrete values, in this case this image can be called as a digital image. Image data is tabulated by integers for processing them easily as multidimensional arrays. Each element of this arrays are called as pixel elements or shortly pixel (Figure 8).

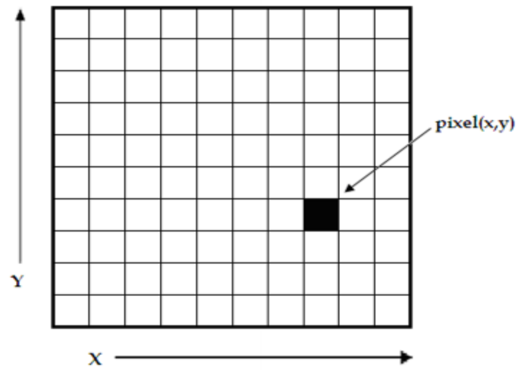


Figure 8. 2D array of pixels

Whereas an image is achieved from a physical process, its values depend on the electromagnetic waves beamed from the source, hereby the amplitude of the $f(x,y)$ must be nonzero and finite; that is $0 < f(x,y) < \infty$. Expression $f(x,y)$ can be defined as two parts; first one is quantity of the illumination of the source on the scene and, the second one is quantity of illumination reflected by the objects. Accordingly, these are named as illumination and reflectance components and, mutually expressed by $i(x,y)$ and $r(x,y)$. Product of i and r gives f which is; $f(x,y) = i(x,y)r(x,y)$.

2.3 IMAGE DIGITIZATION

Word digitization is referred to a process that is used to convert analog signals/data into computer-readable, digitized format.

Nearly all existing signals applicable in surroundings are consistently analog. Analog means; a signal that is continuous and time varying, also gets values from continuum (Figure 9). However, in the field of digital image processing, mostly digitized images are used. Digital means; a signal that is exist on a discrete domain and gathers possible discrete values (Figure 9).

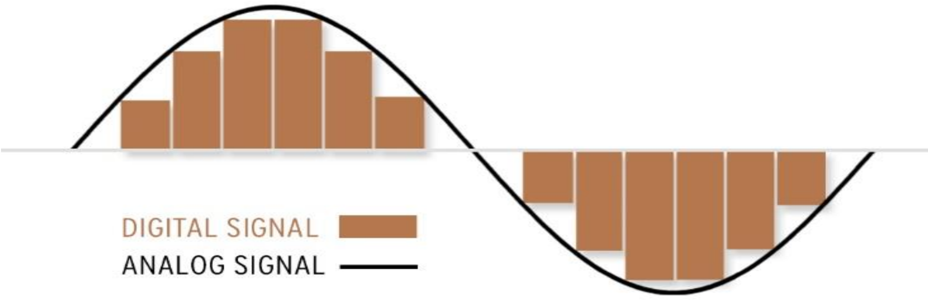


Figure 9. Digital Signal vs. Analog Signal

2.4 IMAGE SAMPLING

Sampling a signal is explained as; acquiring a discrete signal from a continuous signal (Figure 10). The theory of sampling is a comprehensive topic that is efficiently approached with usage of the methods of linear system theory.

In the field of image processing, visual information of the image is not lost during the progression of the sampling. More clearly, sampled image must not be affected too much from the sampling for to be referred as a good looking image.

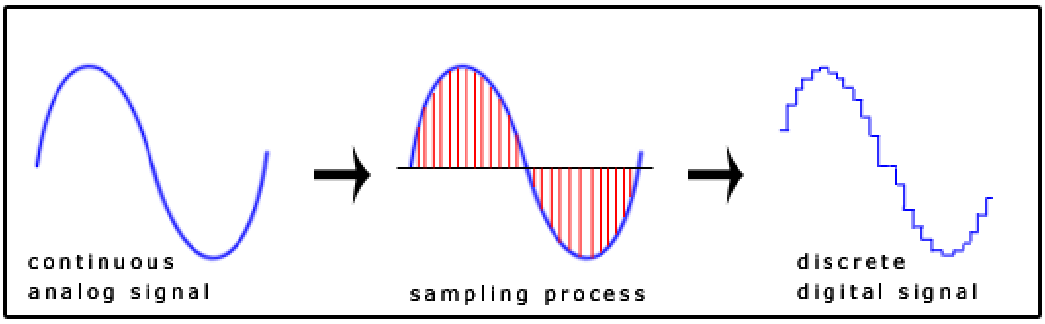


Figure 10. Sampling a signal

Sampled image signals are mainly indexed by integer numbers ahead the dimensions of the image, gathered integers from sampling are arranged in row-column formatted arrays (Figure 11), these arrays of the integer values create the sampled image. Sampled image signals mainly indexed by integer numbers ahead the dimensions of the image.

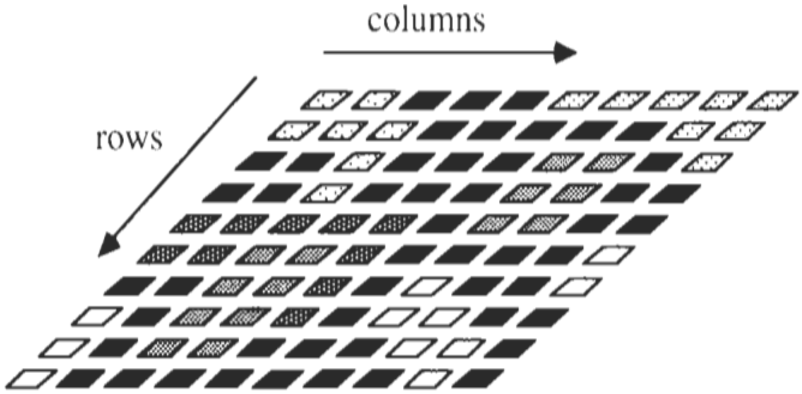


Figure 11. Image array $(10x10)$

2.5 IMAGE QUANTIZATION

Generating a digital image from the acquired data is separated into two parts; first part is sampling and the second part is quantization. Quantization is called transition of a continues-valued signal into a discrete-valued signal that has a discrete range of values (Figure 12).

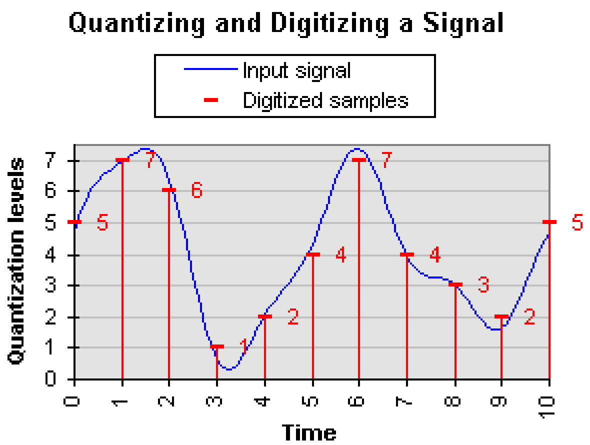


Figure 12. Quantization of a signal

Occurred signals on the sensors are saved as intensity values that an image takes. Intensity is a positive quantity. In case that an image is visually presented by the shades of gray, like a black and white photograph, then the pixel values of this image is introduced as gray scales (or gray levels). In a color image, intensities can have multi-valued numbers at each pixel, or pixel values can have negative values in case that they are not a function of intensity. Under any circumstances of pixel numbers, quantized values must be used for the implementation of digital processing techniques on an image.

Quantized pixel values are assigned to set of integer numbers $\{0,1,\ldots,L-1\}$, that is the gray level range. Different levels of black, white and gray brightness values are linked in grayscale or brightness level of the image. Higher gray level correlates to greater bit depth and can precisely represents a signal dynamic range.

Consistently, by the reason of digital formatting and storage concerns, the number of gray levels are mapped by the power of 2: $L = 2^B$, where L is the number of gray levels and the B is number of bits assigned to gray level of the corresponding pixel. Frequently, most commonly used bit depths are defined as $1 \leq B \leq 8$ in which $B = 1$ for the binary images, and $B = 8$ for a gray level that occupies a byte (Figure 13).

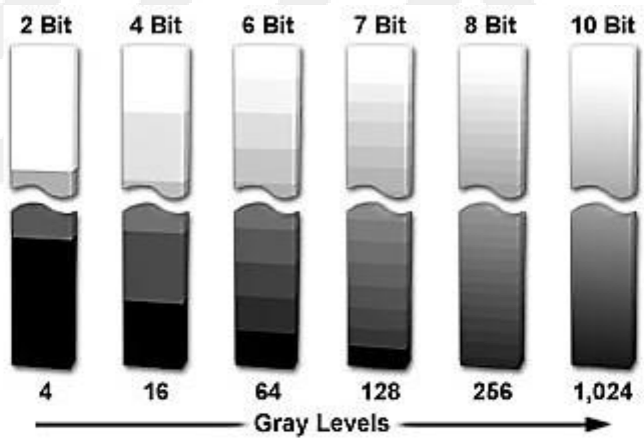


Figure 13. Gray Levels

Gray level reduction effects the appearance of the digital image that can be seen in Figure 14, which depicts a gray scaled picture of Lena. The figure has different gray scale resolutions that is varying between 8-bit and 1-bit. Image begins losing necessarily visual information below 5-bit resolution.

Many regions of the image are subjected to false contours at lower resolutions. False contouring effects firstly occur in the background regions of the image which can be seen at 4-bit gray level of Figure 14. Another visual observation is at lowest resolutions (2-bit and 1-bit) decimates the significant details of the image and make the image unrecognizable.

Figure 14. Gray Levels and Bit Depth of an Image

2.6 COLOR IMAGES

In the field of digital image processing, almost all the techniques have been developed for single valued, intensity images or gray level images, when in fact color images are multi-dimensional vectors. Generally, most of the techniques are applied to color image by separating each color components as different images for processing and after recombining them gives the color image back. Interchangeably, in case that, each color component of the image is accessible (Figure 15), by taking this account, for accomplishing optimum output, color image processing techniques can be developed that is incident to vector signals.

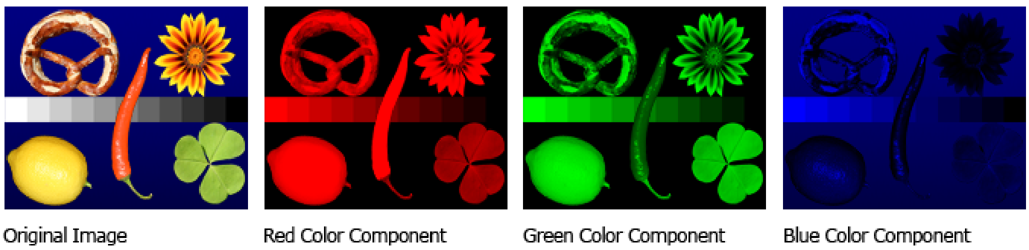


Figure 15. Image with color components (RGB)

2.7 IMAGE DATA SIZE

Consistently visual data take a lot of space for storage, and the occupied space increases mathematically which is depending on the data dimensions. Almost all processes belong to digital image (such as; processing, filtering, storing) are effected from the data storage issue.

