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A Neighborhood Dependent Nonlinear Technique for Enhancement of Color Images Captured Under Non-Uniform Lighting Conditions

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A NEIGHBORHOOD DEPENDENT NONLINEAR TECHNIQUE FOR ENHANCEMENT OF COLOR IMAGES CAPTURED UNDER NON-UNIFORM LIGHTING CONDITIONS

by

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ABSTRACT

A NEIGHBORHOOD DEPENDENT NONLINEAR TECHNIQUE FOR ENHANCEMENT OF COLOR IMAGES CAPTURED UNDER NON-UNIFORM LIGHTING CONDITIONS

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The aim of image enhancement process is to improve the interpretability of the information in images for human viewers or to provide better input for automated image processing techniques. Many image processing applications begin with a nonlinear enhancement process to improve visual quality of video sequences captured under non-uniform lighting conditions. This improves the visibility of the scene captured from physical sensing devices which have limited dynamic range. This physical limitation causes the saturated region of the image to either shadow out or wash out the rest of the scene. When extremely bright and dark regions are present in an image, the object details in the low intensity areas as well as in the high intensity areas cannot be clearly interpreted. It is therefore desirable to bring back a more uniform scene which eliminates the shadows and overexposed regions to a certain extent.

In this thesis, an image enhancement algorithm based on a neighborhood dependent nonlinear model is presented to improve visual quality of digital images captured under extremely non-uniform lighting conditions. This thesis presents techniques for adaptive and simultaneous intensity enhancement of extremely dark and bright images, contrast enhancement, and color restoration. The core idea of the

algorithm is the development of a nonlinear sine transfer function with an image dependent parameter. Adaptive computation of the control parameter increases flexibility in enhancing the dark regions and compressing overexposed regions in an image. A neighborhood dependent approach is employed for contrast enhancement. A linear color restoration process is used to obtain color image from the enhanced intensity image by utilizing the chromatic information of the original image. It is observed that the proposed algorithm yields visually optimal results on images captured under extreme lighting conditions. Further, research work is progressing at application of ratio rule for color restoration to produce color constant images.

This thesis is dedicated to my parents, Anandiben and Parshottambhai Patel.

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CHAPTER 1

INTRODUCTION

The goal of image enhancement technique is to improve the visual quality of an image. Producing visually natural images or transforming the image such as to enhance the visual information within is a primary requirement for almost all vision and image processing tasks. When an image is captured under overly illuminated or is in low lighting conditions, the details in the overexposed and underexposed regions may not be visible. This problem arises from the limitation of physical sensing devices. By adjusting the brightness in the problem areas and enhancing contrast in such images more details can be made visible to the human eye as well as other image processing algorithms. Producing digital images with good brightness/contrast and detail is a strong requirement in several areas like vision, remote sensing, biomedical image analysis, night time vision/surveillance, etc. Thus, in many such image processing applications, image enhancement is used as an essential preprocessing step in order to increase the efficiency of the application.

The theme of this thesis is simultaneous enhancement of extremely dark and bright regions in an image. This method enables the production of images that are aesthetically pleasing and possess high visual quality which human viewers and from which automated image processing applications can benefit. Since the image enhancement process is used as a preprocessing step in many real time image processing applications, the thesis emphasizes on reducing computational complexity of the

The format for this thesis follows the IEEE Transaction on Computers algorithm. The specific objectives of this thesis are listed in Section 1.2 followed by the organization of this book in Section 1.3.

1.1 Motivation of the Research

The fact that a camera does not see exactly the way human eyes do introduces limitations in the formation and display of an image of a real world scene. In nature, scene luminance ranges the span of two to six orders of magnitude thereby producing a very high dynamic range radiance map. The dynamic range represents the amount of contrast that a given device can record. Currently available standard electronic cameras can measure light between 8 to 10 stops (2 to 4 orders of magnitude). A high end camera with wider dynamic range can measure light up to 14-16 stops, which is still inferior to human eye that can see details in a scene containing a contrast range of nearly 24 stops (more than six orders of magnitude). In addition, the dynamic range of a camera is limited by noise levels, meaning that details captured in dark shadow or bright areas may exhibit excessive noise and rendered as black or white [1]. The human eye is capable of handling a wide dynamic range radiance map due to its complex structure and adaptive mechanism. The eye is able to instantly change its contrast-perception ability in order to see, alternatively, details in highlights and in shadow areas. To allow more light into the eye, the dilator muscle makes the iris smaller and therefore the pupil larger. To allow less light into the eye, the sphincter muscle makes the iris larger and the pupil smaller thereby compressing the dynamic range [2]. The majority of the range compression is done by the retina which is the light-sensing portion of the eye. The rod cells of the retina are responsible for vision in low light whereas the cone cells are responsible for color vision and fine details. Hence, much of the construction of the visual images takes place in the retina and the final perception of sight is done in the brain [3]. Clearly, the human eye-brain apparatus is not limited to a fixed dynamic range but instead can adapt to varying luminance. On the other hand, the camera aperture is fixed and sets global exposure when capturing an image. Furthermore, image display devices, like monitors and printers, also demonstrate a limited dynamic range. Consequently, images captured under extremely bright or ill lighting conditions suffer from saturation and underexposure respectively. When displayed on LDR devices, important features and fine details are not visible [1].

In order to improve visual quality of images while dealing with the technical limitations of recording and display devices, compressing the dynamic range (mapping of the natural range of luminance to a smaller range [4]) is important). Several image processing techniques exist that can perform dynamic range compression such as logarithmic compression, gamma correction, histogram equalization, and a variety of tone mapping operators. However, these techniques are not sophisticated enough to preserve all the features and fine details. Also, they may not be able to enhance all the regions proportionately. For example, in logarithmic enhancement, the low intensity pixel values can be enhanced at the loss of high intensity values [5]. In these techniques, regions of the scene where the slope of the mapping operator is low can become difficult to see [6].

To address the brightness and contrast issues, several advanced image processing techniques have been developed to compress the dynamic range along with local contrast enhancement, such as adaptive histogram equalization [7], Retinex [8, 9], Multi-Scale Retinex (MSR) [10,15], INDANE [16], AINDANE [17], IRME[18], MWIS [19], and

LTSNE [20]. Among them, Histogram Equalization (HE) is a fairly simple and fast algorithm but works well only on the images possessing uni-modal or weakly bi-modal histograms [17]. Many variations have been made to the original HE technique to improve contrast and details. The drawback of advanced HE algorithms is that it makes the image look unnatural while bringing out the object's details. Successful efforts have been made to imitate human visual system based on Retinex theory derived by E. Land [9]. Retinex based algorithms efficiently compress the dynamic range and maintain color constancy. Multi Scale Retinex (MSR) [11] theory was developed based on a center/surround method in which the best results were obtained by averaging three images resulting from three different surround sizes. Later, a color restoration step was added to overcome a graying out effect caused by the method. However, the biggest problem with both MSR and standard Retinex is the separate nonlinear processing of three color bands. It not only produces strong "halo" effect and incorrect color artifacts but also makes the algorithm computationally intensive.

In recent years, a more promising technique called AINDANE (Adaptive Integrated Neighborhood Dependent Approach for Nonlinear Enhancement) [17] has been developed. It involves itself in adaptive luminance enhancement and adaptive contrast enhancement. This method handles enhancement of dark or ill-illuminated images very well, however, it does not provide solution for overexposed images. In order to obtain fine details and balance between over and underexposed regions in images, an innovative technique named LTSNE (Locally Tuned Sine Nonlinear Enhancement) has been developed [20], which also forms the basis for the proposed algorithm.

While there are several image enhancement algorithms available, the method which is capable of simultaneous rendering of the luminance and contrast components of the color images is not currently available for efficient design of the architecture. In the proposed algorithm NDNE (Neighborhood Dependent Nonlinear Enhancement of Color Images), efforts have been made to achieve these objectives. The algorithm has been developed and deliberately formulated so as to create opportunity for extremely efficient hardware architecture as well as efficient software implementation. Computation of the image dependent parameters has been simplified to reduce processing time and yield improved visual quality.

1.2 Proposed Research

The theme of this thesis is enhancement of images captured under extremely non-uniform lighting conditions. To simultaneously enhance extremely dark regions and compress extremely bright regions, an optimized spatial domain nonlinear algorithm NDNE (Neighborhood Dependent Nonlinear Enhancement of Color Images) is proposed. In NDNE algorithm, enhancement process is performed in three steps: Adaptive intensity enhancement, contrast enhancement, and color restoration. The primary step of adaptive intensity enhancement is realized with a parameter controlled sine function. The sine function produces different curves based on the value of the control parameter for a given intensity value. Depending on the value of the control parameter, the sine function either pulls up or pulls down the pixels intensity. In this algorithm, to adaptively enhance or compress the intensity of the pixels the value of the control parameter is calculated based on the intensity of the pixel and its neighborhood. To compensate for the degraded contrast or to enhance the original contrast, a center-surround contrast enhancement is performed to bring out fine details. Finally, a linear color restoration process is performed to convert the enhanced intensity image into a color image.

This method allows us to efficiently enhance the visual quality of image captured under extremely non-uniform lighting conditions. In addition, the algorithmic complexity has been simplified to great extent, which makes the algorithm viable for real time processing.

1.3 Specific Objectives

The specific objectives of this thesis can be summarized as follows:

1. Optimizations of a nonlinear intensity transfer function for fast, adaptive, and simultaneous enhancement of the dark regions and compression of the bright regions.
2. Development of a simple and effective method to determine the image dependent control parameters for the nonlinear transfer function.
3. Embedding of a contrast enhancement process in along with the intensity enhancement process. This process is responsible for improving the local contrast in an enhanced intensity image for preservation of fine details and improved visibility.
4. Application of a color restoration technique to obtain the enhanced color image using color information of the original image.
5. Testing and performance evaluation of the proposed algorithm on diverse set of images captured under non-uniform lighting conditions.

1.4 Organization of the Thesis

The remainder of this thesis is organized as following. In Chapter 2, a detailed survey of conventional image enhancement techniques is presented. The chapter covers the illustration of existing methods along with their objectives and challenges associated with the enhancement outcomes. At the beginning of the chapter, some information is provided on different categories of the enhancement techniques. Since the proposed method belongs to a spatial domain category, enhancement techniques methods belonging to this category are investigated in great detail. Some basic intensity transforms, histogram processing methods, and well know tone mapping operators are discussed in detail. Enhancement techniques such as MSR and MSRCR developed based on the prominent local tone mapping operator 'Retinex' are discussed in depth. Techniques inspired from the above mentioned techniques, developed further to improve performance and overcome the drawbacks of existing techniques are discussed to a great extent. These techniques include IRME, AINDANE, MWIS, and LTSNE.

In Chapter 3, the proposed algorithm is presented. This chapter addresses the theoretical model formulation and simplification toward developing efficient and fast algorithm. The method consists of three steps: adaptive intensity enhancement, contrast enhancement, and color restoration. Each algorithmic step is illustrated in depth. Simulation results, performance evaluation and comparison with other state of the art techniques are given in Chapter 4. Conclusions and comments regarding future development are presented in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

The most common goal of many image enhancement techniques is to bring out fine details and to improve the appearance of the images to make them look aesthetically pleasing. When used as a pre-processing step, the aim is to enhance some image features important for further processing [5]. Present day image processing applications require various kinds of images and videos as sources of information for interpretation and analysis. Thus, the aim of image enhancement process is to improve the interpretability or perception of information in images for human viewers or to provide better input for other automated image processing techniques. Automated image enhancement is typically a difficult task because there is no particular measure for determining what good image enhancement is when it comes to human perception. If it is pleasing to the eyes, then it is good. However, when image enhancement techniques are used as pre-processing tools for other image processing techniques quantitative measures can then determine which techniques are most appropriate. In the context of this thesis, the impact of enhancement techniques is to enhance brightness and contrast of the images captured under complex lighting condition. The intent is to transform the visual characteristics of the digital image so that the renditions of the transformed image approach that of direct observation of the scenes.

Many image enhancement techniques have been developed that seek to improve the visual appearance and features in an image. These techniques can be divided into several categories based on their functionality and fundamental development structure. First of all, image enhancement can be performed on a single image using information contained in that image itself as well as using information contained in multiple images. Image fusion is one of the methods that use multiple source images of the same scene either captured from different angles or captured in a sequence from the same angle. Fused image generally possesses more scene information than any single input image. When working with a single source image, the enhancement can be performed by using different signal representations such as 2-D spatial domain, multiresolution (MR) representation in spatial domain (Gaussian and Laplacian pyramids), frequency domains (FFT domain and DCT domain), and spatial-frequency domain (wavelet transfer domain) [17]. Each technique has its pros and cons as they may be targeting various purposes.

This chapter begins with review of the basic intensity transformation techniques such as image negatives, log transforms, Power-law (Gamma) transformations, and Contrast Stretching transformations. The bases of numerous spatial domain techniques, Histogram processing methods are discussed next. Since the proposed algorithm belongs to the spatial domain category, existing spatial domain nonlinear techniques are discussed in depth. Well known tone mapping operators, both global and local, are discussed in detail. To investigate the subject in depth, a thorough discussion of well know Retinex theory based algorithms are discussed at length. Finally, algorithms utilizing various image statistics to enhance images such as AINDANE, IRME, MWIS, and LTSNE are examined in great detail.

2.2 Spatial Domain Techniques

The term spatial domain refers to the image plane itself, and image processing methods in this category are based on direct manipulation of pixels in an image [5]. Two principle categories of spatial domain processing are intensity transformations and spatial filtering. Intensity transformations operate on single pixels of an image whereas spatial filtering deals with convolving mask matrix with the image. In the sections that follow, a discussion on a number of classical spatial domain techniques is provided.

2.2.1 Some basic Intensity Transformation Functions

Intensity transformations are among the simplest of all image processing techniques. The values of pixels, before and after processing, will be denoted by r and s, respectively. These values are related by an expression of the form:

$$s(x,y) = T[\,r(x,y)] \tag{2-1}$$

where T is a transformation that maps an input pixel value r into a pixel value s. Since the output value s depends on the value of r at a single point (x, y), T becomes an intensity (gray-level or mapping) transformation function. Basic intensity transform functions include but are not limited to functions such as negative transformation, log transform, Power-Law (Gamma) transform (correction), and piecewise-linear transforms.

2.2.1.1 Negative Transform

For an image with intensity levels in the range [0, L-1], a negative image can be obtained by using negative transformation as follows:

$$s(x, y) = L - 1 - r(x, y) \tag{2-2}$$

The plot for this transform is show in Figure 2.1. This transform is useful in enhancing white or gray details embedded in dark regions of an image. Reversing the intensity levels of an image in this manner produces the equivalent of a photographic negative.

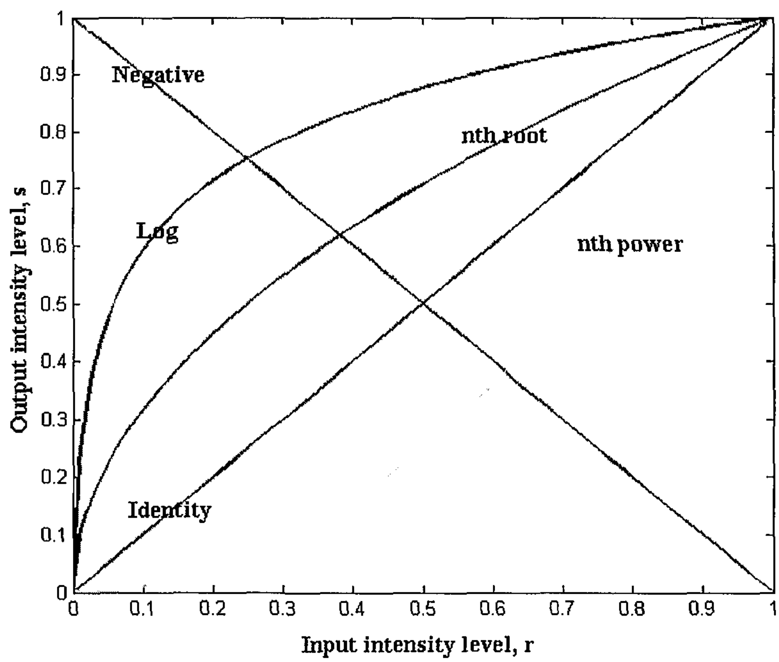


Figure 2.1 Plots of basic gray-level transformation functions.

2.2.1.2 Log Transform

The general form of the log transformation is:

$$s = c\log_{10}(1 + r) \qquad r \geq 0 \tag{2-3}$$

The log transform maps a narrow range of low intensity values of input levels into a wider range of output levels; simultaneously it maps the wider range of high intensity values to a lower range [5]. Hence it expands the values of dark pixels and compresses the values of bright pixels. It compresses the dynamic range which is highly desirable when trying to map a high dynamic range radiance map to a narrower dynamic range.