Recommended size for storing a monochromatic digital image is calculated by the multiplication of row, column and bits of gray level resolution, which is respectively; $N \times M \times B$. Generally, 1 byte (8 bits) ($B = 8$) per pixel ratio is used except the binary images ($B = 1$) or any other special conditions. If the image is multi-dimensional such as color image, then the recommended data size is multiplied by image dimension

Principally, acquired images from digitizer systems which are widely used in the market, frequently have the size of 512×512, which is broad enough to fulfill a monitor. Smaller and broader images, ranging from 16×16 to 4096×4096 and more, are exist in digital world, Figure 16 shows the recommended data size for the different image resolutions.

Spatial Dimensions	Pixel Resolution (bits)	Image Type	Data Volume (bytes)
128 × 128	1	Monochromatic	2,048
256 × 256	1	Monochromatic	8,192
512 × 512	1	Monochromatic	32,768
1024 × 1024	1	Monochromatic	131,072
128 × 128	8	Monochromatic	16,384
256 × 256	8	Monochromatic	65,536
512 × 512	8	Monochromatic	262,144
1024 × 1024	8	Monochromatic	1,048,576
128 × 128	3	Trichromatic	6,144
256 × 256	3	Trichromatic	24,576
512 × 512	3	Trichromatic	98,304
1024 × 1024	3	Trichromatic	393,216
128 × 128	24	Trichromatic	49,152
256 × 256	24	Trichromatic	196,608
512 × 512	24	Trichromatic	786,432
1024 × 1024	24	Trichromatic	3,145,728

Figure 16. Recommended data sizes for different image types and resolutions

2.8 COLOR SPACES

Color sets are represented by color spaces in the field of digital image processing, most common color spaces in image processing are RGB, YIQ, YUV or YCbCr and CMYK. However, these color spaces are not related directly with hue, saturation or brightness of an image, therefore some other models are developed such as HSI and HSV for programming and development.

2.8.1 RGB Color Space

Red, green and blue color space (RGB) is broadly used in the field of computer graphics. Three primary additive colors (RGB) are represented by a 3D Cartesian coordinate system (Figure 17)

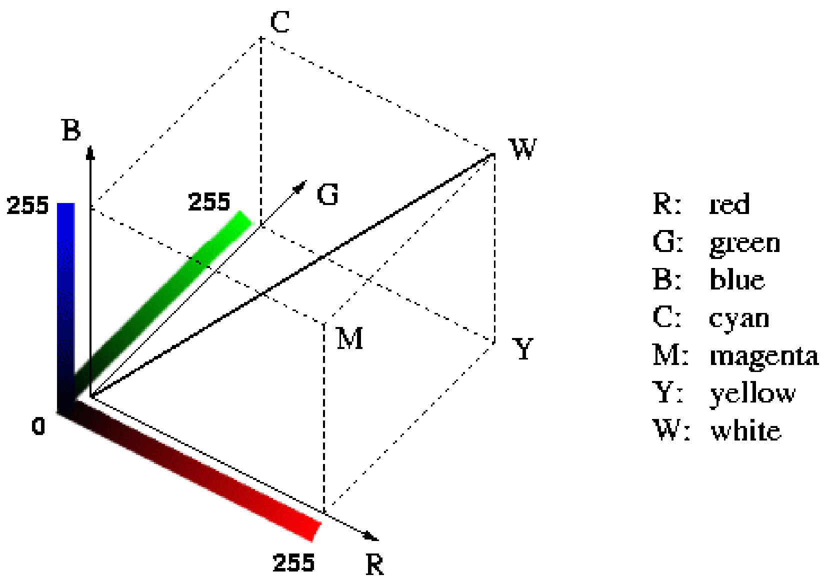


Figure 17. RGB Color Cube

Although, RGB is the most common color space for computer graphics, is not very efficient for the real world images. Components of RGB need to have equal bandwidth for generating any color within the RGB cube, as a result of this situation a frame buffer is occurred which has the same pixel rate and the resolution for each component of RGB.

2.8.2 YUV Color Space

The YUV color space is commonly used by color video standards; PAL (Phase Alternation Line), NTSC (National Television System Committee), and

SECAM (Sequential Color with Memory). The black and white system is used only Y (luma) information, later on information of the colors added by U and V in which color receivers decoded this information for displaying a colored picture on the system.

Elementary equations for conversion of gamma-corrected RGB (notated as R'G'B' and YUV) are described as below;

$$Y = 0.299R' + 0.587G' + 0.114B'$$

$$\begin{aligned} U &= -0.147R' - 0.289G' + 0.436B' \\ &= 0.492\ (B' - Y) \end{aligned}$$

$$V = 0.615R' - 0.515G' - 0.100B'$$

$$R' = Y + 1.140V$$

$$G' = Y - 0.395U - 0.581V$$

$$B' = Y + 2.032U$$

2.8.3 YIQ Color Space

The YIQ (I: in phase, Q: quadrature) uses a modulation method to for transmitting the color information. YIQ color space is derived from the YUV color space which is intentionally used by the NTSC video standards.

Elementary equations for conversion between R'G'B' and YIQ are;

$$Y = 0.299R' + 0.587G' + 0.114B'$$

$$\begin{aligned} I &= 0.596R' - 0.275G' - 0.321B' \\ &= V\cos 33^\circ - U\sin 33^\circ \\ &= 0.736(R' - Y) - 0.268(B' - Y) \end{aligned}$$

$$\begin{aligned} Q &= 0.212R' - 0.523G' + 0.311B' \\ &= V\sin 33^\circ + U\cos 33^\circ \\ &= 0.478(R' - Y) + 0.413(B' - Y) \end{aligned}$$

2.8.4 YCbCr Color Space

The YCbCr is an offset and scaled variant of YUV color space, Y is specified as nominal 8 bit ranging from 16 to 235; Cb and Cr are specified to have range from 16 to 240. There are various sampling formats of YCbCr such as 4:4:4, 4:2:2, 4:1:1 and 4:2:0

2.8.5 HSI and HSV Color Spaces

The HSI (hue, saturation, intensity) and HSV (hue, saturation, value) color spaces are designed to have an approach which is almost accurate the way humans recognize and interpret the color. HSI and HSV are developed.

Calculation of the brightness component (I or V) is the main difference between HSI and HSV color spaces, that specifies the distribution and dynamic range of brightness (I or V) and saturation (S). The HIS color space performs the operations by manipulation of the brightness values by reason of I is equally dependent on R, G and B. his is the leading color space for conventional image processing functions such as equalization, histograms and convolutions. The HSV color space is commonly used for manipulation of hue and saturation since it allows a greater dynamic saturation range.

Figure 18, illustrates the HSV color model, the top of the cone corresponds to V=1, or the maximum intensity, the base point corresponds to V=0 in which cone is black.

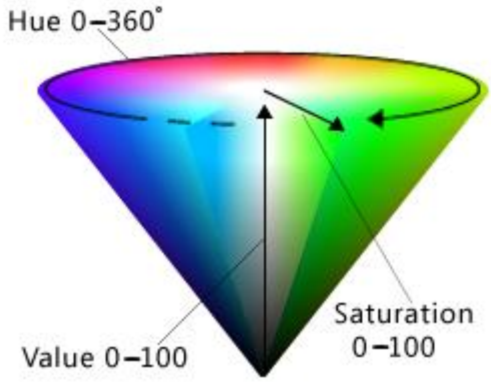


Figure 18. HSV Color Cone

3 IMAGE ILLUMINATION ENHANCEMENT

Illumination enhancement is commonly referred as, one of the most crucial concern in digital image processing. Illumination is formed by the distinction in luminance reflected from two abutting surfaces. In another word, illumination is distinction in ocular substances that makes an item which is discernible from other items and the background. In visual perception, contrast is determined by the difference in the color and brightness of the object with other objects. Ocular system of the human beings is more responsive to contrast than certain luminance; hence, we can notice that the world similarly regardless of the considerable distinctions in illumination conditions. On the other hand, a minor difference in illumination produces large changes in appearance of face even when viewed in fixed pose which makes face recognition more difficult to handle [1, 2].

If the contrast of an image is deeply condensed on a specific particular boundary, e.g. a very dark image; the information in those areas might be missing which are extremely and consistently condensed. The main problem in this case is to enhance the contrast of an image for illustrating all the information in the input image. There exist various different enhancement techniques to defeat this problem [3-6], such as constructing illumination model from several images under different illumination conditions [7], using illumination cone model [8, 9], and illumination compensation based on the multiple regression model [10]. There are many conventional and state-of-art techniques in order to enhance the illumination of an image such as general histogram equalization (GHE), local histogram equalization (LHE), dynamic histogram equalization (DHE) [11], and singular value based image equalization (SVE) [12]. In the following sections each of these techniques will be reviewed in more detail.

3.1 MOST COMMON IMAGE ILLUMINATION ENHANCEMENT TECHNIQUES: GHE, LHE AND DHE

In many image processing applications, the general histogram equalization (GHE) is one of the simplest and most effective primitives for contrast enhancement [5], which attempts to produce an output histogram that is uniform [13]. One of the disadvantages of the GHE is that the information laid on the histogram or PDF of the image will be lost.

For an intensity image (e.g. gray scale image, or an image in a single color channel), A, GHE can be implemented as follows:

$$p_A(i) = \frac{\eta_i}{N} \quad 0 \le i < 255 \quad , \quad N = \sum_{j=0}^{255} \eta_j \tag{1}$$

where ηi is the number of occurrences of gray level i, N is the total number of pixels in the image A, and pA(i) is the probability of an occurrence of a pixel of level i in image A. Given the PDF pA(x), the cumulative distribution function (CDF), PA(x), can be obtained by:

$$P_A(i) = \sum_{j=0}^{i} p_A(j) \tag{2}$$

A transformation of Y = F(A) can be formed in order to produce a new image, Y, such that its CDF will be linearized of the following form:

$$P_Y(i) = \alpha i \tag{3}$$

Where α is constant. The properties of the CDF allow us to perform such a transform. Hence, it is right to write:

$$Y = F(A) = P_A(A) \tag{4}$$

Where here the transformation function F maps the levels into the range [0, 1]. The values can be mapped back into their original range by using the following simple operation:

$$Y_{eq} = Y(\max(A) - \min(A)) + \min(A) \tag{5}$$

Figure 19 (a) shows a low density face image from Caltech frontal face database [14] and its respective histogram in (b). As it has been shown in Figure 19 (d) after the equalization using GHE, the shape of the histogram totally changed.

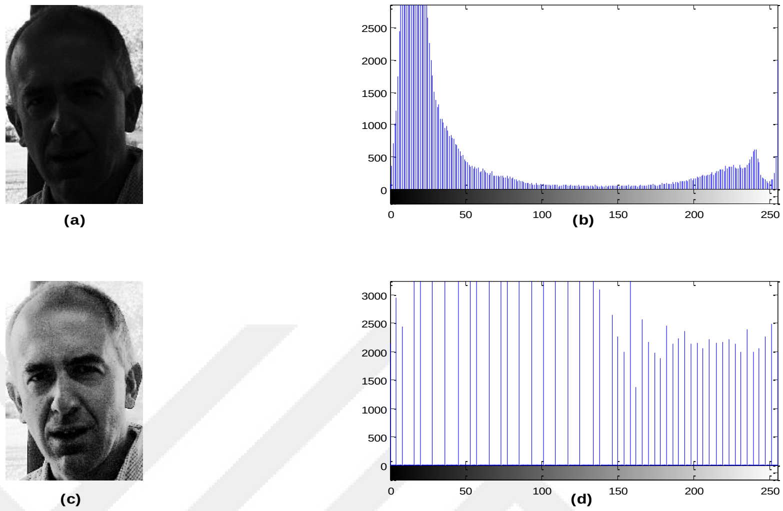


Figure 19: A face image from the Caltech face database (a), its histogram (b), the equalized face image using GHE (c) and its respective histogram (d).

GHE can be also applied to the color images. In this case the problem can be easily solved by equalizing the RGB image in each red (R), green (G), and blue (B) color channels separately. Figure 20 (a) illustrates a low contrast face image from the Caltech database and resultant image in (b) after being equalized by using histogram equalization in R, G, and B channel separately and then using them to reconstruct a new equalized image.

Figure 20. A face image from the Caltech face database (a), and the equalized face image using GHE for R, G, and B (b)

Figure 20 (b) clearly shows that the information laid on the color pixel statistics of the image such as skin color has been lost. Not only that but also the image, visually has become unreliable due to artificial generated color.

After the introduction of GHE, researchers came out with better technique which deals with equalization of portion of the image at a time, called local histogram equalization (LHE). LHE can be expressed as follows: GHE can be applied independently to small regions of the image. Most small regions will be very self-similar. If the image is made up of discrete regions, smallest regions will lie entirely within one or the other region. If the image has more gradual large-scale variation, smallest regions will contain only a small portion of the large-scale variation

However, the contrast issue is yet to be improved and even these days many researchers are proposing new techniques for image equalization. DHE is obtained from dynamic histogram specification [15] which generates the specified histogram dynamically from the input image. DHE algorithm works in the following way [11].

Firstly, the locations of local minimums of the histogram are found and then the histogram is divided into several sub-histograms based on those local minimums. Then the mean, μ, and standard deviation, σ, for each sub-histogram is calculated. If grey levels (GLs) of having frequencies within (μ-σ) to (μ+σ) is more than a specific value, e.g. 68.3% of the total number of GLs of a sub-histogram, then that sub-histogram can be considered as a normal distribution of frequencies and there is no dominating portion. But if it is less than that threshold value, the sub histogram splits again. Then weights for GL range of ith sub-histogram are calculated by the following equation [11]:

$$\text{weight}_i = \text{span}_i \times \left(\log S_i\right) x \tag{6}$$

Where span_i is GL range of sub-histogram i, S_i is summation of all histogram values of ith sub-histogram, and x is a coefficient to control the strength of image contrast. Then the range which is the expansion value to determine how many times to expand its sub-histogram is calculated by using the following formula [11]:

$$\text{range}_i = \frac{\text{weight}_i}{\sum_{i=1}^{n} \text{weight}_i} \times (L-1) \tag{7}$$

3.2 SINGULAR VALUE BASED IMAGE EQUALIZATION

In this thesis we have used the first singular value obtained by SVD in order to correct the frontal uniform illumination problems [12, 7]. In order to study singular value decomposition based image equalization (SVE), we have to recall some mathematics. Since an image can be considered as a numeric matrix, SVD of an intensity image, A, can be written as follows:

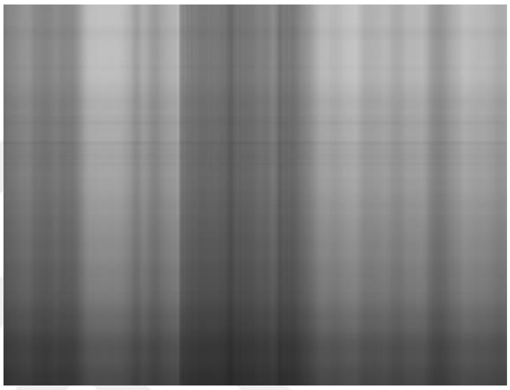
$$A = U_A \Sigma_A V_A^T \tag{8}$$

Where U_A and V_A are orthogonal square matrices known as hanger and aligner respectively, and ΣA matrix contains the sorted singular values on its main diagonal [16].

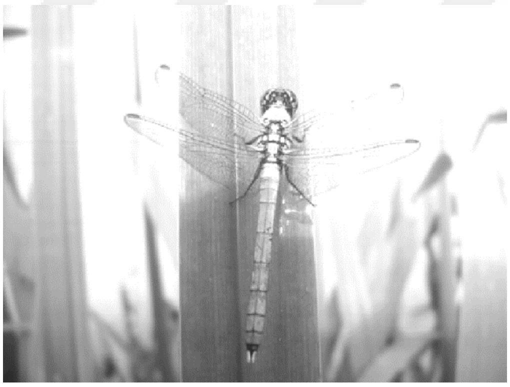
ΣA contains sorted singular values of matrix (intensity image) A. The first singular value, σ1 is usually much bigger than the second singular value, σ2. That is why changing the σ1 will affect the illumination of the image significantly. Figure 21 shows the effect of manipulating σ1.

(a) **(b)**

(c) **(d)**



(e) **(f)**



(g) **(h)**

Figure 21. A gray scale image (a) and the effect of changing the σ1: σ1=0 (b), σ1= σ1+3√σ1 (c), σ1= σ1-3√σ1 (d), σ1= σ1+10√σ1 (e), σ1= σ1 and the rest are zero (f), σ1= σ1+0.75σ1 (g), and σ1= σ1-0.75σ1 (h).

As it is shown in Figure 21 manipulations of σ1 will affect the illumination of the image. Now the question is what if the other singular values are being manipulated. For this purpose, not only σ1 but also other singular values have been zeroed in order to see the effect of change of singular values on illumination of the images. Figure 22 is representing the generated images by manipulating singular values.

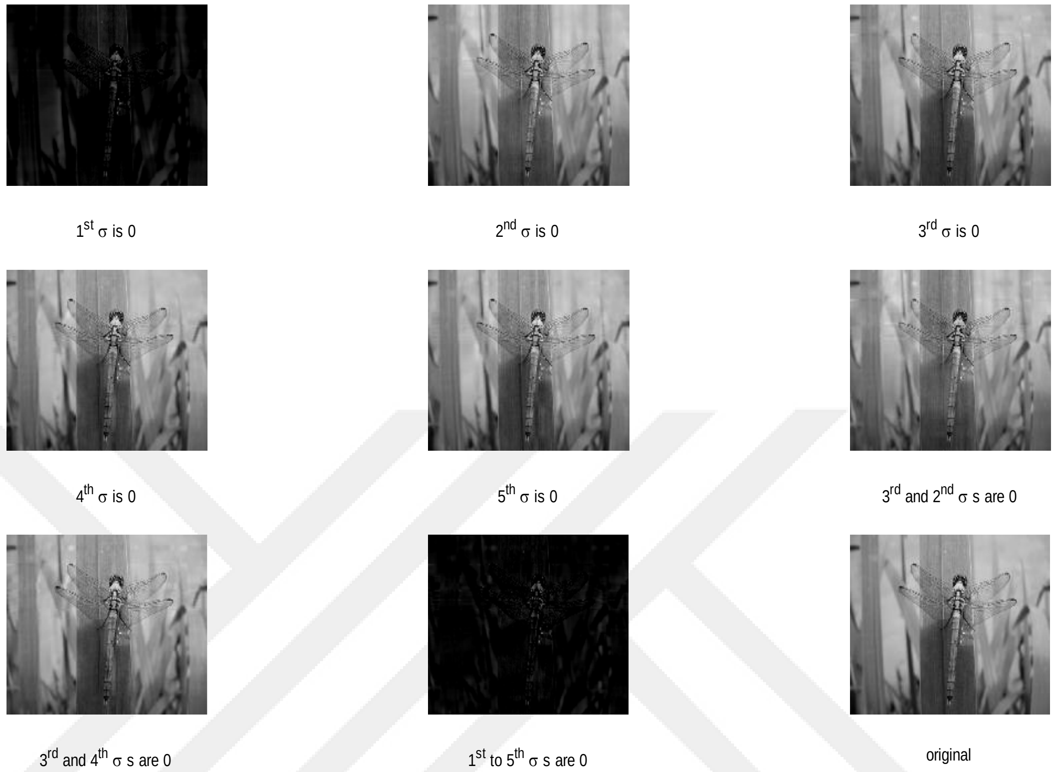


Figure 22. A gray scale image by manipulating several singular values.

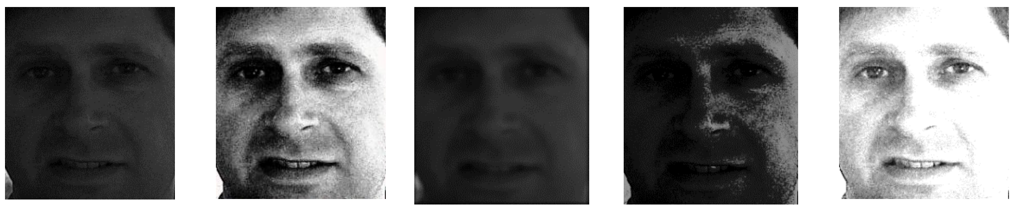
It can easily be observed from Figure 22 that a significant change on the illumination is possible if the first singular value, σ1, is changing. This motivates the idea of using the biggest singular value for frontal uniform illumination correction. In other words, the objective of the SVDWT method [12] is to equalize a low contrast image in such a way that the mean moves towards the neighborhood of 8-bit mean grey value 128 in the way that the general pattern of the PDF of the image is preserved. In [7], the authors used the first singular value obtained by SVD to deal with the illumination problem in their proposed face recognition system. SVE can be described in the following way: The ratio of the largest singular value of the generated normalized matrix over a normalized image which can be calculated according to equation (9) is obtained.

$$\xi = \frac{\max\left(\Sigma_{N\left(\mu=0,\sigma^2=1\right)}\right)}{\max\left(\Sigma_A\right)} \tag{9}$$

Where $\Sigma_{N\left(\mu=0,\sigma^2=1\right)}$ is the singular value matrix of the synthetic intensity matrix. This coefficient can be used to regenerate an equalized image using equation (10).

$$\Xi_{equalized_A} = U_A\left(\xi\Sigma_A\right)V_A^T \tag{10}$$

Where $\Xi_{equalized_A}$ represents the equalized image A. This procedure significantly corrects the illumination problem. It is important to mention that techniques such as DHE or SVE are preserving the general pattern of the PDF of an image. Also as it was mentioned in before each of these equalization techniques can be easily modified and applied to color images. Figure 23 (a) shows another face image from Caltech face database and the output of GHE, LHE, DHE, and SVE equalization techniques in (b)-(e) respectively.