2.2.1.3 Power-Law Transform

A Power-Law transform has the basic form:

$$s(x,y) = cr(x,y)^{\gamma} \tag{2-4}$$

where c and γ are positive constants. Sometimes Equation (2-4) is written as $s = c\,(\varepsilon + r)^{\gamma}$ to account for an offset related to display calibration. Plots of *s* versus *r* for various values of γ are shown in Figure 2.2.

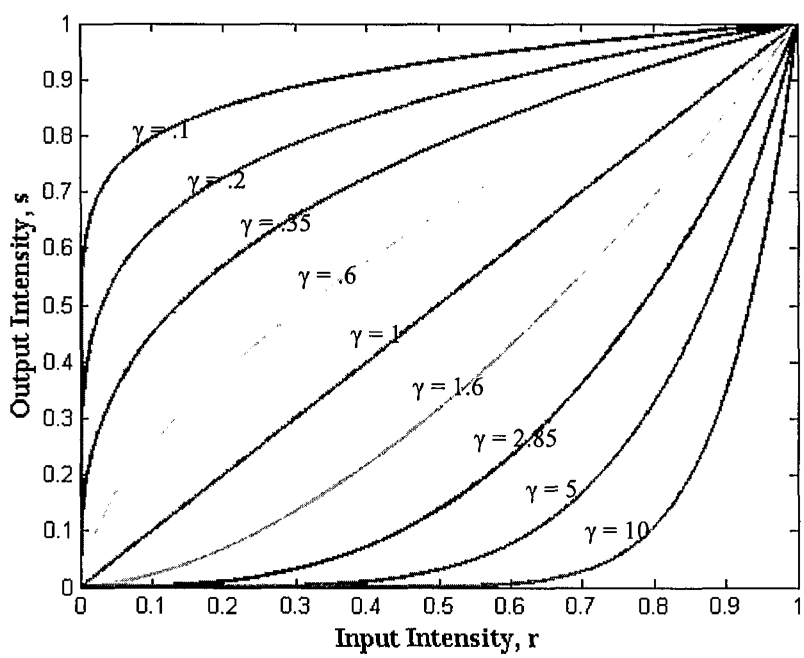


Figure 2.2 Plots of Power-Law transforms for various γ values.

As in the case of log transformation, power-law curves with fractional values of γ 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 levels. Unlike a log transform, however, we notice here a family of possible transformation curves obtained simply by varying γ.

As expected, the curves generated with values of $\gamma > 1$ have exactly the opposite effect as those created by $\gamma<1$. Finally, Equation (2-4) reduces to the identity transform when $c = \gamma = 1$. This transform is used by devices for image capture, printing, and display to correct power-law response. The method is also known as gamma correction referring to the exponent in the equation.

2.2.1.4 Piecewise-linear Transform/Contrast Stretching

A slightly different approach is to use a piecewise linear function of arbitrary complexity.

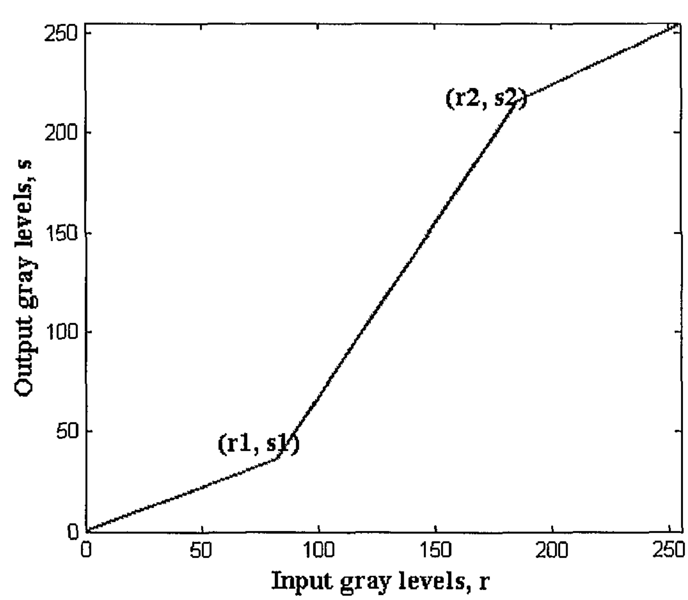


Figure 2.3 Typical contrast stretching function.

One of the simplest piecewise linear functions is contrast stretching transformation. Low-contrast images can result from poor illumination, lack of dynamic range in the imaging sensor, etc. Contrast stretching expands the range of intensity levels in an image to utilize the entire dynamic range of the recording media.

Figure 2.3 shows a typical transformation used for contrast stretching. The locations of points (r1, s1) and (r2, s2) control the shape of the transformation function. If r1 = s1 and r2 = s2, the transformation is linear and produces no change in the intensity level. When (s2-s1) > (r2-r1), the dynamic range is stretched.

2.2.2 Histogram Processing

Histogram processing refers to altering the image by modifying the histogram of an image. Histogram of a digital image with gray levels in the range [0, L-1] is defined as:

$$h(r_k) = n_k \qquad for\ k = 0, 1, \dots L-1 \tag{2-5}$$

where r_k is the k^{th} gray level, n_k is the number of pixels in the image having gray level r_k, and L is the number of gray levels. A normalized histogram is given by:

$$p(r_k) = \frac{n_k}{n} \tag{2-6}$$

where n is the total number of pixels in the image. The $p(r_k)$ is the probability of occurrence of gray level r_k.

Histograms provide useful image statistics and are the basis of many spatial domain techniques. If we study the histogram of dark, bright, low contrast, and high contrast images, we can see some patterns of intensity distribution. Consider the four images in the second column of Figure 2.4 showing basic gray-level characteristics: dark, bright, low contrast, high contrast, and their corresponding histograms in the first column [5]. It can be said that components of the histogram in the dark image are concentrated on the lower (dark) end of the gray scale. Similarly, the components of the histogram in the bright image are concentrated on brighter region of the gray scale. The low-contrast image has a narrow histogram whereas the high-contrast image has a broader range of the gray scale. It is reasonable to say that an image occupying the entire range of possible gray scale will have an appearance of higher contrast and will exhibit a large variety of gray tones. In the following section, techniques whose major objective is to transform histogram of images so as to show greater deal of gray level with wider dynamic range are discussed.

2.2.2.1 Histogram Equalization

Histogram Equalization (HE) is one of the most standard and effective image enhancement techniques which increases the dynamic range of the image histogram. HE's aim is to redistribute the histogram to achieve "uniform" distribution. For digital images, this can be done automatically and effectively with a transformation function based on a discrete Cumulative Distribution Function (CDF). The HE technique involves three main steps. First, compute histogram of the image using equation (2-5). Next, calculate normalized sum of histogram (discrete CDF) as:

$$s_k = T(r_k) = \sum_{j=0}^{k} p(r_j) = \sum_{j=0}^{k} \frac{n_j}{n} \quad for\ k = 0, 1, \dots L-1 \tag{2-7}$$

Finally, transform the input image to the output image by mapping each normalized pixel level r_k in the input image to a corresponding pixel with normalized level s_k in the output image.

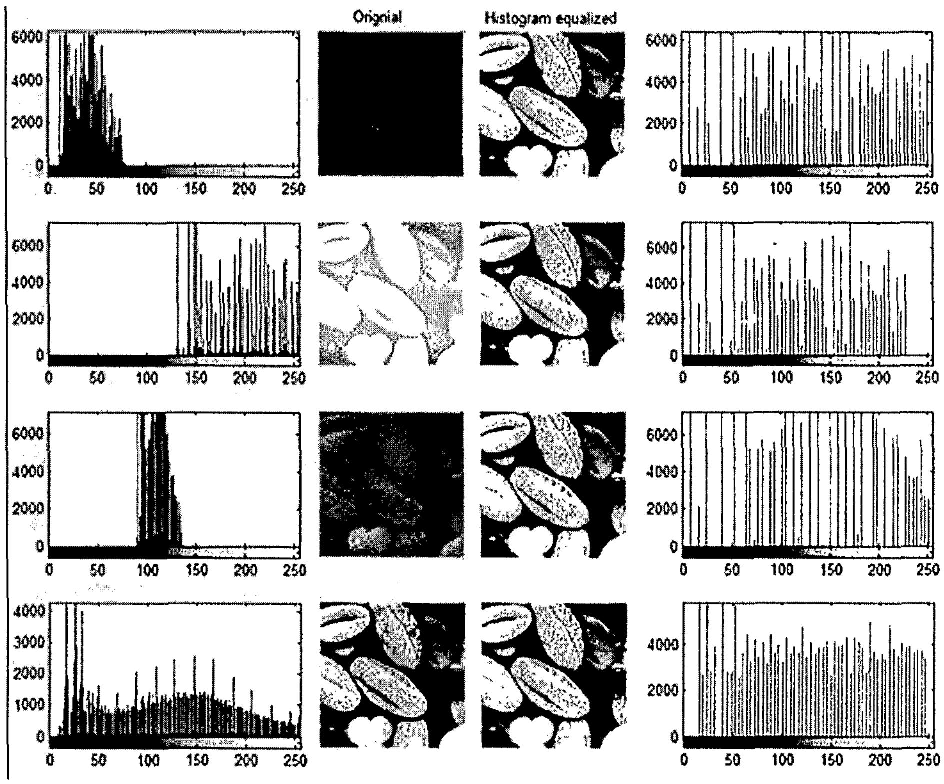


Figure 2.4 Histograms of dark, bright, low contrast, high contrast images: before and after processing with histogram equalization technique.

Figure 2.4 [5] shows the four original images and their corresponding output images (histogram equalized) obtained from IHE technique. The left column shows the histograms of the corresponding original images and the right column shows the histograms of the corresponding output images. Note that histograms of the first three output images cover much broader gray level range compared to the original images. This effectively provides better contrast. For the high-contrast image, the IHE technique has negligible effect on the appearance of the image because the original histogram already covers a wide range of gray levels.

2.2.2.2 Histogram Specification

The Histogram Equalization method is popular primarily because it operates like a black box; no user inputs parameters are required. However, for some applications, enhancement based on a uniform histogram may not be the best approach [5]. For some particular applications, it is useful to be able to specify the shape of the histogram for the processed image. The process of altering the appearance of a digital image in some pre-defined way by transforming its gray level distribution is called histogram specification [7, 15].

The objective of the histogram specification is to determine an order preserving gray level transformation which, when applied to an original image g with gray level distribution p[.], will produce a modified image g' with user-specified gray level distribution p'[.]. Given an original image with gray level distribution p[.] and given a user-specified gray level distribution p'[.], histogram specification is implemented in two steps, as follows [15]:

1. Generate the two cumulative distribution functions P[.] and P'[.] from gray level distributions p[.] and p'[.], respectively.
2. Beginning with $l=0$ and proceeding sequentially, for each $l=0,1,\ldots,L-1$ define $T[l] = t$ where t is the solution to the equation $P'[t] = P[l]$.

2.2.2.3 Adaptive Histogram Equalization

Techniques that transform images based on global histogram do not enhance local contrast as no knowledge of local intensity distribution is available. This could become a problem as human eyes respond to the relative intensity opposed to absolute intensity distribution. To deal with the local contrast issues, AHE (Adaptive Histogram Equalization) was developed.

AHE is an effective method of contrast enhancement in some classes of natural images and most medical images. In the basic form, the method involves applying to each pixel the histogram equalization mapping based on the pixels in a region surrounding that pixel (its contextual region). That is, each pixel is mapped to intensity proportional to its rank in the pixel surrounding. The problem with this method is that it is slow and under certain conditions the enhanced image has undesirable features.

2.2.3 Spatial Filtering

Spatial filtering deals with performing operations such as image smoothing and sharpening by working in a neighborhood of every pixel in an image. Spatial filtering is often referred to as convolution. In simple terms, convolution is a mathematical operation that multiplies each of the pixels in the neighborhood by a weight and adds them together (sum of products); the local weights are sometimes called a mask or kernel. The primary objective of the sharpening filter is to highlight changes in the intensity. In this process, the important visual details can be made clearly visible. On the other hand, when used for smoothing, the convolution results into blurry (smooth) image depending on the weigh matrix for the purpose of noise removal.

2.3 Tone Mapping Operators

One aim of the image rendering process is to recreate images that share the identical appearance attributes as the real scene [21]. The world exhibits a wide range of luminance values but the image acquisition and display devices have far limited dynamic ranges. For example, printers, CRT or LCD monitors, and projectors are all LDR (Low Dynamic Range) devices and cannot reproduce the full range of luminance present in natural scenes. To mimic the realistic scenes on such LDR devices, a wider dynamic range needs to be compressed and mapped to a narrow range. In the conversion of a real-world scene to display luminance, tone mapping operators have played an important role in the field of photography and computer graphics. Tone mapping is a technique aimed at mapping one set of colors to another to approximate the appearance of HDR (High Dynamic Range) images to a media with low dynamic range. By compressing the dynamic range, tone mapping operators reduce the contrast ratio of the image globally while retaining localized contrast preserving the image details and realistic color appearance. Figure 2.5 gives the overview of the tone mapping procedure.

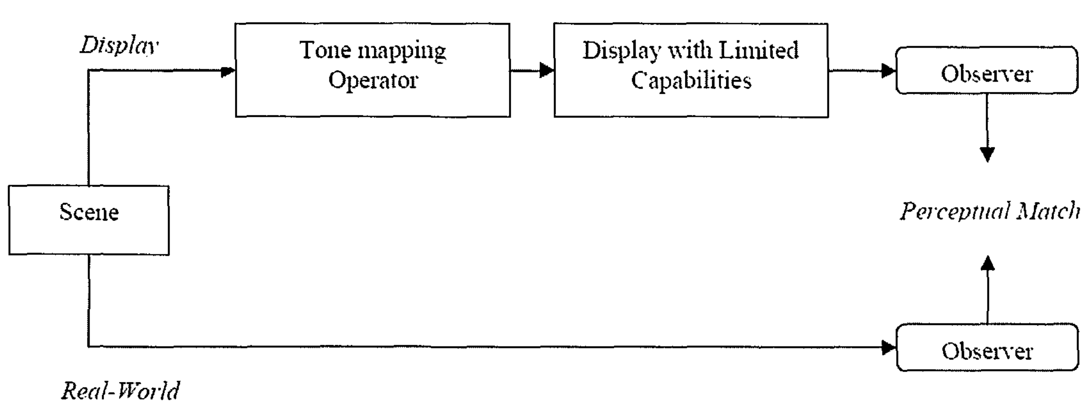


Figure 2.5 Overview of tone mapping process.

Many tone mapping operators have been introduced to overcome the problem of displaying HDR images. To simulate the realistic perception of world luminance levels on standard processing devices, some operators opt for perceptual data gathered from psychophysical experiments while others formulate a mathematical model to simply compress the luminance range in order to obtain maximum visibility on the display device without accounting for perceptual aspects of visual system. In tone reproduction, aimed at simulating reality by rescaling of dynamic range, one of the most important factors is that the final image maintains the lightness integrity of the original scene [21]. Based on their nature, these tone reproduction operators can be classified in two main categories: spatially uniform (global) and spatially varying (local) operators.

2.3.1 Spatially Uniform (Global) Mapping Operators

The operators, which apply the same mapping function across the image, are known as spatially uniform or global operators. These operators do not imitate local adaptation processes of the HVS (Human Visual System) but use an implicit normalizing factor in order to scale the scene luminance to fall within the limited range of display device [Evaluating tone].

Tumblin and Rushmeier [22] proposed a tone mapping operator that focused on preserving the viewer's overall impression of brightness, providing a theoretical basis for perceptual tone mapping. It uses supra-threshold brightness measurements obtained by Stevens et al. [23] regarding the brightness associated with a luminance at a particular adaptation level. Even though this model is not applicable in complex scenes, it was chosen due to its low computational costs. The operator is claimed to be built from mathematical models of human visual system and can be used to enhance images by imitating the light-dependent changes our eyes would experience on viewing the actual scene.

Although the method is most comprehensive and considered as state of the art in tone mapping, it has some drawbacks. First of all, it is limited to grayscale. The brightness is preserved at the cost of visibility as it uses only one level of adaptation. The regions in the extremely bright and dark regions are clipped and thus not visible.

Larson et al. [24, 25] developed a tone reproduction operator that preserves visibility of high dynamic range scenes using a new histogram adjustment technique, based on the population of local adaptation of luminance in a scene. To match subjective viewing experience, the method incorporates models for human contrast sensitivity, glare, spatial acuity, and color sensitivity. This technique and other similar techniques, developed for computer graphic applications, is not suitable for image enhancement due to its global processing approach and lack of contrast enhancement, which may lead to feature loss or degradation at some areas in the image.

Global operators handle the images as a whole and apply the same transformation to every pixel discarding the original intensities of the scene, which may cause perceptual differences.

2.3.2 Spatially Varying (Local) Mapping Operators

The operators in which the mapping varies spatially depending on a neighborhood of a pixel are known as local or spatially varying operators. Local operators imitate the local adaptation process in the retina by applying different scaling factors to different parts of an image. They reduce scene contrast locally, relative to neighborhood intensities, and convert the original intensities to the displayable intensities of the low-dynamic-range device [21].