(a) **(b)** **(c)** **(d)** **(e)**

Figure 23. A face image from the Caltech face database (a), and the equalized face image using GHE (b), LHE (c), DHE (d), and SVE (e).

Where $\Xi_{equalized_A}$ represents the equalized image A. This procedure significantly corrects the illumination problem. It is important to mention that techniques such as DHE or SVE are preserving the general pattern of the PDF of an image. Also as it was mentioned in before each of these equalization techniques can be easily modified and applied to color images. Figure 23 (a) shows another face image from Caltech face database and the output of GHE, LHE, DHE, and SVE equalization techniques in (b)-(e) respectively.

3.3 IMAGE EQUALIZATION USING FIRST SINGULAR VALUE AND DISCRETE WAVELET TRANSFORM

Presently, wavelets are being used frequently in the field of digital image processing. It is being used for feature extraction [17], denoising [18], compression [19], face recognition [20], and image super resolution [21]. The decomposition of images into different frequency subbands permits the isolation of the frequency components introduced by “intrinsic deformations” or “extrinsic factors” into certain subbands [22]. This process results in isolating small changes in an image mainly in high frequency subband images. Hence discrete wavelet transform (DWT) is a suitable tool to be used for designing pose invariant face recognition system. The two-dimensional wavelet decomposition of an image is performed by applying the one-dimensional DWT along the rows of the image first, and then the results are decomposed along the columns. This operation results in four decomposed subband images refer to Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH). The frequency components of those subband images cover the frequency components of the original image.

Using singular value and discrete wavelet transform image illumination enhancement technique (SVDWT) involves two significant parts. The first one is the use of SVD. Therefore, changing singular values will directly affect the illumination of the image hence the other information in the image will not be changed. The second important aspect of this work is the application of DWT as the illumination information is embedded in LL subband and edges are concentrated in other subbands (i.e. LH, HL, and HH). Hence, separating the high frequency subbands and applying the illumination enhancement in LL subband only, will protect the edge information from possible degradation. After reconstructing the final image by using IDWT. Correcting illuminations will expose the high frequency details and thus a sharper looking image will be obtained. The general procedure of this technique is as follows. The input image, A, is first processed by using GHE to generate. Then both of these images are transformed by DWT into four subband images. The correction coefficient for singular value matrix is calculated by using the following equation:

$$\zeta = \frac{\max\left(\Sigma_{LL_{\hat{A}}}\right)}{\max\left(\Sigma_{LL_A}\right)} \tag{11}$$

Where Σ_{LL_A} is the LL singular value matrix of the input image and $\Sigma_{LL_{\hat{A}}}$ is the LL singular value matrix of the output of the GHE. The new LL image is composed by:

$$\begin{aligned} \bar{\Sigma}_{LL_A} &= \zeta \, \Sigma_{LL_A} \\ \overline{LL_A} &= U_{LL_A} \, \bar{\Sigma}_{LL_A} \, V_{LL_A} \end{aligned} \tag{12}$$

Now the end LH_A, HL_A and HH_A subband images of the original image are recombined by applying IDWT, to generate the resultant equalized image $\bar{A}$.

$$\bar{A} = IDWT\left(\overline{LL}_A, LH_A, HL_A, HH_A\right) \tag{13}$$

Daubechies (DB.9/7) wavelet is used in the whole thesis. Figure 24 illustrates all steps of SVDWT image equalization technique. Figure 25 (a) illustrates a low contrast image which has been used in [11]. This image has been equalized by using GHE (b), SVE (c), DHE (d), LHE (e), and SVDWT equalization technique (f). The quality of the visual results indicates that using singular value and discrete wavelet transform equalization SVDWT technique is sharper and brighter than the one achieved by DHE, GHE, and LHE. The resultant image generated by SVE is comparable with the image achieved by SVDWT.

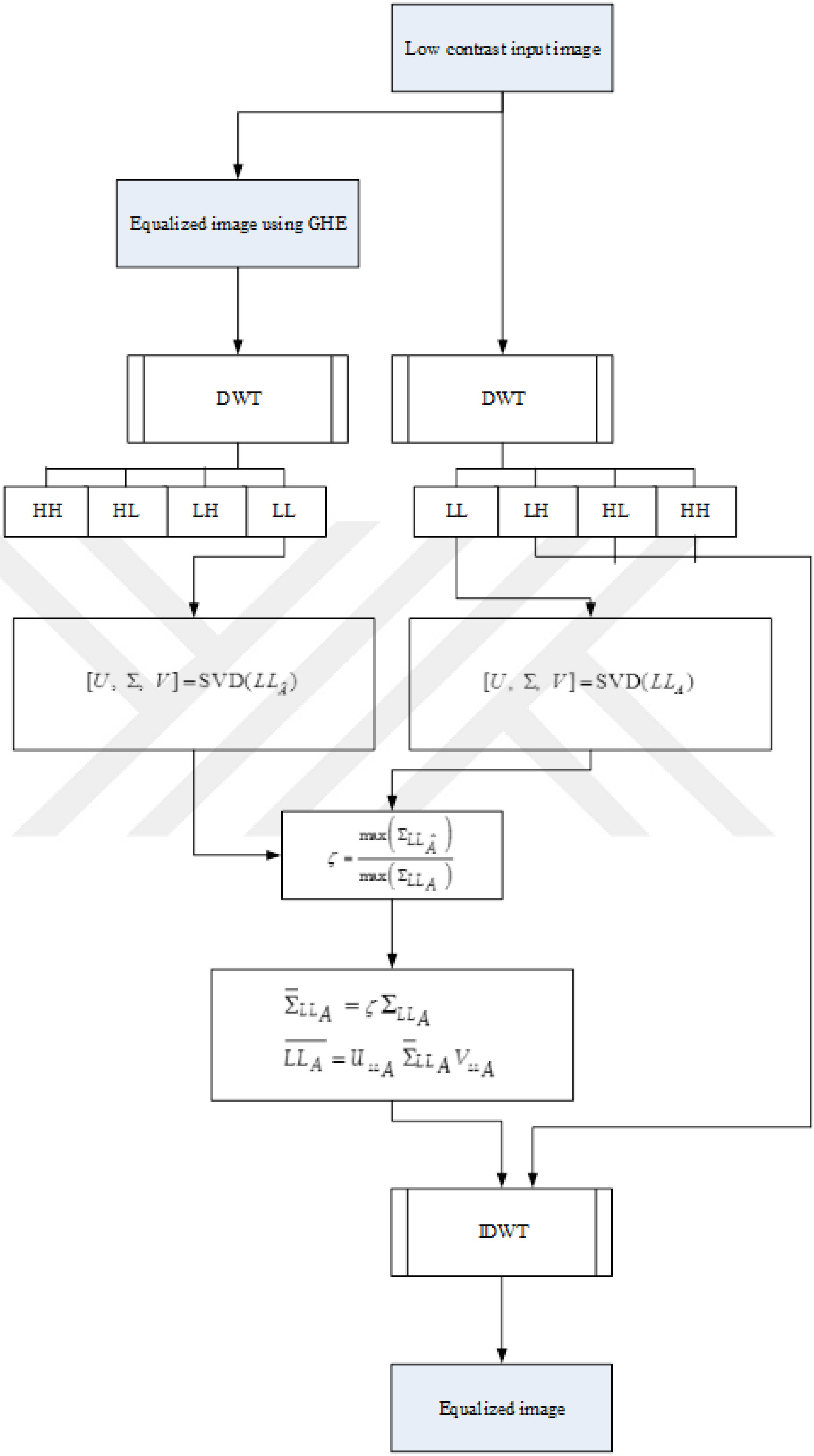


Figure 24. The detailed steps of SVDWT image equalization technique.

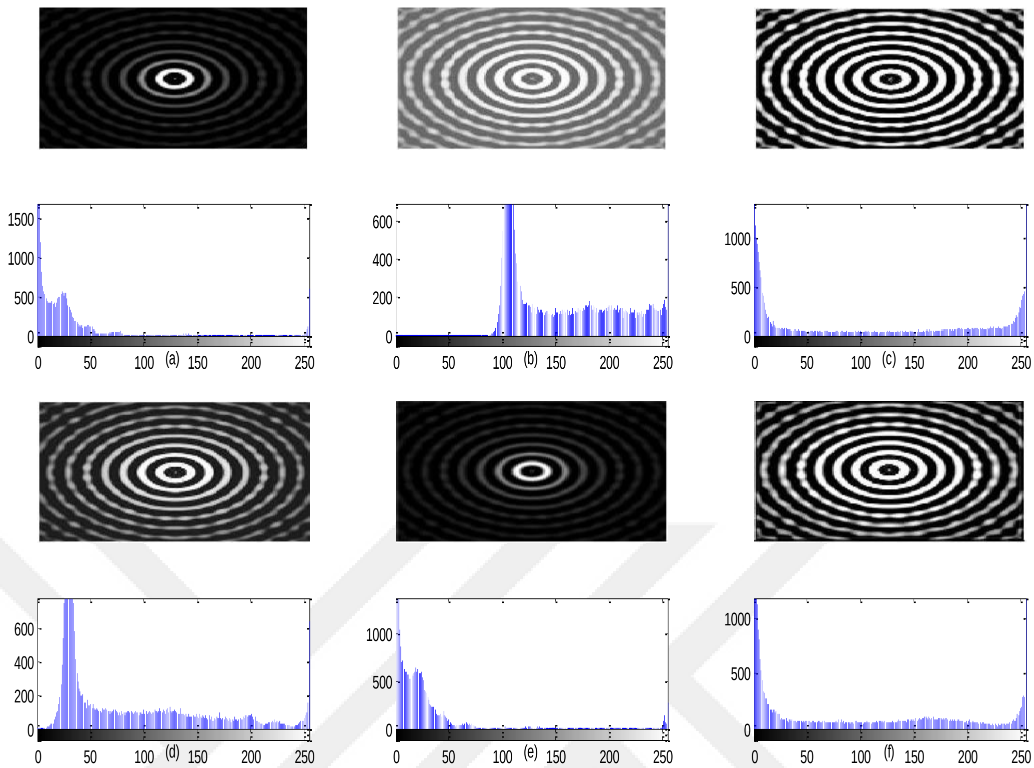


Figure 25. Low contrast image (a), Equalized image using: GHE (b), SVE (c), DHE (d), LHE (e), SVDWT (f), and their histograms.

The same face image used in Figure 23 is used in Figure 26 in order to show the superiority of the SVDWT method over the SVE, DHE, GHE and LHE. Figure 26 is showing that the SVDWT image equalization method has a brighter and sharper output. Additionally, there is no wash out problem as it has occurred in Figure 26 (c) obtained by SVE and there is also no blurring effect like Figure 26 (e) obtained by LHE.

Similar to all illumination enhancement technique, the SVDWT) illumination enhancement has several strengths and weaknesses. The main strength of this method is its ability to correct the uniform frontal illumination problem easily. The most noticeable weakness of the SVDWT equalization method is its disability on correcting the illumination problems caused by directional lightening. However, implementation of SVE by means of locality might overcome this weakness.

Figure 26. Low contrast face image from Caltech face database (a), Equalized image using: GHE (b), SVE (c), DHE (d), LHE (e), SVDWT image equalization technique (f)

As it was mentioned before, the main limitation of the SVDWT image equalization technique is the directional illumination problem. Figure 27 is showing a face image from Yale face database with directional illumination issue and also the output of the SVDWT equalization method.

Figure 27. Low contrast faces images from Yale face database in the first row and the output of the LHE, GHE, and the SVDWT image equalization technique in the 2nd, 3rd, and 4th rows respectively.

3.4 COLOR IMAGES VS GREY SCALE IMAGES

Usually many conventional image processing systems use grey scale images. However, color images have recently become centre of interests of many researches. From the information point of view, a color image has more information than a grey scale image. Hence in this thesis we propose not to lose the available amount of information by converting a color image into a grey scale image. In order to compare the amount of the information in a color and grey scale images, the entropy of an image can be used, which can be calculated by:

$$\mathrm{H} = -\sum_{i=0}^{255} P(i)\log_2\left(P(i)\right) \tag{26}$$

Where H measures the information of the image and P is the histogram or PDF of the image. The average amount of information measured by using 2650 face images of the FERET [24], HP [25], Essex University [26], and Georgia Tech University [27] face databases are shown in Table 1, the entropy values indicate that there is significant amount of information in different color channels which should not be simply ignored by only considering the grey scale image.

Database	**The average entropy of the images (bits/pixel)**		
	HIS	***YCbCr***	***Greyscale***
FERET	19.2907	16.3607	7.1914
Head Pose	15.9434	12.3173	6.7582
Essex Uni.	21.2082	17.3158	7.0991
Georgia Tech	20.8015	16.6226	6.9278

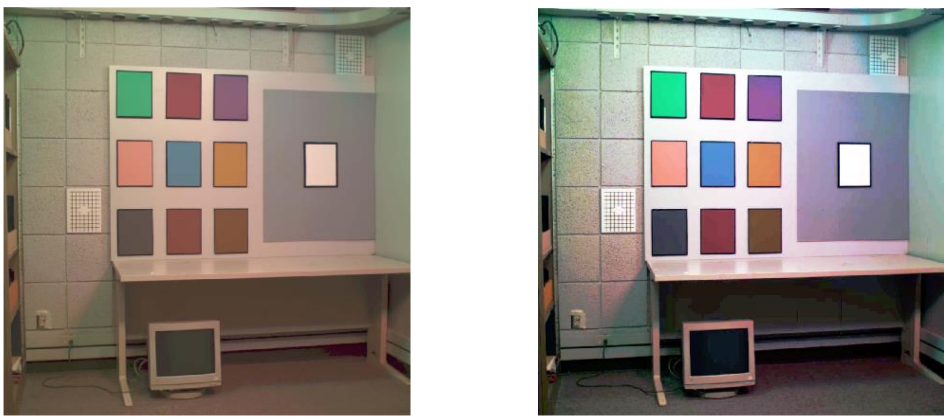
Table 1. The entropy of color images in different color channels compared with the grayscale images.

3.5 METHODS OF EQUALIZATION OF COLOR IMAGES

Nowadays researchers concentrate more on color images. However, almost all algorithms which have been developed for greyscale images can be easily improved and modified to be implemented on color images. There exist several methods in literature to equalize a color image [11], [28-31]. One of the most frequently used and simple methods is to equalize the color image in RGB color space by using any of aforementioned equalization techniques such as GHE in each color channel separately. Because we can treat the image in any of these color space as a greyscale image. Hence the procedure can be stated as follows:

1. Decompose the color image into its R, G, and B color channels,
2. Equalize each image in a respective color channel by using GHE, LHE, DHE, SVE, etc.,
3. Combine all three equalized image in different color channels to obtain a new equalized color image.

Figure 28 shows such an equalization of a color image.



(a) (b)

Figure 28. An image from [31] (a) and the equalized image using GHE in each R, G, and B channels separately (b).

In the equalization process, one can use of the aforementioned equalization technique but here due to simplicity GHE has been used in the simulations. A color image can be expressed not only by using R, G, and B pixel statistics but also by using the luminance and chrominance information. Thus the equalization can be conducted in HSI color space rather than the RGB color space. Because the illumination information is in I color channel hence the equalization process is not required to be implemented three times. Here the procedure can be described in the following way:

1. Convert the color image into HSI color space and decompose it into its hue, saturation and intensity color channels,
2. Equalize the intensity image (I),
3. Combine the equalized images to produce a new equalized color image.

Figure 29 shows the equalized image by using the GHE of the intensity image of a color image obtained from HSI color space.

(a) (b)

Figure 29. An image from [31] (a) and the equalized face image using histogram equalization of intensity image in HSI color channel (b).

From the definition of saturation and hue color channels, it is clear that equalization in hue or/and saturation color channel will lead to loss of huge amount of color/chrominance information (not illumination/luminance information). Figure 30 illustrates that visually proposed image equalization in R, G, and B color channels is over performing than equalization obtained by GHE.

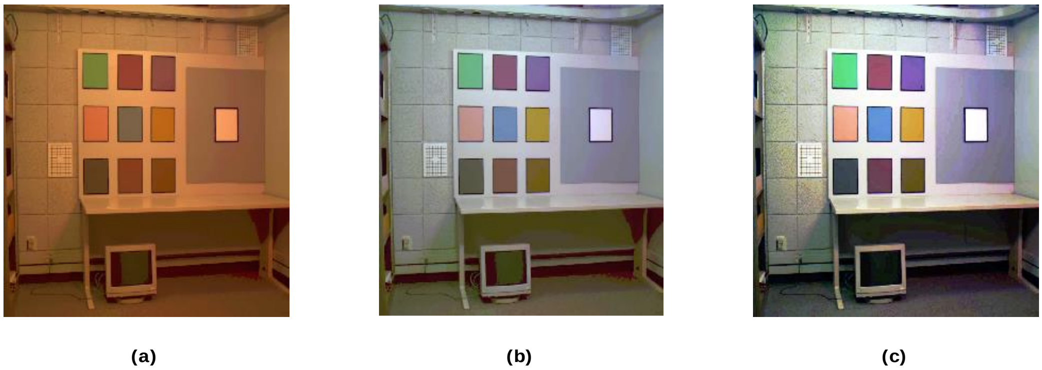


Figure 30. A low contrast color image (a) and its corresponding equalized ones, by using the SVDWT image equalization technique (b) and GHE (c).

It is essential to note that the nonlinear operations such as GHE on RGB channels will create wrong results while linear operations such as SVE will maintain the correct color. Figure 31 shows a face image from the Caltech face database. It also shows the R, G, and B PDFs of the original image and the low contrast image compared with the PDFs of the equalized image by using the SVDWT image equalization technique and the GHE in RGB color space. The PDFs in Figure 31 (e)-(h) have been smoothened with using moving average. As Figure 31 (g) shows the equalized image by using the SVDWT image equalization technique has preserved its main statistics such as the number of peaks or local minimums as well as the general pattern of the PDF of the original image shown in Figure 31 (a).

While comparing different image equalization techniques, it can be seen that easily, the absence of a quantitative metric is an obvious situation. All the conclusions that we have been discussed so far, are based on visual and qualitative assessments. In the following chapter, a novel image illumination assessment metric is introduced, which also confirms the conclusion that we had upon the superiority of the SVDWT image equalization technique over the other conventional and state-of-art techniques.