As shown earlier, with global tone mapping techniques, while brightness is maintained, the values at the high end and very low end are clipped. Hence correct visibility is not maintained. Chiu et al. [26] address this problem of global visibility loss by scaling luminance values based on a spatial average of neighborhood pixels. As a result, the values in bright and dark areas are not clipped but scaled according to different values based on their spatial location. Their concept of variable scaling is effective when the scaling changes slowly relative to image features but suffers from strong halo effects when abrupt intensity changes occur. This is due to the fact that human eyes are highly sensitive to high spatial-frequencies. The method inevitable produces display luminance gradients that are the opposite of the real-world gradients. Any small, bright feature in the image will cause strong attenuation of the neighboring pixels and surround the feature or high-contrast edge with a noticeable dark band or halo [27].

Inspired by Chiu et al., Schlick [28] introduced an alternative mapping operator similar to logarithmic function that account for non-linearities of the display device as well as human perception. In fact, his method is a computational improvement of the logarithmic mapping based on Weber's law. His concentration was on improving computational efficiency and simplifying parameters. This is an automatic method that yields good results for images with overall uniform distribution, though not adaptive and sophisticated enough for high contrast scenes.

Pattanaik et al. [29] proposed a tone mapping algorithm which incorporates human visual system behavior into the model. It accounts for changes of perception at various adaptation levels of brightness. This technique produces dynamic range compressed images with good tonality and accurate color rendering. However, the halo effect in the images produced by their algorithm is strong.

Local operators are generally capable of a significant compression of the dynamic range of a scene while preserving fine details. However, a major concern with spatially-varying operators is that contrast reversals or "halo" artifacts can appear around high contrast edges. Tumblin and Turk [30] developed a method of tone mapping which avoids halo effects and preserves fine details of the scene contents known as low curvature image simplifier (LCIS). To preserve details they build hierarchy using multiple instances of LCIS computed by a partial differential equation inspired from anisotropic diffusion. At each hierarchical level, LCIS reduces the scene to many smooth regions that are bounded by sharp gradient discontinuities. LCIS makes a set of progressively simpler images and image differences form a hierarchy of increasingly important details, boundaries and large features. Finally, a display image is reconstructed with high detail and low contrast from the hierarchical decomposition by compressing the large features and adding back small details. They claim that the method eliminates/ avoids halo artifacts since LCIS hierarchies do not smooth across scene boundaries. Though their algorithm significantly reduces the dynamic range, it over enhances fine details. Furthermore, the algorithm is computationally intensive and requires selection of lot of parameters.

2.4 Retinex and Retinex-Based Algorithms

The major challenges in image renditions are associated with limited dynamic range. Retinex based algorithms provide effective solutions for dynamic range compression and color constancy. In the following sections, the basic concepts of Retinex are examined. Then spatial domain nonlinear enhancement techniques that extend these concepts further for improving the visual quality of low-contrast images with poor brightness will be discussed.

2.4.1 Theory of Retinex

The theory of Retinex was originally developed by E. Land as a model for human visual perception of lightness and color [9]. The name "retinex" is a combination of the words "retina" and "cortex" emphasizing the involvement of retina as well as cerebral cortex responsible for human vision. The basic concept in the Retinex theory is that light coming to our eye is a product of two components: illuminance and reflectance. As presented in [31], and cited by Land, mathematically the expression takes the form:

$$I(x,y) = L(x,y) \cdot R(x,y) \tag{2-8}$$

Illuminance $L(x,y)$ refers to the incident light where as reflectance $R(x,y)$ is amount of light reflected by object's surface refereeing to reflective properties of the surface. The problem is that our eye can not determine reflectance unless the illuminance is uniform, and the eye could not determine illuminance unless the reflectance is uniform. Instead, human vision system figures the ratio between the object's reflectance and the reflectance of its surround. Generally, across the field of view, neither reflectance nor illuminance is known; and neither is uniform [9]. Based on the facts stated above, the Retinex output $Ret_{out}(x,y)$ for a pixel is derived as follows:

$$Ret_{out}(x,y) = \frac{I(x,y)}{\bar{I}(x,y)} = \frac{L(x,y) \cdot R(x,y)}{\bar{L}(x,y) \cdot \bar{R}(x,y)} \tag{2-9}$$

where the Retinex output is derived by dividing the intensity value of a pixel $I(x,y)$by the spatially weighted average value of its surrounding $\bar{I}(x,y)$. The intensity values are represented using Equation (2-8), $\bar{L}(x,y)$ and $\bar{R}(x,y)$ represent spatially weighted average values of surrounding luminance and reflectance respectively.

In [31], the claim is that the spectral distribution of ambient light and surface reflectance can be separated in image data. The claim is supported by the physical property of images that variation in the ambient lighting occurs at a much lower rate than the spatial variation of the surface reflectance of the objects. As long as the changes in illuminance are gradual and smooth, the following equation holds true:

$$Ret_{out}(x,y) = \frac{I(x,y)}{\bar{I}(x,y)} \approx \frac{R(x,y)}{\bar{R}(x,y)} \tag{2-10}$$

Modeling the human visual system, Retinex measures "lightness" as the log of the ratio of the intensiy per pixel with the average intensity over surrounding neighborhood, [32] defined as:

$$Ret_{out}(x,y) = \log \frac{I(x,y)}{\bar{I}(x,y)} \tag{2-11}$$

$\bar{I}(x,y)$ is a spatially weighted average of a pixel obtained by convolving with an operator $F(x,y)$. The general form of the center/surround Retinex is similar to the difference-of-Gaussian (DOG) and is defined as:

$$Ret_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)] \tag{2-12}$$

where $I_i(x,y)$ is the image distribution in the i$^{\text{th}}$ color spectral band, '*' denotes the convolution operation, $F(x,y)$ is the surround function and $Ret_i(x,y)$ is the associated Retinex output. The surround function proposed by Land is of the form:

$$F(x,y) = \frac{1}{r^2} \tag{2-13}$$

where $r = \sqrt{x^2 + y^2}$. The function can be further modified to make space constant dependent as:

$$F(x,y) = \frac{1}{\left(1 + \frac{r^2}{c_1{}^2}\right)} \tag{2-14}$$

Moore et al. [33, 34] examined an exponential absolute value as:

$$F(x,y) = e^{\frac{-|r|}{c_2}} \tag{2-15}$$

whereas Hurlbert [35] proposed the following Gaussian:

$$F(x,y) = e^{\frac{-r^2}{c_3{}^2}} \tag{2-16}$$

In Equations (2-14), (2-15), and (2-16), c_1, c_2, and c_3 are surround space constants which determines the size of the neighborhood. Both exponential and Gaussian produce good dynamic range compression over a range of space constants. The inverse square changes very rapidly exceeding the response of both exponential and Gaussian; ultimately exponential exceeds the response of Gaussian. Gaussian is used widely used in modeling machine vision, as it is operates closer to the human vision behavior and also provides most experimental flexibility.

2.4.2 Retinex-based Algorithms: SSR, MSR, and MSRCR

Retinex theory provides solution for the challenges associated with limited dynamic range. Aside from that, there are other problems that arise during the capturing process. Even when the dynamic range of the scene is narrow enough to be completely captured by the imaging device, the resultant image could be a poor representation of the original scene being too dark and low contrast. In Single-Scale and Multiscale Retinex algorithms, Retinex theory is used as a platform to develop a full scale automatic image enhancement algorithm by synthesizing local contrast improvement, color constancy and lightness/color rendition.

The Single Scale Retinex (SSR) for a pixel at an image location (x, y) is defined as:

$$Ret_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)] \tag{2-17}$$

where

$$F(x,y) = Kexp^{\left(\frac{-r^2}{c^2}\right)} \tag{2-18}$$

c is a Gaussian surround space constant, K is determined as:

$$\iint F(x,y) \cdot dxdy = 1 \tag{2-19}$$

Single-Scale retinex [36] can either provide dynamic range compression using a smaller scale at the at the cost of poorer color rendition, or produced natural looking global tonal rendition at the cost of dynamic range compression using a bigger scale. This limitation is overcome in Multiscale Retinex (MSR) algorithm. The output of MSR is a weighted sum of outputs of several different SSR. The basic form of the MSR is given by:

$$Ret_i(x,y) = \sum_{k=1}^{K} w_k\{log\, I_i(x,y) - \log[F_k(x,y) * I_i(x,y)]\} \quad i = 1,2..N \qquad (2\text{-}20)$$

where N is the number of spectral bands, I refers to the ith spectral band, I is the input image, Ret is the output of MSR process. F_k is the k^{th} Gaussian surround function, w_k is the weight associated with F_k, and K is the number of surround functions, or scales. The F_k are given as:

$$F_k(x,y) = Kexp^{\left(\frac{-(x^2+y^2)}{\sigma_k{}^2}\right)} \qquad (2\text{-}21)$$

where σ_k are the standard deviations of the Gaussian surround. The effectiveness of MSR lies in its ability to control the extent of the surrounds and the weighted contribution of each surround. The output of MSR is then normalized by:

$$k = \frac{1}{[\sum_x \sum_y F(x,y)]} \qquad (2\text{-}22)$$

Multiple surrounds enable MSR achieve a graceful balance between dynamic range compression and tonal rendition. The authors suggest a combination of three scales, narrow, medium, and wide surrounds to produce a 'nice' output with sufficient brightness, contrast and fine details with $K = 3$.

MSR produces better results than SSR for most images, but has difficulties enhancing images with large monochrome areas. For such images, Retinex computations force the pixels in monochrome areas toward middle gray resulting in color desaturation; specific regions or image globally looks bleached out. This graying effect occurs because in MSR a pixel's value in each channel is replaced with the ratio of its value to its neighbors. In monochrome areas, the ratio in all three spectral bands will be equal to one. Such graying-out can produce an unexpected color distortion. Therefore, a color restoration step is added to MSR to provide good color rendition resulting into a modified algorithm MSRCR (MSR with Color Restoration). The color restoration step begins with computation of the chromaticity co-ordinates $I_i^{'}(x,y)$ as:

$$I_i^{'}(x,y) = \frac{I_i(x,y)}{\sum_{i=1}^{N} I_i(x,y)} \tag{2-23}$$

where N is the number of spectral bands. The output of MSRCR is given as:

$$R_{MSRCR_i} = C_i(x,y) R_{MSR_i}(x,y) \tag{2-24}$$

where

$$C_i(x,y) = f[I_i^{'}(x,y)] \tag{2-25}$$

is the ith band of the color restoration function (CRF) in the chromaticity space, and R_{MSRCR_i} is the ith spectral band of the Multiscale Retinex with color restoration. Finally, to provide best overall color restoration, the CRF is determined to be:

$$C_i(x,y) = \beta\ log[I_i^{'}(x,y)] = \beta \left\{ \log[\alpha I_i(x,y)] - log\left[\sum_{i=1}^{S} I_i(x,y)\right]\right\} \tag{2-26}$$

where β is a gain constant and α is a constant that controls the strength of the nonlinearity. According to the authors' judgment, a singe set of values of β, and α work for all images and these values are implementation platform dependent. Finally, a canonical gain constant, independent of the spectral channel and the image content is applied for transition from the logarithmic to the display domain. Overall, the method is general, or "canonical", and can be applied automatically to most images without manual adjustments. The final version of the MSRCR is represented as:

$$R_{MSRCR_i}(x,y) = G\big[C_i(x,y)R_{MSR_i}(x,y) + b\big]$$

$$= G\big[C_i(x,y)\{\textstyle\sum_{k=1}^{K} w_k(\log I_i(x,y) - \log[F_k(x,y) * I_i(x,y)])\} + b\big] \qquad (2\text{-}27)$$

where G and b are the final gain and offset values. A complete block diagram of MSRCR is provided below in Figure 2.6.

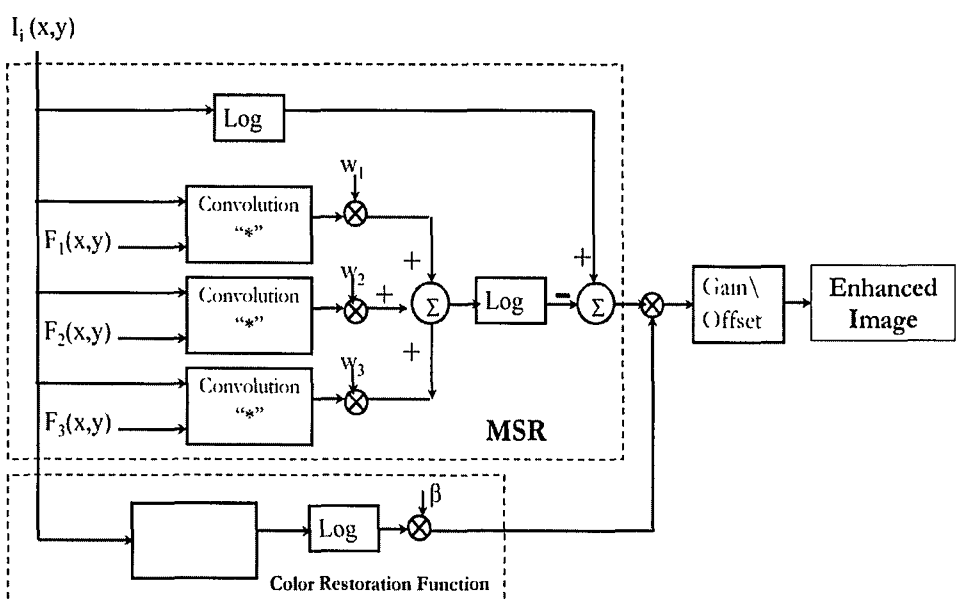


Figure 2.6 Block diagram of MSRCR.

Although MSRCR keeps the images from graying out, it contradicts the objective of color constancy. In the monochrome areas, instead of the MSR output, chromatics of the original image is used to restore the color. Considering the fact that the human visual system is not accurately color constant and color restoration is stronger in rare case images, this problem can be overlooked. The real drawbacks of MSRCR are strong halo effects and computational complexity leading to slower processing speed.

2.5 Integrated Neighborhood Dependent Approach for Nonlinear Enhancement (INDANE) Algorithm

INDANE (Integrated Neighborhood Dependent Approach for Nonlinear Enhancement of Color Images) [16] aims at improving the visibility of the dark regions in digital images. The algorithm consists of two processes: luminance enhancement and contrast enhancement. Luminance enhancement is performed by applying an intensity transformation based on a specifically designed nonlinear transfer function, which also compress the dynamic range. The contrast enhancement attenuates or enhances the pixel's intensity based on its relationship with the surrounding pixels.

For color images, they are first converted to intensity (grayscale) images prior to enhancement. The intensity image I is then normalized to the range [0, 1]. The normalized intensity image I_n is then transformed by applying the transfer function defined as:

$$I_n'(x,y) = \frac{I_n(x,y)^{0.24} + \big(1 - I_n(x,y)\big)0.5 + I_n(x,y)^2}{2} \tag{2-28}$$

where I_n' is the enhanced intensity image. This nonlinear transformation can sufficiently increase the luminance of the dark pixels while compressing the brighter pixels as shown in Figure 2.7. In order to achieve optimal results, the constants in Equation (2-28) can be fine tuned based on the overall intensity level of the input image.

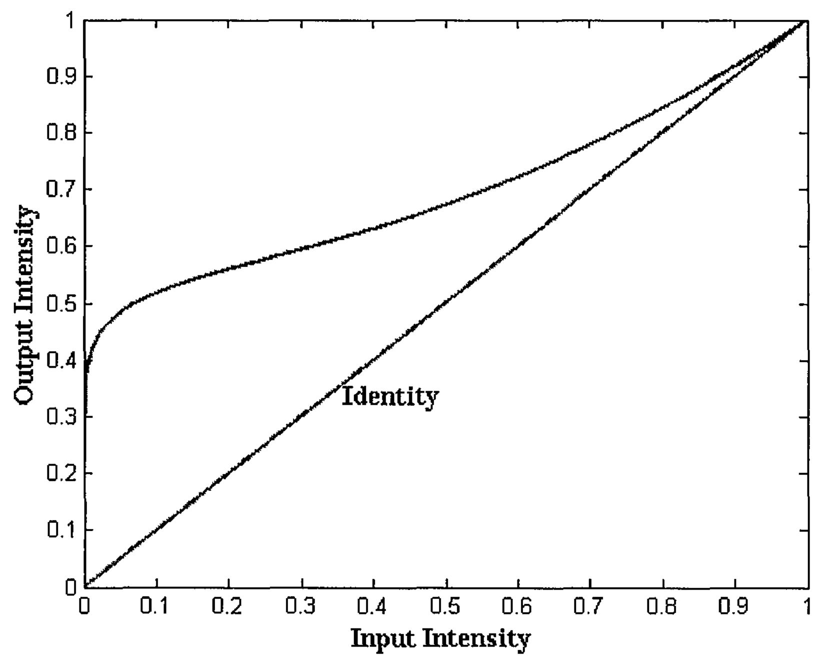


Figure 2.7 Intensity transfer function of INDANE algorithm.