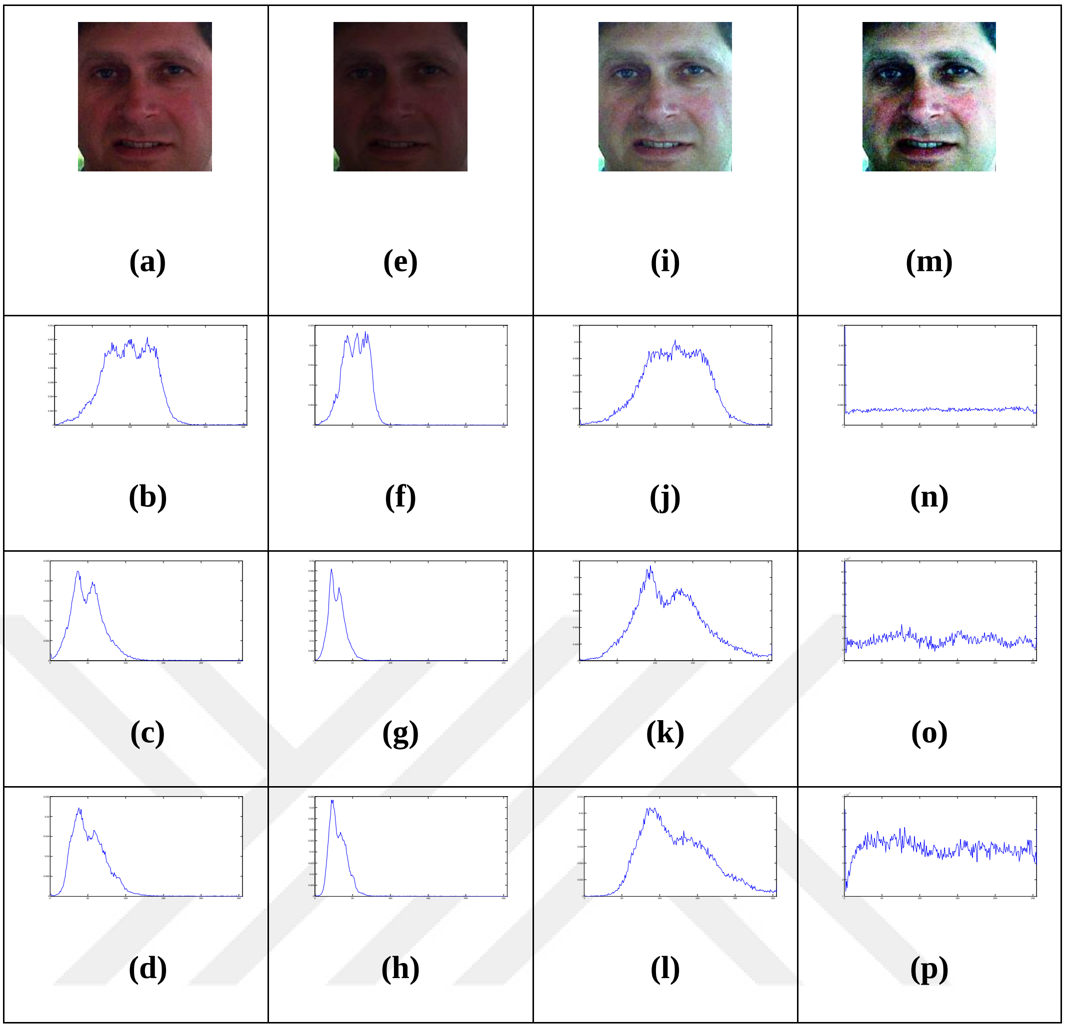


Figure 31. A face image from Caltech database (a), and its R, G, and B PDFs (b)-(d), a low intensity color image of the same scene (e), and its R, G, and B PDFs (f)-(h), the equalized image using SVDWT image equalization technique (i) and its respective R, G, and B PDFs (j)-(l) and the equalized image using GHE (m) and its respective R, G, and B PDFs (n)-(p).

4 A NEW APPROACH TO ASSESS THE IMAGE ILLUMINATION QUALITY

As it was mentioned in the previous section, there are many alternative techniques for image contrast enhancement problem. However, other than visual analysis evaluation methods (i.e. subjective evaluation), there is no quantitative evaluation method (i.e. objective evaluation) to assess the quality of the enhanced images. Some researchers are using the mean opinion score (MOS) in order to compare different illumination techniques but yet MOS is a subjective metric. Existence of the ground truth image is a necessity in many quality measurement methods such as the PSNR calculations. This is the main motivation for introducing a metric which can be used to measure the illumination quality independent of the ground truth image. The proposed metric in this thesis is based on statistical pixel intensity distributions of the given image and the so called ideal image. The main issue in ground truth image independent approach is to identify the desired statistical pixel intensity distribution of a so called ideal image.

Gokmen et al. [23] stated that “The well-lit faces do not have a uniform histogram”, hence using GHE “will rise to an unnatural illumination to the face”. “It is possible to normalize a poorly illuminated image” by using appropriate technique “to a similar well illuminated image”. Hence, according to various applications, one can define a “well illuminated image”. Here in this work we define the distribution of ideally a good illuminated image to have a mean of 128 ($\mu=128$ for an 8-bit intensity image). The standard deviation (σ) of the desired distribution should be calculated in order to estimate the Gaussian distribution of a desired ideal image. It is clear that an 8-bit grey level image has the pixel range of [0, 255]. Hence, the σ should be calculated in such a way that the Gaussian distribution covers this range effectively. Without loss of generality normalization of the distribution is possible in the way that the area under the distribution is 1, hence it can be treated as a probability distribution function. It is known that the following transformation is valid:

$$X = G\left(\mu,\sigma^2\right) \xrightarrow{z=\frac{x-\mu}{\sigma^2}} Z = N\left(0,1\right) \tag{14}$$

Where N is representing a normal distribution and G is a Gaussian distribution. Assume that we want our estimated distribution to satisfy the following condition:

$$P\left(0 \le x \le 255\right) = 0.998 \tag{15}$$

Given that μ=128, in order to find σ, one can easily follow the proceeding steps:

$$P\left(0 \le x \le 255\right) = 0.998 \xrightarrow{z=\frac{x-128}{\sigma^2}} P\left(-Z_0 \le z \le Z_0\right) = 0.998$$

$$\rightarrow P\left(0 \le z \le Z_0\right) = \frac{0.998}{2} = 0.499 \xrightarrow[\text{Normal curve areas}]{\text{by using table of}} Z_0 = 3.09 \tag{16}$$

$$z = \frac{x-128}{\sigma^2} \rightarrow Z_0 = 3.09 = \frac{255-128}{\sigma^2} \rightarrow \sigma = \sqrt{\frac{255-128}{3.09}}$$

$$\Rightarrow \sigma = 6.4110$$

This calculation can be held for other probability values given in equation (15). Table 2 shows different values of σ obtained by the procedure in equation (16) for different probabilities.

$P(0 \le x \le 255)$	**σ**
0.998	6.4110
0.990	7.0160
0.950	8.0496
0.900	8.7600
0.850	9.3912
0.800	9.9609
0.500	13.7167

Table 2. Different values of σ of various occurrence probabilities

Therefore, a Gaussian distribution with mean *128* and standard deviation of *6.4110*, $G_{desired}$ *(μ=128, σ^2=41.1003)*, can be considered as a desired distribution. Also, for a given image (which can be an output of any illumination enhancement technique) the estimated Gaussian distribution of such image can be calculated by using the following formula:

$$G_{image}\left(\mu_{image},\sigma^2{}_{image}\right)\{x\} = \frac{1}{\sqrt{2\pi}\,\sigma_{image}} e^{-\frac{\left(x-\mu_{image}\right)^2}{2\sigma_{image}{}^2}} \qquad (17)$$

where μ_{image} and σ_{image} are the mean and standard deviation of the input image respectively. Now the KLD value between the estimated Gaussian distribution of the input image, G_{image}, and the desired Gaussian distribution, Gdesired, can be calculated. The lower the KLD value, the better the illumination, because it represents how similar G_{image}, to Gdesired is. This value, κ, can be formulated as follows:

$$\kappa\left(G_{image}, G_{desired}\right) = \sum_j G_{image_j} \log\left(\frac{G_{image_j}}{G_{desired_j}}\right) \qquad j=0,\ldots,255 \qquad (18)$$

The variable j is representing the possible gray level range which is [0, 255]. Hence there is no need to include the $(-\infty,-1]\cup[256,\infty)$. In order to avoid any division by 0 or logarithm of 0 we can modify the KLD formula into the following form:

$$\kappa\left(G_{image},G_{desired}\right)=\sum_{j}G_{image_j}\log\left(\frac{G_{image_j}+\varepsilon}{G_{desired_j}+\varepsilon}\right)\qquad j=0,...,255 \tag{19}$$

Where ε is a very small number, e.g. 10-6.

In order to normalize κ, the KLD value should be divided by its maximum possible value. The maximum distance occurs when we have an impulse on one of the gray levels with the peak value equal to $\sum G_{desired}$, e.g. δ_{black} (j=0) or δ_{white} (j=255). The reason for that is in impulse the value of the function is zero everywhere except the place that impulse occur and also a Gaussian distribution with mean which is around 128 has lowest value at the black or white. Let assume that this maximum KLD value is shown by κ_{max}, which is as follows:

$$\kappa_{\max}=\sum_{j}\delta_{white}\log\left(\frac{\delta_{white}+\varepsilon}{G_{desired_j}+\varepsilon}\right)\qquad j=0,...,255 \tag{20}$$

Therefore, the normalized divergence can be calculated by:

$$\bar{\kappa}\left(G_{image},G_{desired}\right)=\frac{\kappa\left(G_{image},G_{desired}\right)}{\kappa_{\max}}\qquad,\qquad 0\le\bar{\kappa}\le 1 \tag{21}$$

When $\bar{\kappa}$ is equal to 0,that means we have the perfect match between the G_{image} and $G_{desired}$ distributions, which means that input image has the ideal/desired illumination. Let's define ξ to be the illumination metric that would generate a measurement of the estimated Gaussian distribution of the input image and the desired Gaussian distribution, which has a value between 0 and

1. ξ can be formulated by equation (21) as follows:

$$
\begin{aligned}
\xi_{\left(G_{image},G_{desired}\right)} &= sign\left(\mu_{G_{image}} - 128\right)\frac{1}{2}\bar{\kappa} + 0.5 \\
&= sign\left(\mu_{G_{image}} - 128\right)\frac{\kappa_{\left(G_{image},G_{desired}\right)}}{2*\kappa_{\max}} + 0.5 \qquad j = 0,\cdots,255 \\
\rightarrow \xi_{\left(G_{image},G_{desired}\right)} &= sign\left(\mu_{G_{image}} - 128\right)\frac{\sum_j G_{image_j}\log\left(\frac{G_{image_j}+\varepsilon}{G_{desired_j}+\varepsilon}\right)}{2\times\left[\sum_j \delta_{white}\log\left(\frac{\delta_{white}+\varepsilon}{G_{desired_j}+\varepsilon}\right)\right]} + 0.5
\end{aligned}
\tag{22}
$$

Where,

$$
sign(x) = \begin{cases} 1 & x \geq 0 \\ -1 & x < 0 \end{cases} \tag{23}
$$

Introducing sign function helps to differentiate the input image into dark and bright images. Image with $0 \leq \xi < \frac{1}{2}$ represents a dark image and image with $\frac{1}{2} < \xi \leq 1$ represents a bright image. It is clear that $0 \leq \xi \leq 1$

In order to enrich the equation (22) so that the result can also give some idea about the contrast of the distribution of the image (i.e. the image has a low contrast or high contrast), we need to incorporate with variance of the distribution into the equation. Hence by considering all these issues we are modifying the equation (22) and proposing the following metric for illumination quality:

$$
\xi_{\left(G_{image},G_{desired}\right)} = sign\left(\sigma^2_{G_{image}} - 41.1003\right)\left[sign\left(\mu_{G_{image}} - 128\right)\frac{\sum_{j=0}^{255} G_{image_j}\log\left(\frac{G_{image_j}+\varepsilon}{G_{desired_j}+\varepsilon}\right)}{2\times\left[\sum_{j=0}^{255} G_{white}\log\left(\frac{G_{white}+\varepsilon}{G_{desired_j}+\varepsilon}\right)\right]} + 0.5\right] \tag{24}
$$

Where,

$$-1 \leq \xi \leq 1 \,, \qquad \xi_{\text{ideally illuminated image}} = \frac{1}{2} \tag{25}$$

In its final form, the sign of ξ indicates the contrast of the image. If ξ is a positive number, it means that the image has a high contrast and if it is a negative number then it indicates that the image has a low contrast. Figure 32 is showing several distributions with $\mu=128$, different variances (σ^2), and respective ξ values for low contrast and high contrast images with the same mean.