In the next step, a center surround contrast enhancement technique is implemented. Conventional global contrast enhancement techniques simply increase the luminance for bright pictures and decrease the luminance for dark pictures and thus expand the dynamic range which limits the ability of the method to bring out fine details. In this algorithm, to enhance the contrast without counteraction the dynamic range compression, a neighborhood dependent contrast enhancement method is utilized as follows:

$$S(x,y) = 255 \cdot I_n'(x,y)^{E(x,y)} \tag{2-29}$$

where the exponent is defined by:

$$E(x,y) = \left(\frac{I_{conv}(x,y)}{I(x,y)}\right) \tag{2-30}$$

$S(x,y)$ is the contrast-enhanced pixel intensity, $E(x,y)$ is the intensity ratio between low-pass filtered $I_{conv}(x,y)$ and original intensity image $I(x,y)$. Here $I_{conv}(x,y)$ is obtained by performing a convolution operation on the original image as follows:

$$I_{conv}(x,y) = I(x,y) * G(x,y) \tag{2-31}$$

where $G(x,y)$ is a Gaussian convolution kernel of the form:

$$G(x,y) = K \cdot e^{\left(\frac{-(x^2+y^2)}{c^2}\right)} \tag{2-32}$$

and K is determined by

$$\iint K \cdot e^{\left(\frac{-(x^2+y^2)}{c^2}\right)} \cdot dxdy = 1 \tag{2-33}$$

where c is the scale or Gaussian surround constant.

The contrast enhancement process defined in Equations (2-29) and (2-30) is a type of intensity transformation process, which can be understood from the plots in Figure 2.8. If the center pixel is brighter than surrounding pixels leading to E(x, y) < 1, then the intensity of the pixel is increased. Likewise, for a center pixel darker than the surrounding pixels, the ratio will be > 1, and in turn the pixel's intensity is decreased.

Note that the ratio E(x, y) is obtained from the original intensity image I(x, y) and its low pass filtered result $I_{conv}(x, y)$, since during luminance enhancement process, the contrast information in the luminance enhanced image has been degraded.

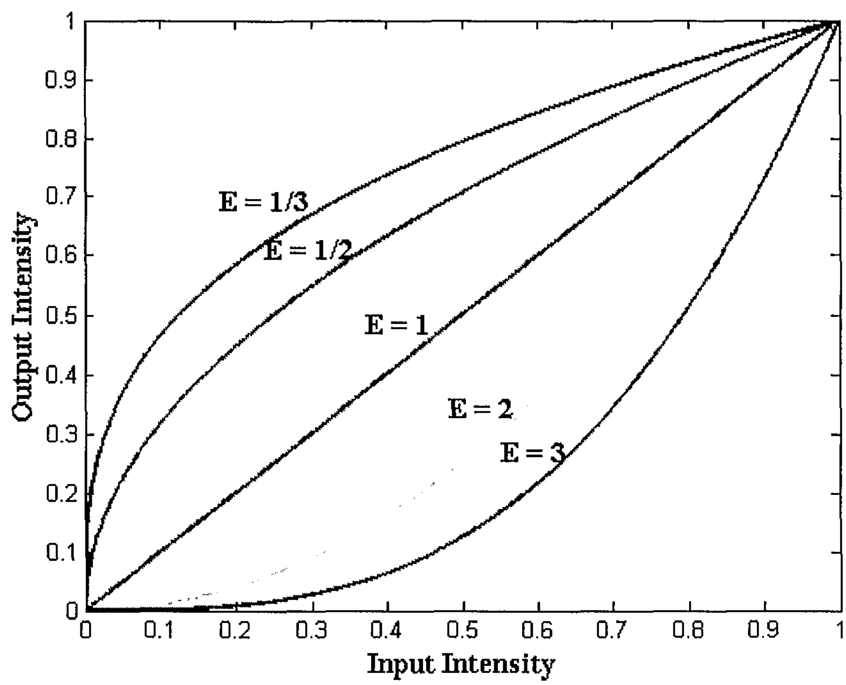


Figure 2.8 Intensity transformations for contrast enhancement.

For optimal results, contrast enhancement can be performed with multiple convolution results from different scales. The final output is a linear combination of the contrast enhancement results based on multiple scales expressed as:

$$S(x,y) = \sum_i w_i S_i(x,y) \tag{2-34}$$

where $i = 1,2,3\ldots n$, indicates different scales, w_i is the weight factor for each contrast enhancement output with $w_i = 1/n$, (n is the number of the scales).

To convert the enhanced grayscale image to color image, a linear color restoration process is applied which uses the chromatic information contained in the original image. This process can be describes in the mathematical form as:

$$S_j(x,y) = S(x,y)\frac{I_j\,(x,y)}{I(x,y)} \cdot \lambda_j \qquad j \in \{R,G,B\} \tag{2-35}$$

where j represents the R,G, and B spectral bands and λ is a parameter that adjusts the color hue. $S(x,y)$ is the final enhanced intensity image and $S_j(x,y)$ is the enhanced color image.

2.6 Adaptive and Integrated Neighborhood Dependent Approach for Nonlinear Enhancement (AINDANE) Algorithm

AINDANE [17] is an adaptive version of INDANE in which both luminance enhancement and contrast enhancement process are automatically fine tuned based on image statistics. Adaptive luminance enhancement is performed by applying a global intensity transformation based on a specifically designed nonlinear transfer function, which is self-tuned by the histogram statistics of the input image. An adaptive contrast enhancement alters the intensity of each pixel based on its relative magnitude with respect to the neighboring pixels. Again, this process is adaptively controlled by the global statistics of the image.

The first step in AINDANE is to convert a color image from RGB color space to gray scale image. This is done according to the NTSC [37] standard as follows:

$$I(x,y) = \frac{76.245 I_R(x,y) + 149.685 I_G(x,y) + 29.07 I_B(x,y)}{255} \tag{2-36}$$

The intensity image I is then normalized to [0 1] range:

$$I_n(x,y) = \frac{I(x,y)}{255} \tag{2-37}$$

The global intensity transformation function is then applied to the normalized image I_n to brighten the dark pixels while compressing dynamic range and is defined by:

$$I_n^{'} = \frac{I_n^{(0.75z+0.25)} + (1 - I_n)0.4(1 - z) + I_n^{(2-z)}}{2} \tag{2-38}$$

where $I_n^{'}$ is the enhanced intensity image and z is an image dependent parameter. The shape of nonlinear transfer function is determined based on the value of the parameter z. Here, z is computed based on statistics derived from the histogram of the image and is defined by:

$$z = \begin{cases} 0 & for\ L \leq 50 \\ \frac{L - 50}{100} & for\ 50 < L \leq 150 \\ 1 & for\ L > 150 \end{cases} \tag{2-39}$$

where L is the intensity level corresponding to a cumulative distribution function (CDF) of 0.1. The effect of the z parameter on the transfer function in relationship with L can be well understood from Figure 2.9, which shows a set of curves for z ranging form 0 to 1 for input intensity ranging from 0 to 1.

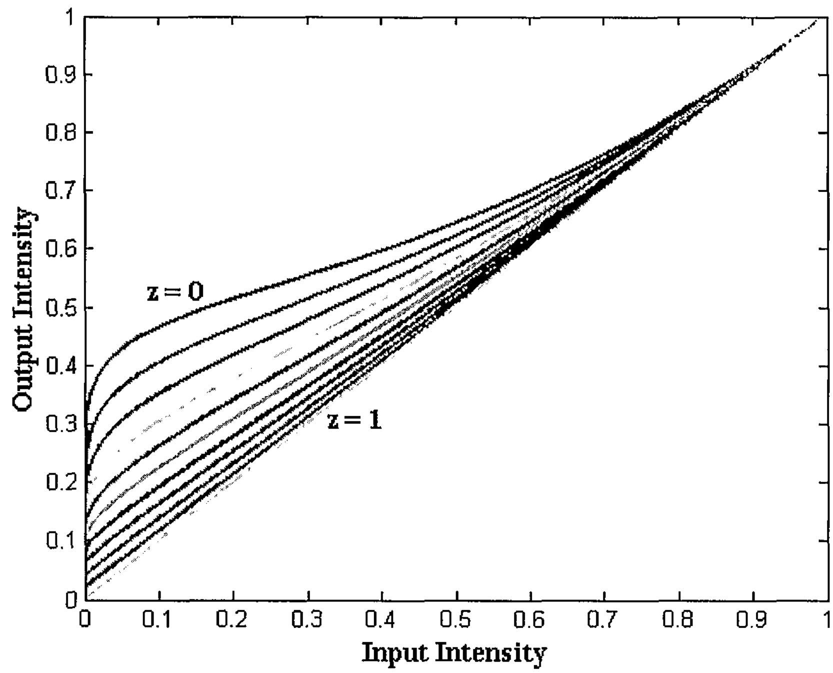


Figure 2.9 Intensity transfer function of AINDANE with different 'z' values.

When 90% percent or more of the pixels have intensity levels higher than 150, most pixels are sufficiently bright and intensity does not need to be enhanced. For this case, the value of the z parameter is 1 and the corresponding curve is an identity function. When 10% or less of the pixels has intensity level below 50, the pixels are really dark and need to be further enhanced. So the value of z is chosen to be 0 which, in turn, produces a curve for significant enhancement as shown in figure. For the rest, z is computed from the ratio such that z is an increasing function between 0 and 1 for the corresponding L ranging from 51 to 150.

Next, a contrast enhancement process adapted from INDANE algorithm is performed with some significant improvements. Unlike INDANE, the contrast is enhanced adaptively using a parameter P applied as a power function to the ratio $E(x,y)$ of smooth and original intensity images as follows:

$$E(x,y) = \left(\frac{I_{conv}(x,y)}{I(x,y)}\right)^{P} \tag{2-40}$$

where parameter P is derived from the global standard deviation σ of the intensity image given as:

$$P = \begin{cases} 3 & for\ \sigma \le 3 \\ \dfrac{27-2\sigma}{7} & for\ 3 < \sigma < 10 \\ 1 & for\ \sigma \ge 10 \end{cases} \tag{2-41}$$

If the original image is low-contrast, its global standard deviation will be much lower, for this condition, P will be assigned the highest value of 3 to strongly enhance the contrast. For images with standard deviation higher than 10, parameter P has no effect and enhancement strictly depends on the ratio of the smooth and original intensity images. Similar to INDANE, for optimal results, contrast enhancement is performed using multiscale convolution. Finally, the enhanced image is converted back to color image using the same color restoration method described earlier for INDANE algorithm.

AINDANE works well on the images that are captured under dark illumination. However, this algorithm does not address the issues related to overexposed images.

2.7 An Illuminance-Reflectance Model for Nonlinear Enhancement (IRME) Algorithm

IRME [18] algorithm is based on illuminance-reflectance model which provides a physical description of the image formation and human vision behavior. In the illuminance-reflectance model, object radiance depends on two factors: (1) illumination, the light intensity incident on an object's surface (2) reflectance, associated with the light reflection properties of the object's surface. Separation of these factors provides a method to process images for the purpose of obtaining an improved visual perception of those scenes.

The algorithm is composed of four major steps: (1) illuminance estimation and reflectance extraction (2) adaptive dynamic range compression of illuminance (3) adaptive mid-tone frequency components enhancement, and (4) image restoration. For color images, an intensity image or the V component in the HSV color space is obtained as:

$$I(x,y) = max[R(x,y), G(x,y), B(x,y)] \tag{2-42}$$

where R, G and B correspond to red, green, and blue color channels, respectively. The intensity image I is then formulated as a product of illuminance and reflectance defined by:

$$I(x,y) = L(x,y) \cdot R(x,y) \tag{2-43}$$

To extract the illuminance $L(x, y)$ and reflectance $R(x, y)$ components, either one needs to be estimated. Many techniques have been developed that estimate scene luminance among which a Gaussian low-pass filtered result image is used as an approximation to the illuminance in this algorithm. The normalized luminance image L_n is obtained by convolving with a Gaussian kernel of chosen scale using Equations (2-31) to (2-33).

In the second step, a dynamic range compression is performed. A common assumption is that luminance L contains the low frequency component while the reflectance R includes the high frequency component of the image. In a real world scene, the dynamic range of the illumination variation can be several orders larger than the dynamic range of the reflectance. Based on these assumptions, the dynamic range of the illuminance is compressed for effective image enhancement while keeping important image features. This task is realized using a Windowed Inverse Sigmoid (WIS) function defined by:

$$f(v) = \frac{1}{1 + e^{-av}} \tag{2-44}$$

A WIS function $f(v)$ is used as an essential part of the formula with curve adjustment parameter v for an intensity transfer function using Equation (2-44).

$$L_n{}' = L_n[f(v_{max}) - f(v_{min})] + f(v_{min}) \tag{2-45}$$

$$L_n{}'' = \frac{1}{a} ln\left(\frac{1}{L_n{}'} - 1\right) \tag{2-46}$$

$$L_{n,en} = \frac{L_n{}'' - v_{min}}{v_{max} - v_{min}} \tag{2-47}$$

where Equation (2-45) linearly maps the input range [0 1] of the normalized illuminance L_n to obtain $L_n{}'$ in the range $[f(v_{min})\ f(v_{max})]$ for windowed-inverse sigmoid. Equation (2-46) is the inverse sigmoid function. Equation (2-47) is applied to normalize the output illuminance $L_n{}''$ back to range [0 1]. Parameters v_{max} and v_{min} are used to tune the shape of the transfer function. Figure 2.10 [18] shows the resultant curves of the transfer function for various v_{min} values.

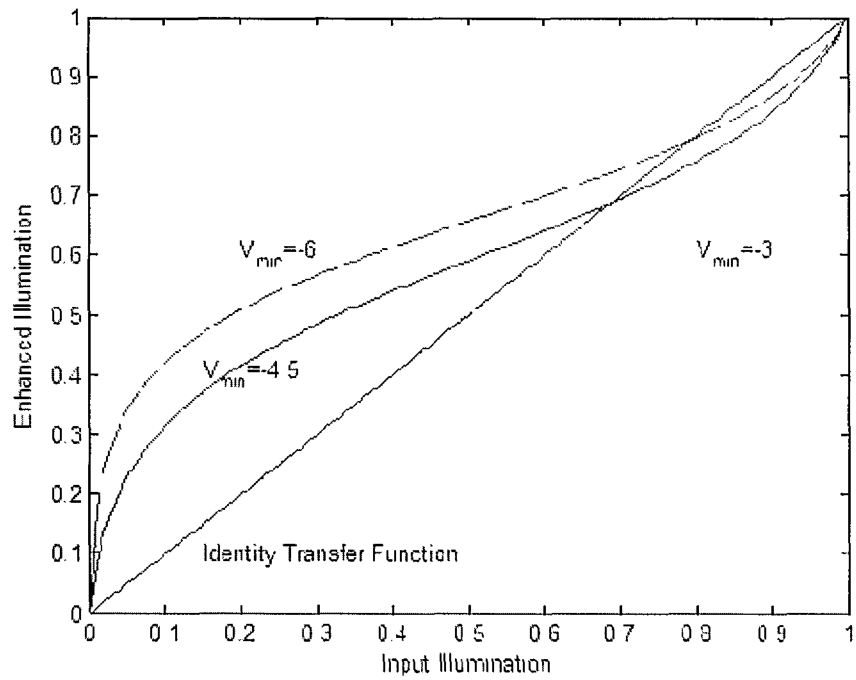


Figure 2.10 WIS with different parameters applied for intensity transformation.

In the equations above, $a = 1$, v_{max} is kept constant with value set to 3 for all images while the value for v_{min} is derived from the global image mean I_m of the intensity image I. Parameter v_{min} is determined from I_m as:

$$V_{min} = \begin{cases} -6 & for\ I_m \leq 70 \\ \frac{I_m - 50}{80} \times 3 - 6 & for\ 70 < I_m < 150 \\ -3 & for\ I_m \geq 150 \end{cases} \tag{2-48}$$

The third step involves adaptive mid-tone frequency components enhancement. This process utilizes the contrast enhancement method of INDANE tuned using an adaptive parameter P. The resultant image $L_{n,en}'$ is obtained using Equations (2-29) and (2-40) with following formula for parameter P:

$$P = \begin{cases} 2 & for\ \sigma \leq 30 \\ -0.03\sigma + 2.9 & for\ 30 < \sigma \leq 80 \\ 1/2 & for\ \sigma > 80 \end{cases} \tag{2-49}$$

In the final steps, the final intensity image is obtained by combining final illuminance $L_{n,en}{}'$ and reflectance R as:

$$I'(x,y) = L'_{n,en}(x,y) \cdot R(x,y) \tag{2-50}$$

Finally, a color restoration process based on the chromatic information of the original image is applied to I' to recover the RGB color bands (r', g', b') as:

$$r' = \frac{I'}{I}r \quad g' = \frac{I'}{I}g \quad b' = \frac{I'}{I}b \tag{2-51}$$

2.8 Multiple Windowed Inverse Sigmoid (MWIS) Algorithm

MWIS [19] uses multilevel windowed inverse sigmoid function to enhance images captured under non-uniform lighting conditions. The algorithm is composed of three steps: adaptive intensity enhancement, contrast enhancement, and color restoration.

Adaptive intensity enhancement step is further broken down into four tasks. First, the intensity image, I(x, y), is obtained using NTSC standard. The next step is to estimate illumination. The luminance L is estimated using a Gaussian low-pass filtering, following Equations (2-31) to (2-33). Such estimation of illumination is effective when the illumination changes quite smoothly in the image illuminated from the same luminous source. When the scene is illuminated by different light sources with abrupt variations in luminance the task becomes difficult. To reduce the influence of neighborhood areas in which luminance produces a high contrast, which would lead to artifacts, a weighted averaging method is used for bright pixels. So the illumination estimate values for less than 80% of the highest gray-scale value (i.e. 255 for 8-bit image) are the illumination that is obtained in Equation (2-31). For the other gray-scale values, it is a weighted average of illumination and intensity values, which decreases the contribution of the illumination linearly as the value of the gray scale increases. This averaging can be mathematically expressed for 8-bit image as:

$$L'(x,y) = \frac{I(x,y) - 204}{51} I(x,y) + \left(1 - \frac{I(x,y) - 204}{51}\right) L(x,y) \tag{2-52}$$

The proposition is that averaging produces minimum halo effect in bright regions by reducing the influence of dark neighboring pixels. The reflectance can be estimated using equation (2-43) with new illumination estimation $L'(x,y)$.

The next step is to enhancing dark illumination and compress bright illumination. The new illumination value $L'(x, y)$ is normalized to the range [0 10] as:

$$L''(x,y) = \frac{L'(x,y)}{25.5} \qquad for\ 8\ bit\ depth\ images \tag{2-53}$$

MWIS transfer function is then applied to the normalized illuminations value $L''(x,y)$ to enhancement the intensity of dark pixels and compress the brightness of the over-illuminated pixels. The transfer function is defined by:

$$L''_{enh} = \frac{1}{1 + e^{(-\alpha \times L'')}} + \frac{1}{1 + e^{(-\beta \times (L'' - 10))}} - 0.5 \tag{2-54}$$

where α is a parameter to adjust the curve for dark pixels and β is a parameter to adjust the curve for bright pixels. The resulting function is a sum of two sigmoid function shifted down by 0.5 to be used as a intensity transfer function.

To make the enhancement process adaptive, intensity image is divided into sub images of sizes as:

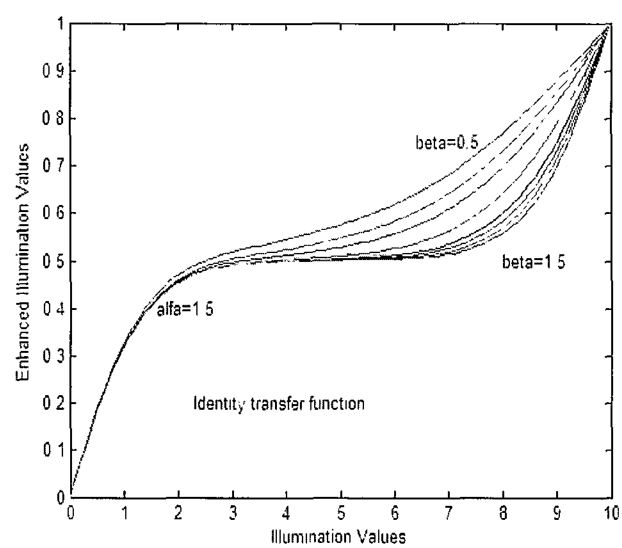
$$m = 0.0625 \times M \qquad\qquad n = 0.0625 \times N$$

where m and n define the size of the sub image, M and N define the size of the intensity image. The parameters α and β are determined based on the mean of the darkest sub-image L_{m_min} and mean of the brightest sub image L_{m_max} as:

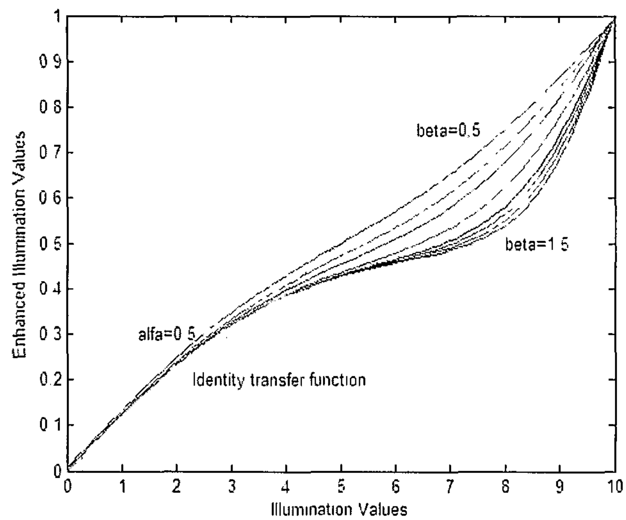
$$\alpha = \begin{cases} \dfrac{76.5 - L_{m\_min}}{51} & for \quad 0 \leq L_{m\_min} \leq 51 \\ 0.5 & for \quad 51 < L_{m\_min} \leq 127 \end{cases} \tag{2-55}$$

$$\beta = \begin{cases} \dfrac{L_{m\_max} - 255}{51} + 1.5 & for \quad 204 \leq L_{m\_max} \leq 255 \\ 0.5 & for \quad 128 \leq L_{m\_min} < 204 \end{cases} \tag{2-56}$$

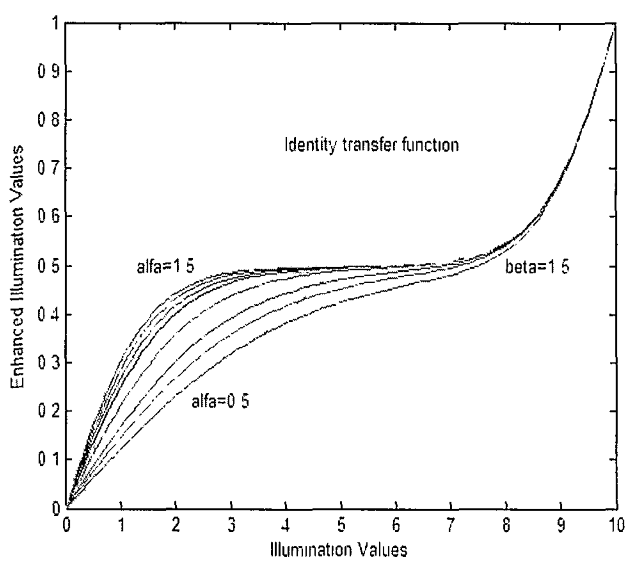
Figure 2.11 [18] shows curves of the MWIS transfer function for various values of α and β parameters.



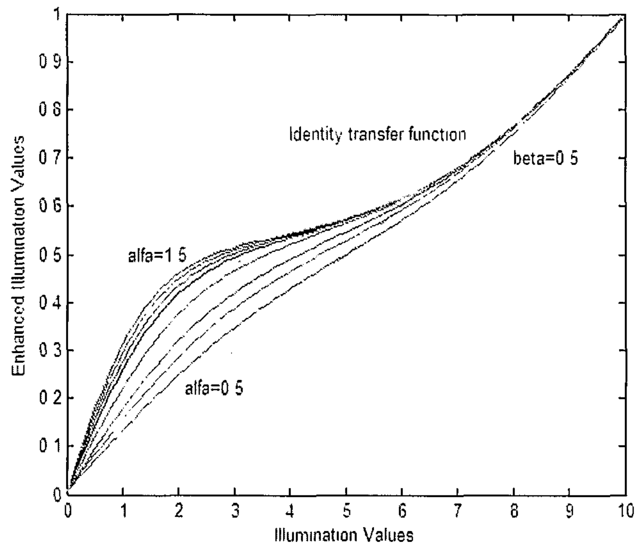
(a) MWIS transfer function with α = 1.5



(b) MWIS transfer function with $\alpha = 0.5$



(c) MWIS transfer function with $\beta = 1.5$



(d) MWIS transfer function with $\beta = 0.5$

Figure 2.11 Various curves for MWIS function.

Figure 2.11(a) describes the first scenarios where the image is assumed to have extremely dark regions along with some not so dark regions. For this class of images, the WIS transfer function is used to pull up the dark pixels significantly with $\alpha = 1.5$ and the magnitude of the bright pixels is pulled down according to the value of β determined based on mean of the brightest sub image L_{m_max} using.

Figure 2.11(b) illustrates the second scenario in which image is assumed not having very dark regions. For this case, $\alpha = 0.5$ and bright pixels are pulled down according to the value of β.

In Figure 2.11(c), the image is assumed to have very bright regions. Here β is set to 1.5 to pull down the bright pixels noticeably. The dark pixels are pulled up based on the value of α determined from the mean of the darkest sub-image L_{m_min}.

Figure 2.11(d) shows the curves for image that do not contain very bright regions. Thus β is set to 0.5 and the dark pixels are pulled up according to the value of α using Equation (2-55).

For the remaining two scenarios, the image has no bright sub image (considered as a dark image), and an image has no dark sub image (considered as bright image), the shapes of the curves are tuned from the image's global mean I_m as:

$$\alpha = \frac{127 - I_m}{63.5} + 1.5 \quad for \quad L_{m\_max} < 127 \tag{2-57}$$

$$\beta = \frac{I_m - 128}{63.5} + 1.5 \quad for \quad L_{m\_min} > 127 \tag{2-58}$$

The final task of the adaptive intensity enhancement step is to combine visually significant image features (high frequency components) with enhanced illumination to obtain enhanced intensity image. This is mathematically expressed as:

$$I_{enh}(x,y) = L''_{enh}(x,y)R(x,y) \tag{2-59}$$

The remaining two steps, contrast enhancement and color restoration, are performed on the enhanced intensity image $I_{enh}(x,y)$ using the method previously described in the INDANE algorithm.

2.9 Locally Tuned Sine Nonlinearity Enhancement (LTSNE) Algorithm

LTSNE [20] is a nonlinear image enhancement algorithm, based on an image dependent non linear function, Locally Tuned Sine Nonlinearity (LTSN), for enhancement of extremely high contrast images. The algorithm simultaneously compresses bright regions and enhances dark regions by preserving the main structure of the illuminance - reflectance characteristics. The overall structure of the algorithm consists of three steps: (a) adaptive intensity enhancement, (b) contrast enhancement, and (c) color restoration.

Similar to the AINDANE algorithm, gray scale image is first computed using Equation (2-36) following the NTSC standards. Further, the normalized intensity image I_n is obtained using Equation (2-37).

The next step is to enhance dark pixels and compress bright pixels. This task is realized by using a specifically designed squared sine nonlinear transfer function defined as:

$$I_{enh}(x,y) = sin^2\left(I_n(x,y)^q * \frac{\pi}{2}\right) \tag{2-60}$$

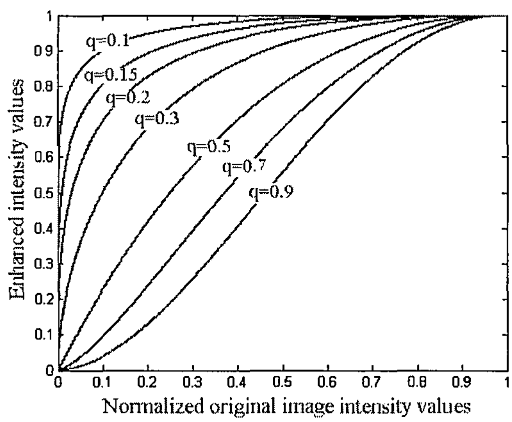
.

The non-linear transfer function is image dependent with a parameter q. The relationship of the q parameter with the transfer function can be illustrated from Figure 2.12. The curves for different q values indicate that if q is less than 1, the normalized intensity values will be greatly boosted. On the other hand, if q is greater than 1, the resulting curves will decrease intensity of the bright pixels.

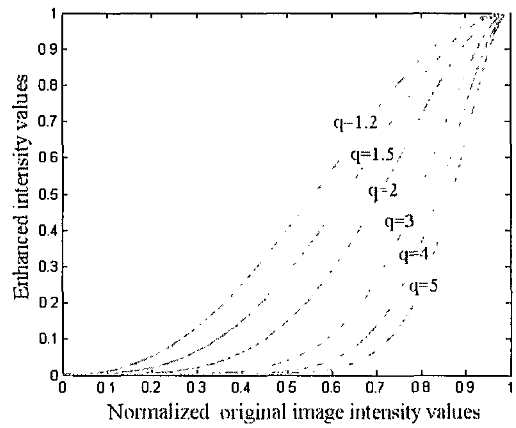
For simultaneous enhancement and compression, parameter q is computed adaptively using a tangent function with a normalized mean of the pixel as its input value described as:

$$q = tan\left(\frac{I_{M_n}(x,y) * \pi}{c_1}\right) + c_2 \tag{2-61}$$

where $I_{M_n}(x,y)$ is the normalized mean value of the pixel intensity at location (x, y), and c_1 and c_2 are empirical constants. The normalized mean intensity image is obtained by convolving with a low-pass Gaussian kernel using Equations (2-31) to (2-33). Selection of c_1 affects the compression of bright pixels mostly and for better results, the author recommends c_1 should be set to 2.25.



(a) Dark pixels



(b) Bright pixels

Figure 2.12 Curves of nonlinear transfer function for various values of parameter q.

For intensity values closer to 0, there is a possibility of the noise in the extreme dark regions being enhanced. Pixels with mean intensity values below 0.2 are considered as extreme dark regions, and for those, q is calculated by:

$$q = \frac{\left[\log\left(2I_{M_n}(x,y)\right) + 2\right]}{2} \tag{2-62}$$

The value of c_2 is calculated by equating the q value at $I_{M_n}(x,y) = 0.2$ in Equations (2-61) and (2-62) to maintain continuity. Figure 2.13 [20] shows the curves of squared sine nonlinear function for normalized mean intensity values in the range [0 1] produces with q parameters obtained from Equations (2-61) and (2-62) adaptively.

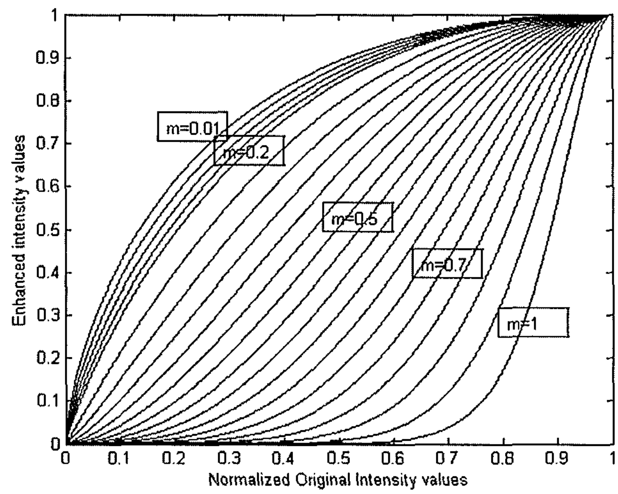


Figure 2.13 Curves of the nonlinear transfer function corresponding to various mean values.

In the next step, to enhance sharp edges and fine details in an image, a high frequency filtered image is added to the enhanced intensity image. The computation of high frequency components is achieved by a Laplacian operator.

The Laplacian is a 2D measure of the second spatial derivative of an image. It is a type of spatial filtering process that measures how abruptly gray-scale values change from pixel to pixel. It highlights regions of rapid intensity changes in an image. The Laplacian operator is an example of an isotropic second order or second derivative method of enhancement often used to restore fine details in images smoothed for the purpose of noise removal. The Laplacian *L(x, y)* of an image with pixel intensity values *I(x, y)* is given by:

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{2-63}$$

Since the input image is a set of discrete pixels, a discrete convolution kernel is formulated to approximate the second derivatives in the definition of the Laplacian. Figure 2.14 shows examples of Laplacian kernels that give isotropic results for rotations in the increments of 90°, and 45°.

0	-1	0
-1	4	-1
0	-1	0

0	1	0
1	-4	1
0	1	0

(a) Laplacian kernel with 90° direction

-1	-1	-1
-1	8	-1
-1	-1	-1

1	1	1
1	-8	1
1	1	1

(b) Laplacian kernel with 45° direction

Figure 2.14 Laplacian kernels.

In order to improve the overall quality of the images, a contrast enhancement process must be applied to restore or even enhance the original image. In the LTSN algorithm, the contrast enhancement process, which is used in AINDANE, IRME, and

MWIS, is implemented due to its high quality contrast process and control in the dynamic range expansion.