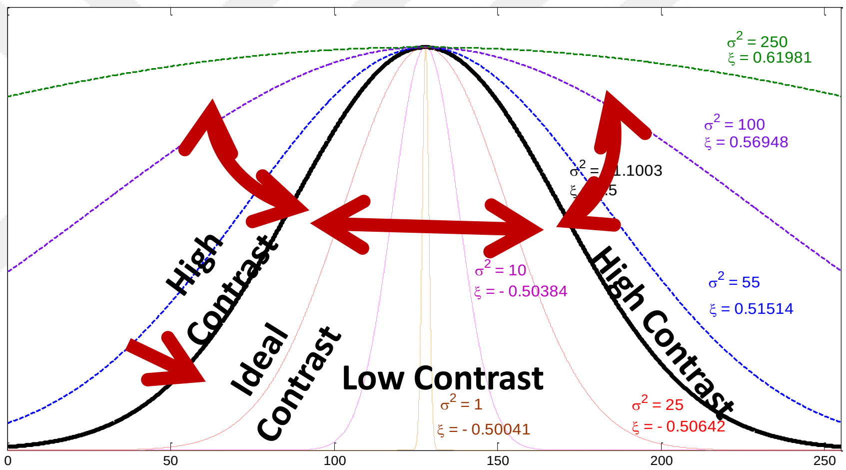
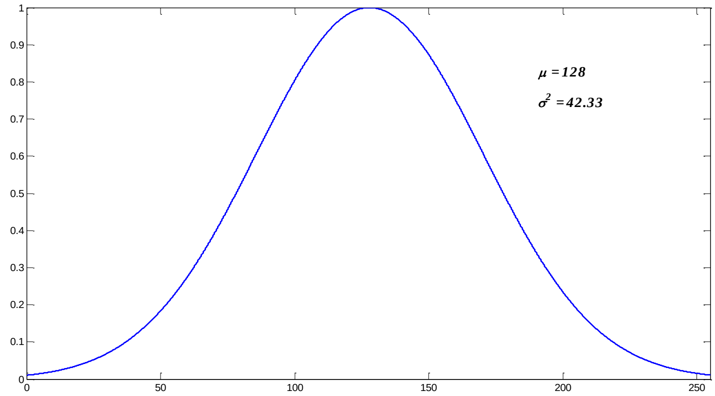


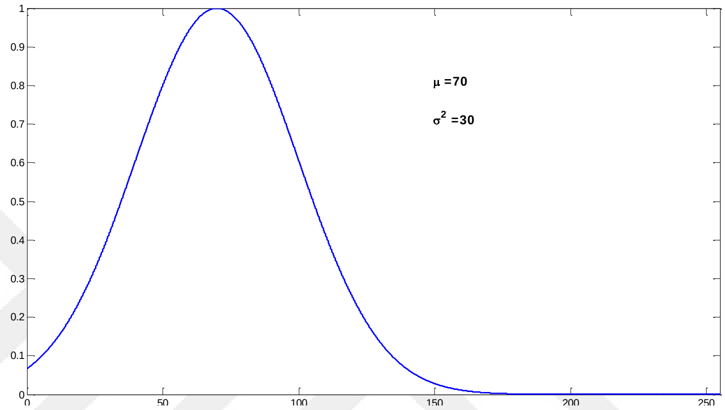
Figure 32. Several distributions with mean of 128, changing variances and their respective ξ values.

An ideal image would have ξ to be 0.5 which is stated in equation (25). Consider the five distributions in Figure 33.

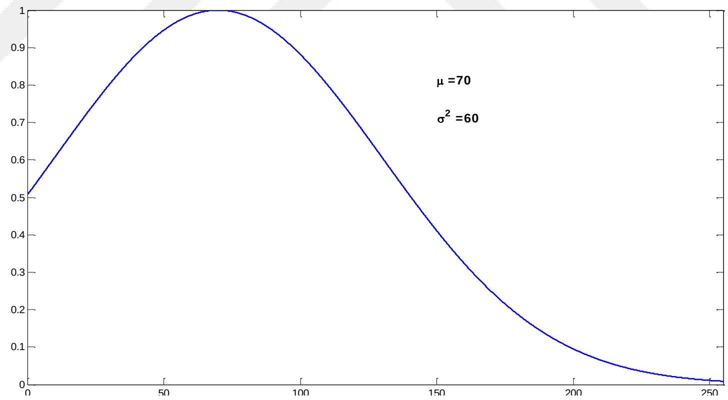
(a)



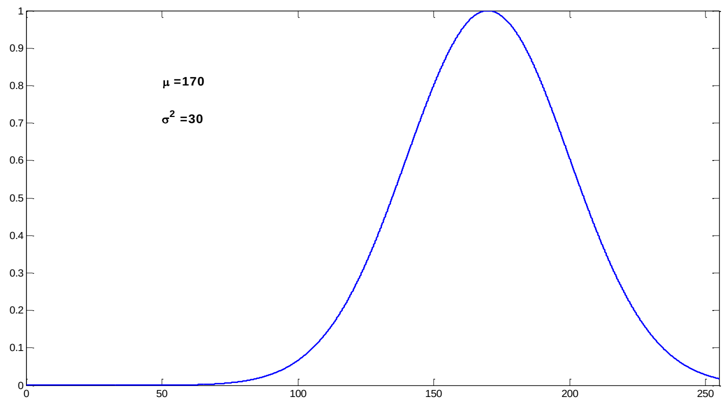
(b)



(c)



(d)



(e)

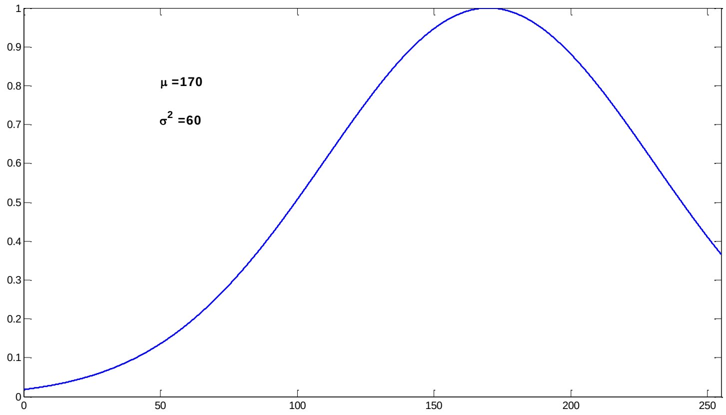


Figure 33. An estimate Gaussian distribution of an image with ideal illumination (a), a dark image with low contrast (b), a dark image with high contrast (c), a bright image with low contrast (d), bright image with high contrast (e).

By using equation (24) the respective ξ values of Figure 33 can be calculated. Table 3 shows the calculated metric (ξ) values. According to these values Figure 33, (a) shows estimated Gaussian distribution of approximately an ideally illuminated image. Figure 33, (b-c) shows estimated Gaussian distributions of two dark images with low and high contrasts respectively. Figure 33 (d-e) illustrates estimated Gaussian distributions of two bright images with low and high contrasts respectively.

Estimated Distributions	Proposed Metric (ξ)	Illumination Analysis
$G_{(128,42.33)}$	$\xi\left(G_{(128,41.1003)}, G_{(128,42.33)}\right) = 0.5010$	Close to ideally illuminated image
$G_{(70,30)}$	$\xi\left(G_{(128,41.1003)}, G_{(70,30)}\right) = -0.4819$	Dark image with low contrast
$G_{(70,60)}$	$\xi\left(G_{(128,41.1003)}, G_{(70,60)}\right) = 0.4598$	Dark image with high contrast
$G_{(170,30)}$	$\xi\left(G_{(128,41.1003)}, G_{(170,30)}\right) = -0.5070$	Bright image with low contrast
$G_{(170,60)}$	$\xi\left(G_{(128,41.1003)}, G_{(170,60)}\right) = 0.5325$	Bright image with high contrast

Table 3. The proposed metric values and their analysis for different estimated distributions

Figure 34 summarizes entire analysis of the representation of ξ values.

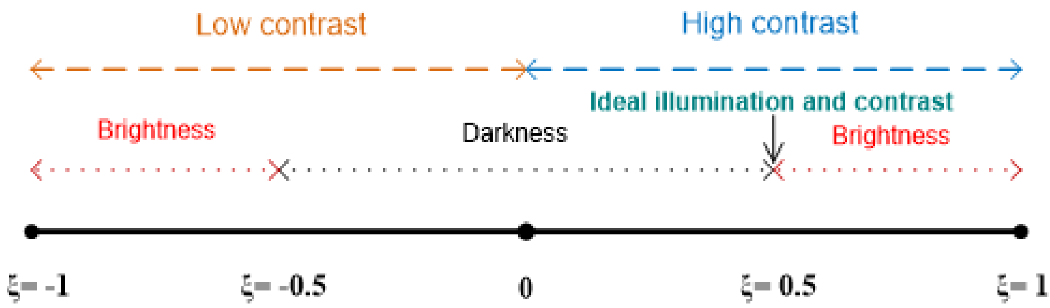


Figure 34. Calculated metric's (ξ) guideline.

In Figure 35, low and high contrast images with their estimated Gaussian distributions have been shown. The Figure 35 (a-i) shows an approximately ideally illuminated image. As expected, the ξ in Figure 35 (b-i) is negative (ξ = -0.4883), which means it is a low contrast dark image, and ξ is positive (ξ = 0.5231) in Figure 35 (c-i), which means it is a high contrast bright image. These observations are in line with the visual analysis of the respective images.

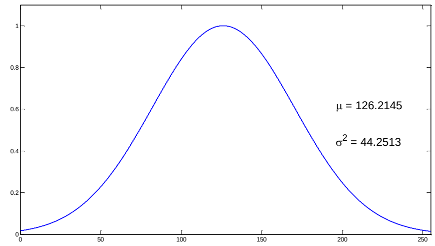
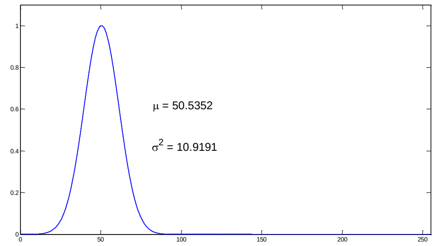
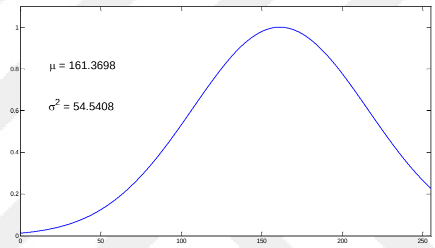
(a)			**ξ = 0.4972**
(b)			**ξ = -0.4883**
(c)			**ξ = 0.5231**
	(i)	**(ii)**	**(iii)**

Figure 35. An almost ideally illuminated image (a), low contrast dark image (b), and a high contrast bright image (c), and their respective estimated Gaussian distributions (ii) and their ξ values (iii).