In the next step, another enhancement function is applied to the contrast enhanced image, namely autolevels. After the contrast enhancement process, some pixels, with values close to the threshold point, have very small intensity differences with their adjacent pixels. For the enhancement of an overexposed image, there might be many colors at the high end. Similarly in the process of enhancement of under exposed images the low end has many colors. The autolevels technique scans trough the levels of intensity within the image and chooses new endpoints. It then maps the new points (levels to be regarded as black and white) of the histograms to the full representation dynamic range by applying a gain. It then stretches the levels in the image so that all the intensities present in histogram lie between the black and the white points produce an image with a good span of color intensities. This process is similar to a contrast stretch process except a predefined parameter is used to clip the tails of the histogram as a percentage of the total number of pixels in the image. Finally, a linear color restoration is performed on the final intensity image using Equation (2-33).

This method provides an effective enhancement and compression for dark and bright regions in an image simultaneously. However, the method requires several steps to be performed to obtain well enhanced intensity image. While the algorithm compresses bright regions, it also introduces a band of dark pixels or dark halo.

2.10 Summary

In this chapter, basic intensity transformation techniques and advanced nonlinear spatial domain techniques are investigated. Basic intensity transformation techniques use one global function to process entire image. As a result, these techniques are limited in their ability to improving brightness as well as contrast to bring out fine details. Famous Retinex based nonlinear algorithms and advanced techniques such as AINDANE, IRME, MWIS, and LTSNE perform dynamic range compression well and improve local contrast to achieve high visual quality.

CHAPTER 3

NEIGHBORHOOD DEPENDENT NONLINEAR ENHANCEMENT BASED ON ADAPTIVE SINE NONLINEAR FUNCTION

Digital image enhancement is the process of modifying the appearance of a digital image by altering its pixel values. In the spatial domain, such alteration can be done using either linear or nonlinear transform functions. When an image contains underexposed and overexposed regions simultaneously, the enhancement process becomes difficult. A proper enhancement method should enhance dark regions, compress overexposed regions and leave the well lit regions unaltered. Conventional methods using linear transfer functions work well for either underexposed or overexposed regions but not for both simultaneously. Hence an adaptive nonlinear transfer functions is needed to address these issues and achieve desired results.

In this chapter, an optimized neighborhood dependent nonlinear enhancement (NDNE) technique based on sine nonlinearity is proposed. The algorithm is implemented in three steps: adaptive intensity enhancement, contrast enhancement, and color restoration. Figure 3.1 shows the structure of the proposed NDNE algorithm. The goal of this algorithm is to enhance the visual quality of images captured under extremely non-uniform lighting conditions. Hence the primary step is the adaptive intensity enhancement of dark and bright pixels. For fast processing, instead of performing intensity enhancement on R, G, and B color bands separately, the input image is first converted to a gray scale image using a NTSC [37] standard and enhancement is performed on the intensity of the image. After intensity enhancement, the contrast is degraded in the intensity-enhanced image, hence contrast enhancement process is applied to restore contrast and, in turn, preserve or enhance important visual details. Finally, after the contrast enhancement, the enhanced color image is obtained by performing a linear color restoration process on the enhanced intensity image using the chromatic information in the input image. The key contributions of this algorithm, optimization of the nonlinear sine transfer function and computation of control parameters involved in adaptive intensity enhancement are discussed in detail in the following section.

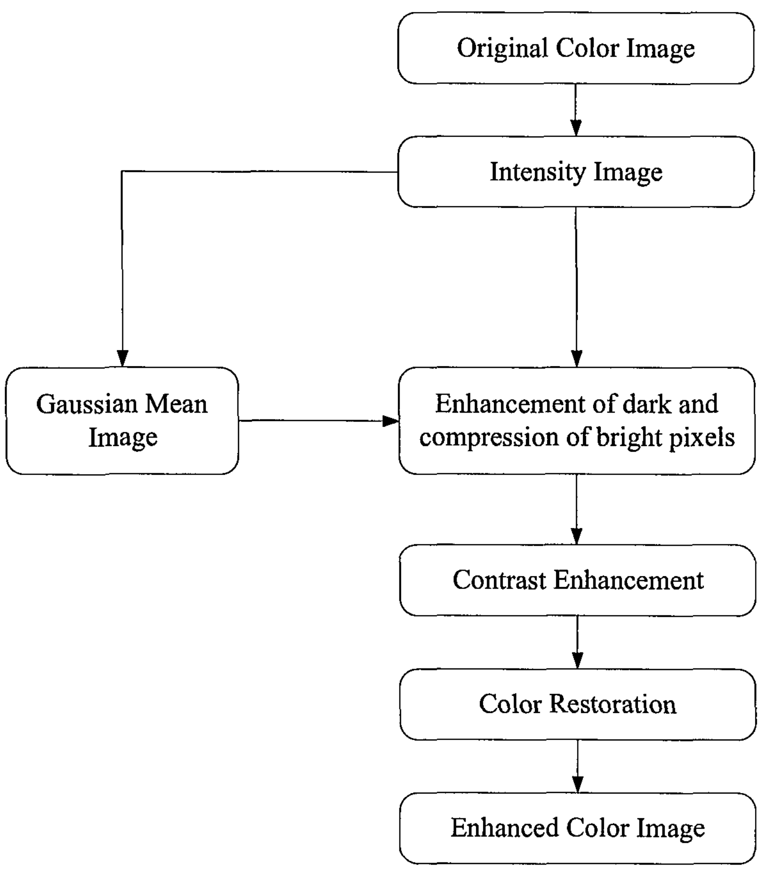


Figure 3.1 Block diagram of the NDNE algorithm.

3.1 Adaptive Intensity Enhancement

In this primary step of the algorithm, the intensity of the input image is altered using a parameter controlled sine nonlinear transfer function in order to increase the intensity of the dark pixels and reduce the intensity of the bright pixels. By means of adaptive intensity enhancement, the dynamic range of the intensity image is compressed while maintaining important image features.

3.1.1 Intensity computation

One of the major goals of enhancement technique is to make objects in the image visible. The visibility depends upon the illumination and the amount of light reflected by the object. Thus enhancement could be achieved by enhancing the luminance component of the image. The luminance component Y (intensity) can be obtained using the widely used NTSC standard. Opposed to processing three color bands separately, the adaptive enhancement can be performed on the intensity component and the luminance-enhanced image can be converted back to color image using the chrominance components. There are several ways of obtaining intensity information from a color image, among which NTSC is the only method that separates luminance and chrominance components completely. Therefore, in this algorithm, prior to performing intensity enhancement, the input image is first converted to gray scale image using NTSC standard [37] as follows:

$$I(x,y) = \frac{76.245 I_R(x,y) + 149.685 I_G(x,y) + 29.07 I_B(x,y)}{255} \tag{3-1}$$

where $I_R(x,y)$, $I_G(x,y)$ and $I_B(x,y)$ are red, green, and blue color values, respectively, of a pixel located at (x, y) position in the image. The intensity image I is further normalized to [0 1] range for 8-bit images by:

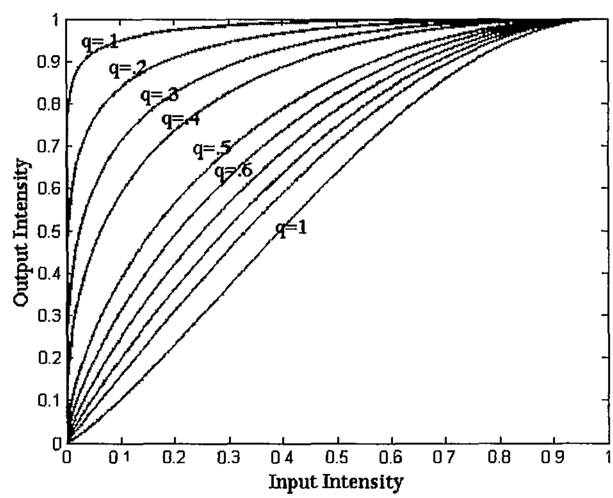
$$I_n(x,y) = \frac{I(x,y)}{255} \tag{3-2}$$

3.1.2 Enhancement of Dark and Compression of Bright Pixels

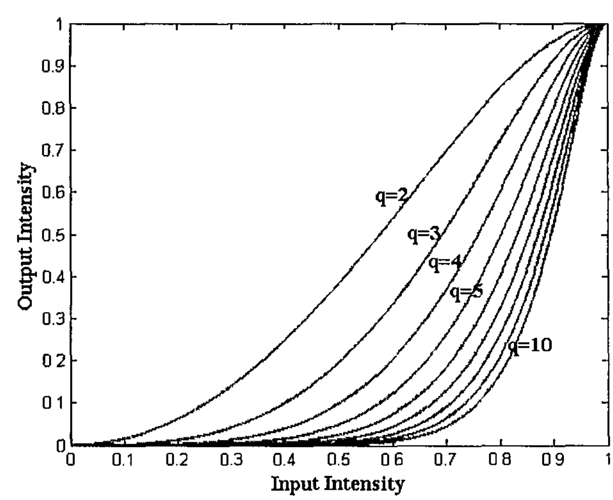
Compressing the dynamic range of the intensity image is an efficient method of image enhancement. Thus, an enhancement and compression process is performed on the normalized intensity image using a nonlinear sine transfer function. One of the key contributions of this thesis is the optimization of the core sine function. In a LTSNE algorithm, the transfer function utilizes a sine squared function. In this research, it is realized that similar or better results can be obtained using the sine function thus eliminating the need for square operation. Similarities and differences between the sine and sine squared functions with respect to the intensity transformation are explained in detail later with a set of graphs for both functions. The fine tuned sine transfer function is defined as:

$$I_E\ (x,y) = Sin\left(I_n\ (x,y)^q * \frac{\pi}{2}\right) \tag{3-3}$$

where I_E is the enhanced intensity image. In Equation (3-3), the functionality of the sine function is controlled by an image dependent parameter q. If the value of q is less than 1, the intensity of the dark pixels is pulled up greatly. On the contrary, if q is set to greater than 1, the intensity of the bright pixels is pulled down. These characteristics of the q parameter are illustrated in Figure 3.2. In Equation (3-3), the sine function merely performs as a black box with two inputs, intensity of the input image and the q parameter. The enhancement or compression of a pixel is directly controlled by the value of q parameter. Therefore, to obtain optimal results, effective computation of the q is critical. From the properties of q, one global value for the parameter can not fulfill the requirement of simultaneous enhancement of non-uniform luminous scene. Parameter q must be determined adaptively to effectively process an image.



(a) Curves for enhancement of bright pixels



(b) Curves for compression of bright pixels

Figure 3.2 Curves of nonlinear transfer function for various values of q.

In this research, a new method for the computation of the image dependent parameter q is proposed to obtain desired enhancement with less computational complexity. The formula for q is expressed as:

$$q = \frac{I_{M_n}(x,y)}{c1*(1-I_{M_n}(x,y)+\varepsilon)} + c2 \qquad (3\text{-}4)$$

where I_{M_n} is the normalized mean intensity value of the pixel at location *(x, y)*, *c1* and *c2* are constants determined empirically, and $\varepsilon = 0.01$ is a numerical stability factor introduced to avoid division by zero when $I_{M_n} = 1$. The role of the control parameter q in intensity transfer function can be demonstrated in the figure below which shows the plot of parameter q for normalized mean intensity values ranging from 0 to 1.

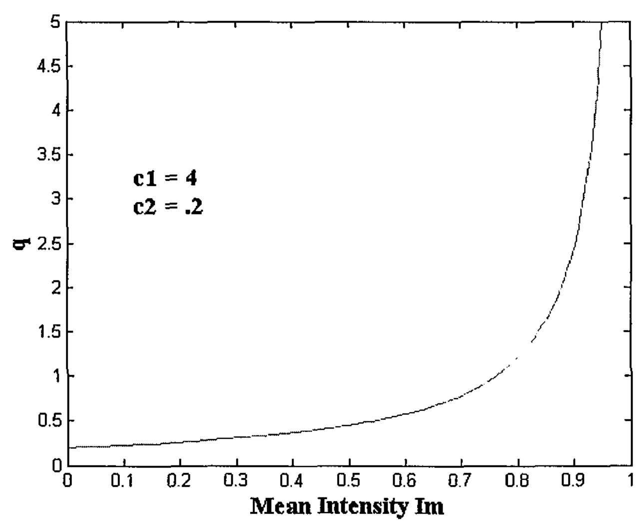
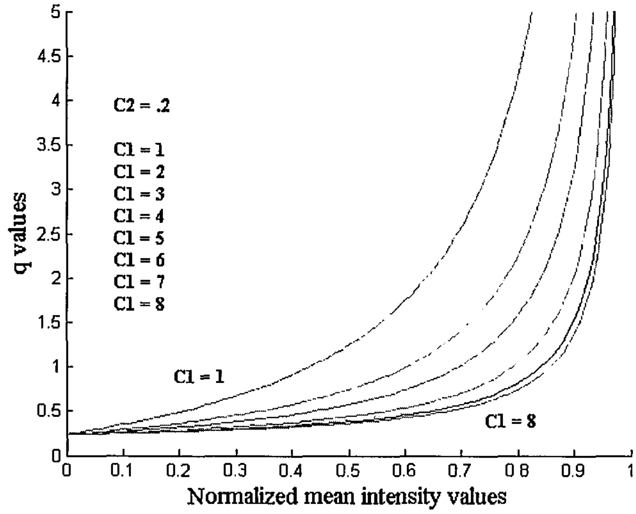


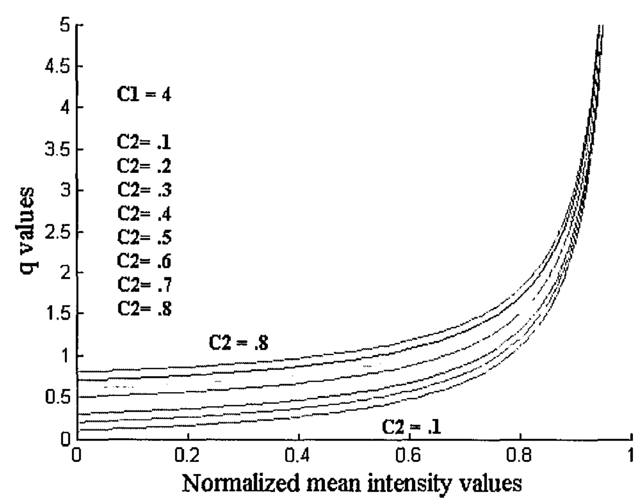
Figure 3.3 Plot of q for I_{M_n} *(mean intensity Im)* values ranging from 0 to 1.

The transfer function is a decreasing function of the q parameter. Therefore, to boost the intensity, the value of the q parameter should be kept small and to lower the intensity, q should be large. This makes q directly proportional to the ratio of

$I_{M_n}(x,\ y)/(1-\ I_{M_n}(x,\ y)+\varepsilon\,)$. Hence, when the mean intensity of the pixel $I_{M_n}(x,\ y)$ is very high, it generates a larger q and vice versa.



(a)



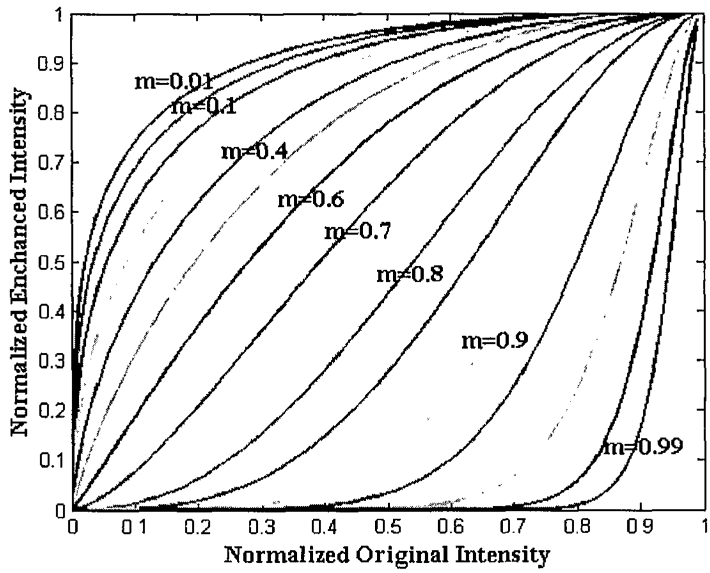
(b)

Figure 3.4 Curves of q to analyze impact of constants c1 and c2.

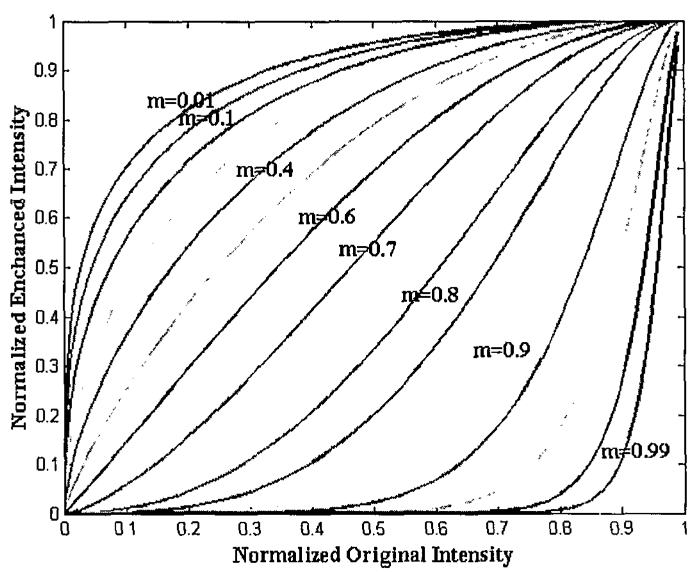
For the excessively bright pixels, the transfer function may produce very low or almost zero intensity values (when intensity value is close to 1, ratio of $I_{M_n}(x, y)$ / (1-$I_{M_n}(x, y)$) produces a much larger q). To avoid this phenomenon, the denominator is multiplied with c1, where q is inversely proportional to c1. This scenario is demonstrated in Figure 3.4(a). For overexposed images, cl in the range of 2 to 4 gives good results. If the image is very dark, then the cl value in the range of 5 to 8 helps to sufficiently to boost the luminance.

For mean intensity values close to 0, there is a strong possibility of noise being enhanced in the extreme dark regions. Therefore, c2 is added in Equation (3-4) to counteract the noise enhancement. The range of c2 in this experiment is empirically determined to be .13 to .7. Note that the addition of c2 has almost negligible effect on the pixels with intensity values close to 1 for which Equation (3-4) produces a much larger q compared to that of dark pixels. Effect of various values of c2 on parameter q can is shown in Figure 3.4(b).

In this method, as stated earlier, one of the findings is that the sine nonlinear function in Equation (3-3) can produce curves almost identical to the curves produced by sine squared function in Equation (2-60) used in LTSNE using the proposed method for computation of q parameter. The set of curves of the proposed sine transfer function for various mean intensity values ranging from 0.01 to 0.99 can be seen in Figure 3.5(b). By eliminating the square operations previously used in the LTSNE algorithm, the computational complexity can be reduced. As shown in the Figure 3.5, the graphs generated by the sine and sine squared functions are almost identical. Consequently, the



(a) Curves of the transfer function based on sine squared operation



(b) Curves of the transfer function based on sine function

Figure 3.5 Curves of the transfer functions corresponding to mean values ranging from 0.01 to 0.99 (a) curve of the sine square function with c1 = 4 and c2 = 0.17 (b) curve of the sine function with c1 = 2 and c2 = 0.3.

functionality of the sine functions is analogues to that of the sine squared function. The key idea is to use different values of c1 and c2 parameters to obtain desired curves. Using the sine transfer function, the luminance of dark pixels is greatly pulled up, the intensity of bright pixels is pulled down, and the well illuminated pixels are left unaltered. In addition, the transfer function compresses dynamic range while preserving fine details and provides good enhancement results.

3.1.3 Calculation of Mean Image

In this method, the mean image is computed using a Gaussian smoothing operator. The Gaussian mask is defined as follows:

$$G(x,y) = K \cdot e^{\left(\frac{-(x^2+y^2)}{c^2}\right)} \quad (3\text{-}5)$$

where c is the Gaussian surround space constant and K is the constant to ensure that the area under the Gaussian is 1. K is determined by evaluating the following integral across the Gaussian kernel:

$$\iint K \cdot e^{\left(\frac{-(x^2+y^2)}{c^2}\right)} \cdot dxdy = 1 \quad (3\text{-}6)$$

Choosing the right scale is very important as it determines the size of the neighborhood for 2D discrete spatial convolution with a Gaussian kernel. A convolution using a small scale uses few neighboring pixels, thus luminance information of the nearest neighboring pixels is available. On the other hand, large scale convolution provides information of global luminance distribution. In other words, Gaussian smoothing with small scale preserves details whereas large scale convolution provides global tonality, which helps produce more natural looking enhanced images [17]. In this method, a multiscale Gaussian is used to produce the mean intensity image I_{M_n} as multiple convolutions yield more complete information about the overall luminance distribution. The neighborhood averaging with multi scale Gaussian can be described as follows:

$$I_M\,(x,y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(m,n)\; G_{i(m+x,n+y)} \tag{3-7}$$

where G_i indicates the weighted sum of i Gaussian functions with different scales. In this method, a combination of small scale (1-5% of the image size), medium scale (10-15 % of the image size), and a large scale (25-45% of the image size) Gaussians were used to obtain optimal results.

3.2 Contrast Enhancement

Image contrast is an intuitive concept that relates to the global amount of image gray level dispersion (about the mean gray level). Contrast enhancement is a method of improving visual quality by enhancing details of the image contents. In the process of dynamic range compression, the mid-tone and low frequency components responsible for fine details and local contrast are degraded. As a result, the appearance of the image looks grayed out. In order to restore or even enhance the details contained in the original scene, a contrast enhancement process needs to be applied. In conventional contrast enhancement process, the contrast is enhanced globally either by starching or using a transfer function. Enhancing contrast simply by making the dark pixels darker and bright pixels brighter could produce harsh results. The modified image contrast is frequently excessively high resulting in an image whose appearance is displeasing to the eye and unnatural. Furthermore, human eyes respond to local variations better than absolute brightness levels. Global enhancement methods fail to bring out fine details where neighboring pixels have minor intensity differences. Therefore, to bring a scene with better balance between luminance and contrast, a neighborhood dependent contrast enhancement technique is needed.

In this algorithm, an effective center surround contrast enhancement approach similar to IRME algorithm [18] is applied. This method efficiently compensates for image features degradation and restores the contrast of the luminance-enhanced image using luminance information of the neighboring pixels. The luminance information of surrounding pixels is obtained by using 2D discrete spatial convolution with a Gaussian kernel using equations (3-5) to (3-7). In the next step, a center-surround contrast enhancement method is performed as follows:

$$S(x,y) = 255 \cdot I_E(x,y)^{E(x,y)} \tag{3-8}$$

where the exponent is defined by:

$$E(x,y) = R(x,y)^P = \left(\frac{I_{conv}(x,y)}{I(x,y)}\right)^P \tag{3-9}$$

$S(x,y)$ is the contrast-enhanced pixel intensity, $R(x,y)$ is the intensity ratio between low-pass filtered $I_{conv}(x,y)$ and original intensity image $I(x,y)$. P is an image dependent parameter determined by the global standard deviation of the input intensity image $I(x,y)$. In this step, magnitude of the center pixel's intensity is compared with the neighboring luminance (convolution result). As shown in Equation (3-9), if the center pixel is brighter than surrounding pixels then the ratio $R(x, y)$ is smaller than 1, the intensity of this pixel is pulled up. Likewise, if the center pixel is darker than the neighboring pixels then the ratio $R(x, y)$ is grater than 1 and the intensity of the pixel is lowered. This process in fact is an intensity transformation process. Figure 3.6 shows the plots obtained using Equation (3-8) of various exponent E values against the enhanced-intensity values in the range [0 1]. By performing this method, contrast and fine details of the compressed luminance image can be sufficiently improved while maintaining the image quality.

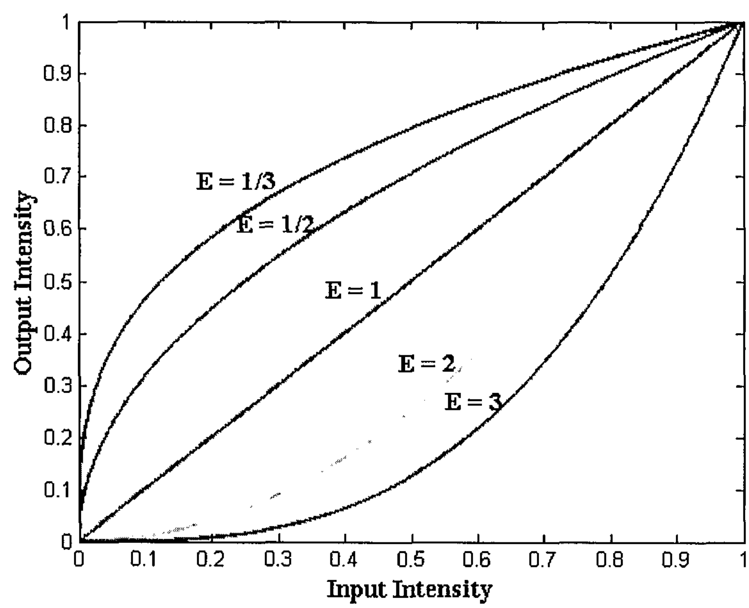


Figure 3.6 Illustration of contrast enhancement.

For optimal enhancement, contrast enhancement can be performed using multiple convolution results of different scales. The final output can be obtained from a linear combination of the contrast enhancement results based on multiple scales. A general rule of thumb is that small scale convolutions contain intensity information of the nearest neighboring pixels and large scale convolutions provide intensity information of the overall scene (large region). Therefore, contrast enhancement with smaller scale convolutions tend to enhance local contrast or fine details and the contrast enhancement with larger scale convolutions can produce a global tonality approaching the original image for smooth and natural looking results. A medium scale convolution can serve the purpose of both large and small scale convolutions as it provides a mixture of both details and image rendition. Contrast enhancement using linear combination of multiscale convolutions can be described by following equations:

$$G_i(x,y) = K \cdot e^{\left(\frac{-(x^2+y^2)}{c_i^2}\right)} \tag{3-10}$$

$$I_{conv,j}(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m,n)\, G_{i(m+x,n+y)} \tag{3-11}$$

$$E_i(x,y) = R_i(x,y)^P = \left(\frac{I_{conv,j}(x,y)}{I(x,y)}\right)^P \tag{3-12}$$

$$S_i(x,y) = 255 \cdot I_E(x,y)^{E_i(x,y)} \tag{3-13}$$

$$S(x,y) = \sum_i w_i S_i(x,y) \tag{3-14}$$

Although contrast enhancement using multiple scale yield more balanced results, it can become computationally expensive. For this algorithm, only medium scale convolution results are used for faster processing.

3.3 Color Restoration

Recall from Section 3.1 that the color image was first converted to a grayscale image using the NTSC standard. The enhanced gray scale image is now converted back to a color image using the chromatic information of the original image as follows:

$$S_j(x,y) = S(x,y)\frac{I_j(x,y)}{I(x,y)} \cdot \lambda_j \qquad j \in \{R,G,B\} \tag{3-15}$$

where j = R, G, B represents the red, green, and blue spectral bands respectively, $I_R(x,y)$, $I_G(x,y)$ and $I_B(x,y)$ are R, G, and B color values in the original color image, $I(x,y)$ is intensity image computed using Equation (3-1), $S(x,y)$ is the enhanced intensity image computed using Equation (3-8), and S_R, S_G and S_B are the RGB values obtained to form the enhanced color image. The parameter λ adjusts the color hue of the enhanced color images. It takes different values in different spectral bands. Normally its value is close to 1. However, when all λs are equal to 1, according to Equation (3-15) the chromatic information of the input color image is preserved for minimal color shifts [17].

3.3 Summary

In this chapter, a new nonlinear image enhancement technique NDNE has been proposed. The specific objectives presented are:

1. Simultaneous enhancement and compression of dark and bright pixels respectively using an optimized parameter controlled sine nonlinear transfer function.
2. A new method for fast and adaptive computation of the control parameter.

3. Application of center-surround enhancement process to preserve/enhance fine details.
4. Application of linear color restoration method to obtain color image using chromatic information of the original image and enhanced intensity image.

CHAPTER 4

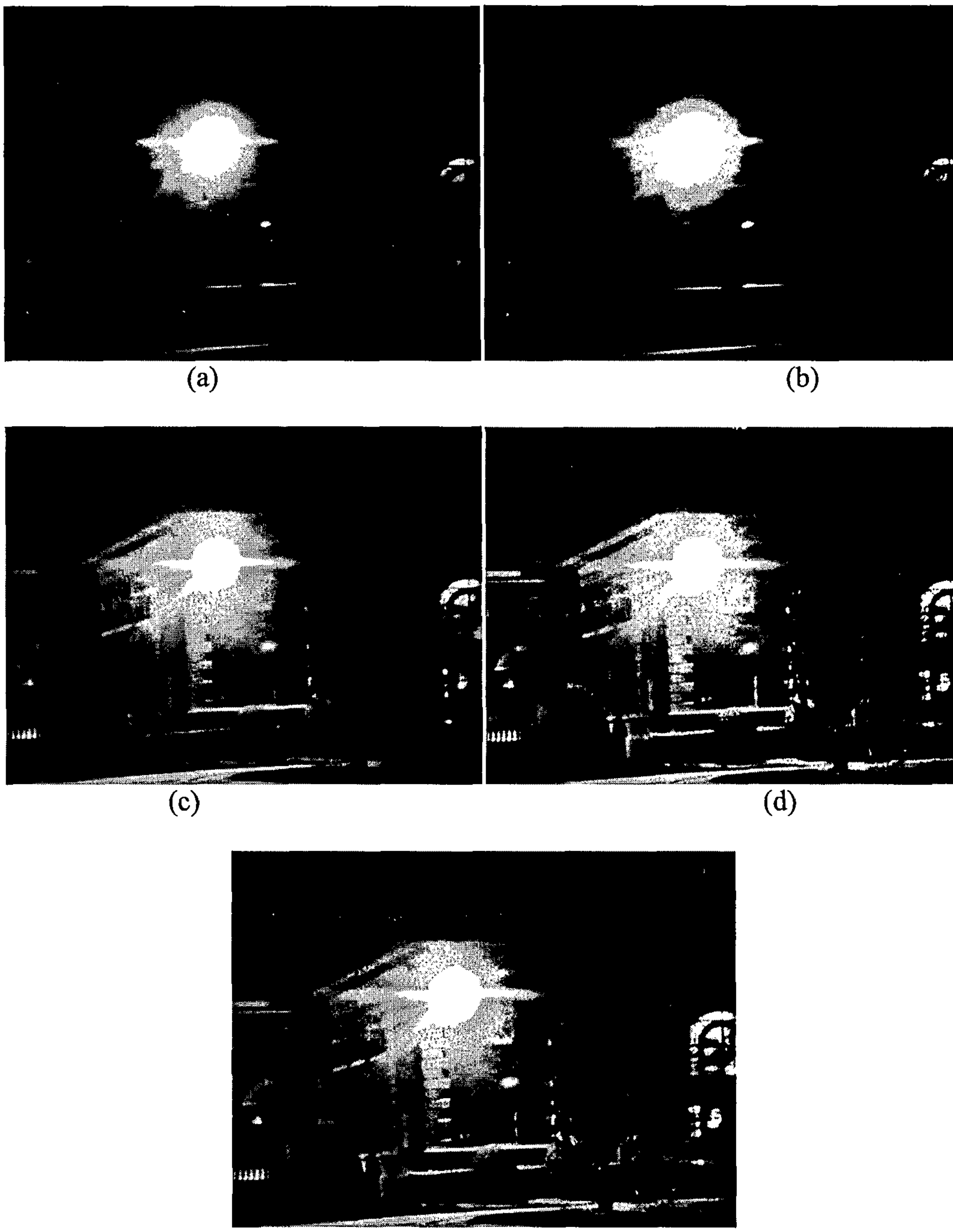
RESULTS AND DISCUSSION

The focus of this chapter is testing and performance evaluation of the proposed algorithm. The very first task is to test whether the proposed algorithm is capable of producing expected outcomes. To verify the intended functionality, a NDNE algorithm is applied to a large number of images captured under extremely diverse lighting conditions. A detailed analysis of the actual outcomes is provided for a large number of test images that belong to different categories. Also, the algorithm provides flexibility in producing desired results via setting of the control parameters. The impact of parameter selection is illustrated by enhanced image obtained using different values for the parameter. In the next step, the efficiency of the proposed algorithm is compared with other state of the art enhancement techniques. Since there is no general theory for good enhancement for a very diverse set, the images are first evaluated visually in terms of sufficient brightness, details, and contrast while keeping consistency with the original scene. Finally, the performance of the algorithm will be evaluated using image statistics and an evaluation method developed by Rahman et al. [38]. Since the thesis focuses on computational time optimizations, the processing time required for the proposed algorithm is compared with that of other present techniques for images of different sizes.

4.1 Experiments

4.1.1 Illustration of NDNE algorithm

In a NDNE algorithm, the enhancement process is implemented in several steps beginning with obtaining intensity image, intensity enhancement via sine nonlinear function, center surround contrast enhancement, and finally color restoration. The results of each intermediate stage are illustrated in Figure 4.1. The scene is captured at night time and contains majority dark background and a very bright light source in the center. The algorithm compresses the over illuminated region and enhances the dark regions. Figure 4.1(a) and (b) show the original image and intensity image obtained using the NTSC standard. The intensity image is transformed using a sine nonlinear function which is the core step of the algorithm. As we can see in Figure 4.1(c), the brightness of the darker regions is pulled up greatly and the intensity of the overexposed region is reduced. As a result, in the enhanced intensity image, the glare from the light source is removed and the objects in the background are made visible. A center surround contrast enhancement is performed on the enhanced intensity image and the resulting image is show in Figure 4.1(d). Notice that after contrast enhancement, the edges of the building appear sharper and the contrast is increased. The resultant image appears more pleasing than the rather flat looking image in 4.1(c). Finally the color image show in Figure 4.1(d) is obtained using the color information of the original image and enhanced intensity image.