Figure 36 shows the Gaussian distributions of the images used in Figure 25. The estimated Gaussian distribution of the SVDWT equalization method covers wider grey level range, which is why it has better illumination. Also the calculated ξ values confirm our claim that the proposed method produces an image with a better illumination as ξ proposed method is closer to 0.5. Thus, this analysis supports the qualitative observation that the SVDWT equalization method over performs the conventional and state-of-art techniques.

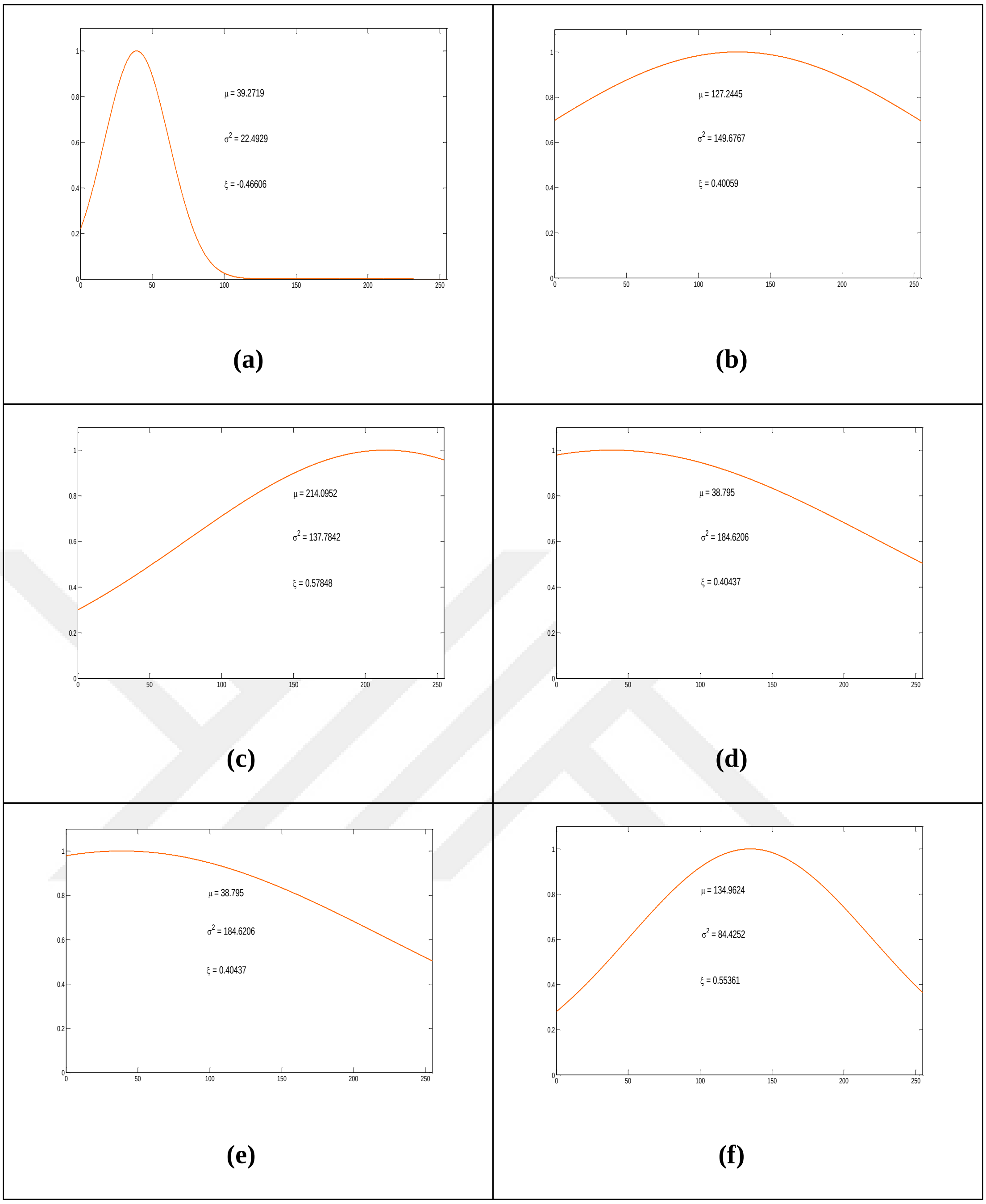


Figure 36. Estimated Gaussian distribution for Figure 21 (a)-(e) respectively.

5 RESULTS AND DISCUSSION

Table 4 presents several images and their measure values for those, prior to and after applying singular value equalization based illumination enhancement technique. In order to verify the effectiveness and accuracy of the proposed approach for assessment of the illumination of an image, also a mean opinion score (MOS) has been studied. MOS analysis has been done by asking 200 randomly selected people from internet to vote for 360 sample images with different illumination states namely; 90 dark images, 90 bright images, 90 low contrast images, and 90 high contrast images. The participants where provided by all the images in random order and they were asked to divide those images in the aforementioned categories. Table 5 shows the average results of MOS. Also the calculated metric (ξ) value for each of these images are calculated by using equation (24) that is explained in below chapter, and then the illumination state of the images has been assigned by using metric (ξ) guideline shown in Figure 34. Table 5 presents the results of MOS and proposed measurements. Table 5 shows that the proposed approach for assessment of the illumination state of an image is very effective and reliable in determining the illumination state of a given image. Some of the sample images that are provided for the MOS analysis are shown in Figure 37.

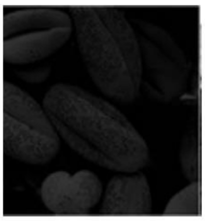
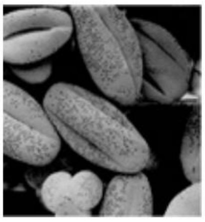
	Image	μ	σ	ξ
prior to enhancement		167.96	28.61	-0.5082
after enhancement		121.5	54.42	0.4936
prior to enhancement		64.05	36.33	-0.4817
after enhancement		120.88	68.09	0.4856
prior to enhancement		17.98	24.74	-0.4818
after enhancement		85.63	67.34	0.4826

Table 4. Experimental results before and after the image illumination enhancement

Illumination state of the image		Decision (%)			
		Bright	Dark	Low Contrast	High Contrast
Bright	decision based on average ξ(%)	100	0		
	decision based on average MOS (%)	94.62	5.38		
Dark	decision based on average ξ(%)	0	100		
	decision based on average MOS (%)	8.46	91.54		
Low Contrast	decision based on average ξ(%)			100	0
	decision based on average MOS (%)			96.15	3.85
High Contrast	decision based on average ξ(%)			0	100
	decision based on average MOS (%)			88.08	11.92

Table 5. State of illumination assigned on an average to the images


Figure 37. Sample images used in MOS analysis

As an another experiment for the proposed approach, the metric value (ξ) is calculated for the face images which are shown in Figure 38, after the calculation, the obtained results shows that the metric is independent of the image and the efficiency is sufficiently descriptive. Also the results have high accuracy for the evolution of the contrast and the brightness states of a given image.

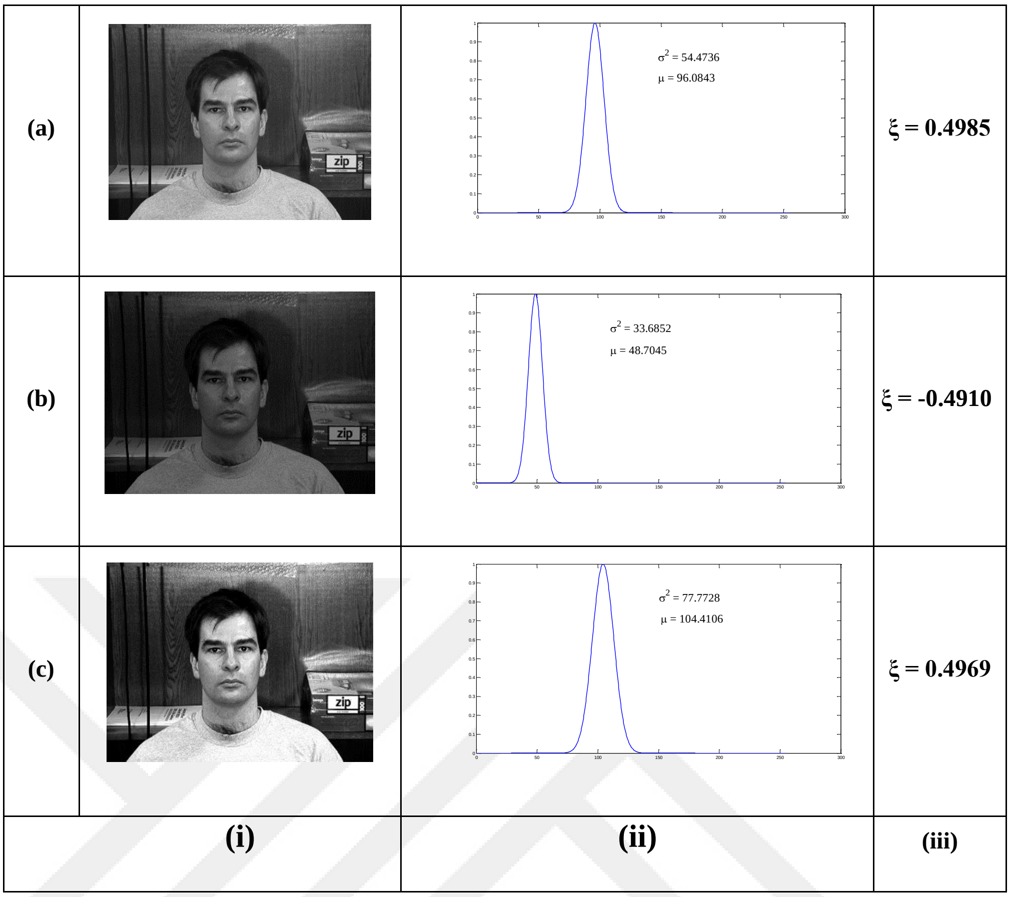


Figure 38. A face image (a), low contrast dark image (b), and a high contrast bright image (c), and their respective estimated Gaussian distributions (ii) and their ξ values (iii).

In conclusion, it can be clearly observed from the results of the experiments, proposed metric provides reliable and finite results about the given image's state of illumination, also proposed metric can be used for other image processing applications which are belongs to enhancement of the image's brightness, contrast or the resolution. Besides all this, proposed metric could be a good evolution and assessment method for the future proposed illumination enhancement techniques during the academic studies in the field of digital image processing.

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