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

Figure 4.1 Illustration of NDNE algorithm (a) Original Image (b) Intensity image (c) Enhanced intensity image (d) Enhanced intensity image after contrast enhancement (e) Enhanced color image.

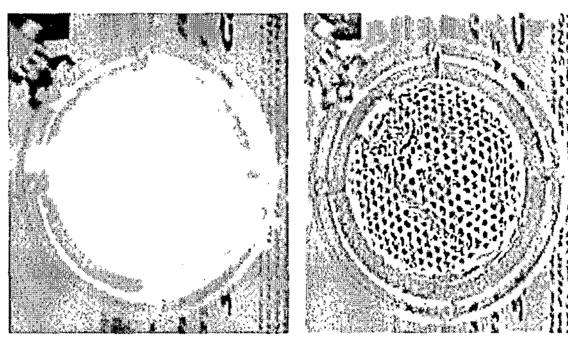
4.1.2 Enhancement of Overexposed Images

The uniqueness of the NDNE algorithm among many enhancement techniques is that it can bring out details in the overexposed regions as well as in the dark regions. In this section, the potential of this algorithm to enhance overexposed images is tested. The set of images presented in this section is captured under extremely bright illumination. The original images contain washed out regions due to over illumination and thus the quality of the images in Figures 4.2(a), (c), and (e) is degraded. The proposed algorithm was applied with the control parameters suggested for overexposed condition (as suggested in the third chapter) to compress the bright regions. The enhanced images shown in Figure 4.2(b), (d), and (f) possess improved contrast and reveal more details. For example, the letters indicating the name of the river can be seen which is not visible in the original image shown in Figure 4.2(e).

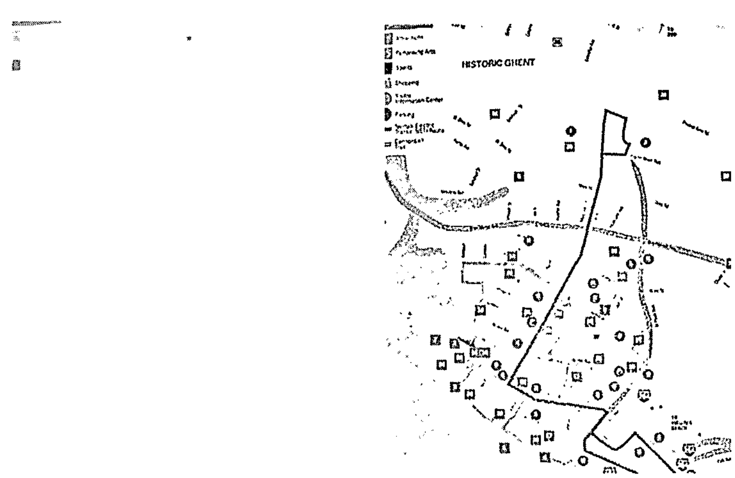
4.1.3 Enhancement of Images containing Dark and Bright regions

In this section, simultaneous enhancement capability of the NDNE algorithm is tested. The rationale is to enhance an image containing dark and bright regions simultaneously. The set of images presented in this section is captured under mixed lighting conditions. The original images contain dark as well as bright regions as shown in Figures 4.3(a), (c), (e) and (g). The images were processed with a NDNE algorithm and the resulting images are shown in the Figures 4.3(b), (d), (f), and (h). In Figure 4.3(a), person standing in the shadow is not visible due to poor lighting; however, the person is clearly visible in the processed image along with clearly visible background. Similarly in Figure 4.3(c), the objects behind the window glass possess poor brightness. NDNE increases the brightness

(a) Original Image (b) Enhanced Image



(c) Original Image (d) Enhanced Image



(e) Original Image (f) Enhanced Image

Figure 4.2 Image Enhancement by NDNE on overexposed images.

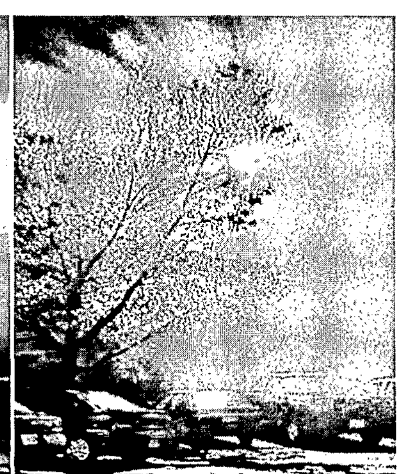
(a) Original Image

(b) Enhanced Image

(c) Original Image

(d) Enhanced Image

(e) Original Image



(f) Enhanced Image

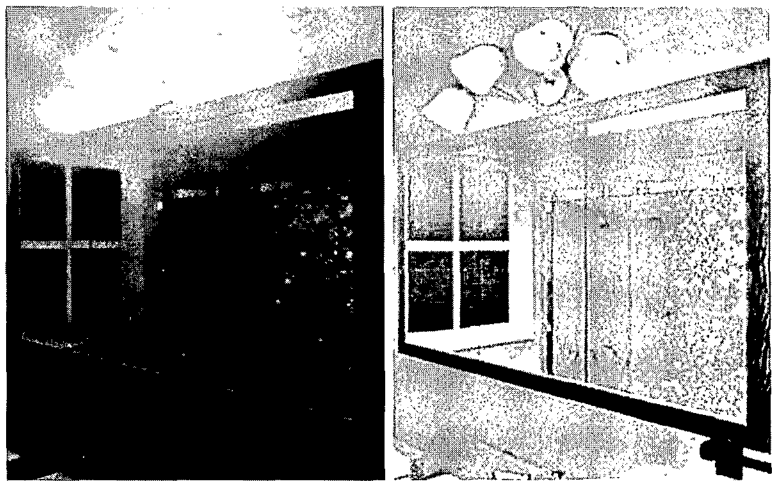
(g) Original Image (h) Enhanced Image

Figure 4.3 Enhancement of images captured under complex lighting condition using NDNE.

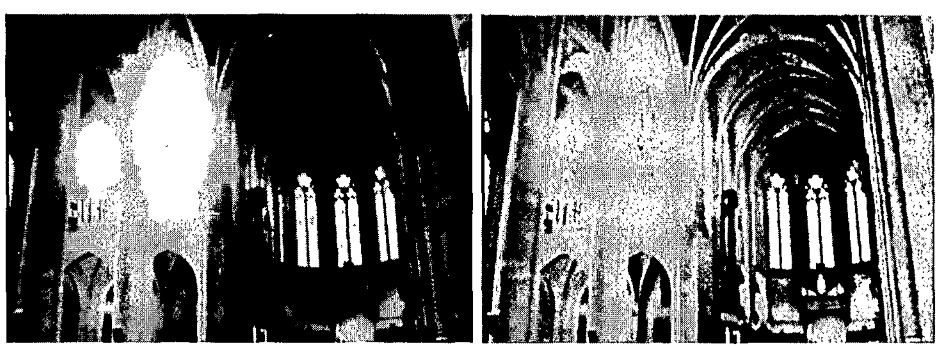
of the dark objects without washing out the objects in the bright regions. In Figure 4.3(f), glare from the sun's rays is reduced and we can see the pattern of the light source due to compression of bright regions. At the same time, cars and other objects under and behind the tree are clearer than the original image. Likewise, in figure 4.3(h), the glare from the headlight of the car is removed.

4.1.4 Enhancement of Indoor scene with mixed illumination

The image in Figure 4.4(a) was captured under medium scale lighting conditions where some objects are well lit while others are not. The algorithm produces well balanced image in which, the regions that are already sufficiently illuminated are left unaltered which can be verified from Figure 4.4(b). By decreasing the intensity around the lamp, the details are enhanced while the intensity around the window as well as the mirror frame is increased. In the same way, the image in 4.4(c) is enhanced while maintaining balance between dark, medium, and bright regions.



(a) Original Image (b) Enhanced Image



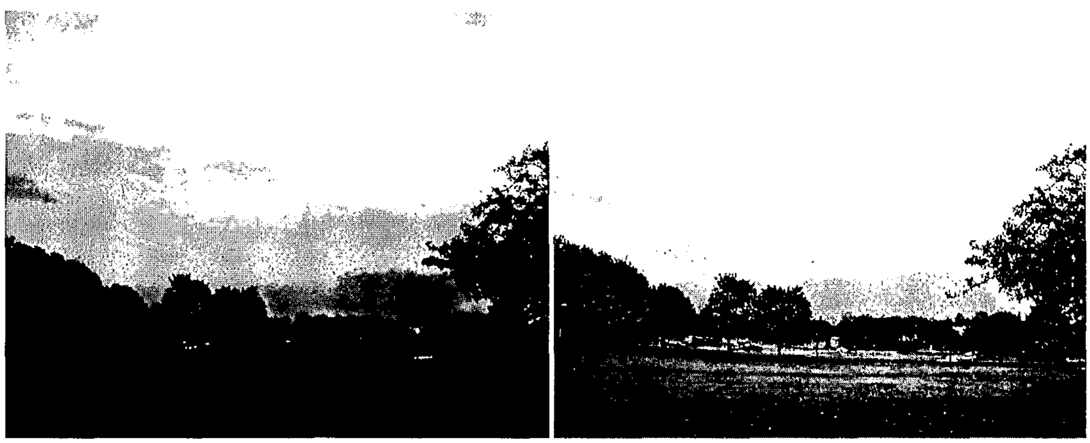
(c) Original Image (d) Enhanced Image

Figure 4.4 Enhancement of indoor images, captured under complex lighting.

4.1.5 Enhancement of High Dynamic Range Scene

One of the biggest limiting factors of typical cameras is that they are unable to capture and render scenes that span a large luminance range. These types of scenes are generally a challenge for typical cameras because it sets a global exposure for the entire scene. Generally to capture details in the highlighted areas, exposure should be set so as to let less light enter the lens and to capture details in dark or shadow areas. The exposure setting should allow more light to enter the lens. But with a global exposure, there are two exclusive options: it either obtains details from dark regions at the loss of details in the highlighted areas or vice versa. The sample images in Figures 4.5(a), (c), and (e) demonstrate such a scenario. In Figure, 4.5(b), we can see that enhancement using NDNE brings out details in the dark areas of the bushes while preserving the details in the highlighted areas covering clouds in the sky. In Figure 4.5(c), due to underexposure, the details of the trees and objects on the ground are not visible. The NDNE algorithm successfully adjusts the luminance of the scene to produce an image that resembles the high dynamic range of the original scene as close as possible. After processing these images with a NDNE algorithm, the resulting images show balanced luminance distribution while maintain local contrast. Note that the enhanced image provides the quality similar or better than the images captured with a very high dynamic camera and processed from a sequence of images (blending of underexposed, medium exposed and overexposed images to produce one HDR image).

(a) Original Image (b) Enhanced Image

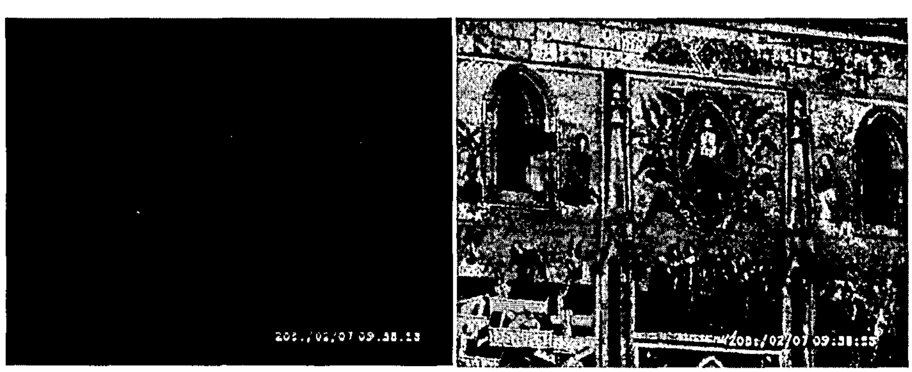


(c) Original Image (d) Enhanced Image

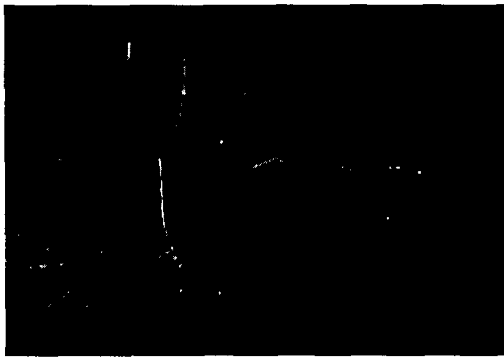
(e) Original Image (f) Enhanced Image

Figure 4.5 Enhancement of outdoor images possessing high dynamic range.

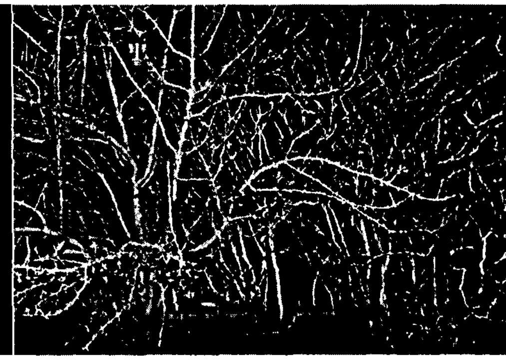
4.1.6 Enhancement of Dark Images



(a) Original Image (b) Enhanced Image

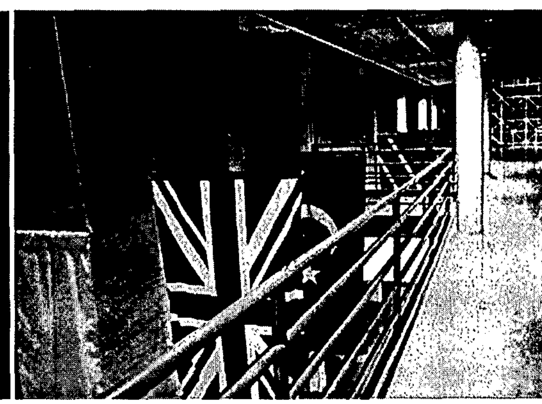


(c) Original Image

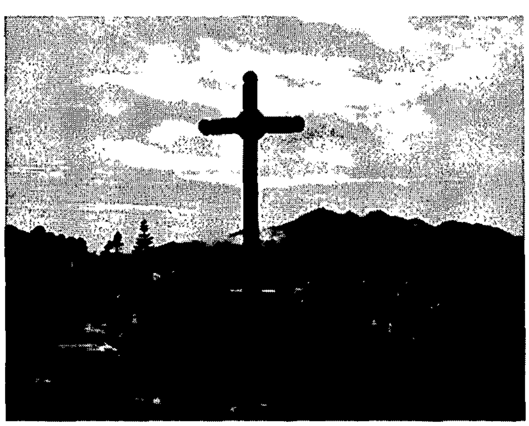


(d) Enhanced Image

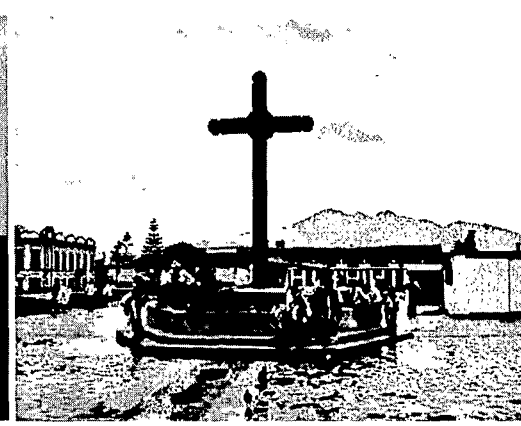
(e) Original Image



(f) Enhanced Image



(g) Original Image



(h) Enhanced Image

Figure 4.6 Enhancement of dark images by NDNE.

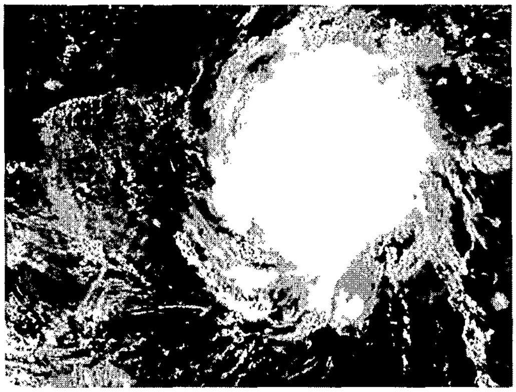
The sample images in Figure 4.6(a), (c), (e) and (g) are captured under extremely dark or poor lighting conditions. After processing them with NDNE, the visual quality is highly improved as can be seen in Figure 4.6(b), (d), (f) and (h). In Figure 4.6(a) the entire sample image is underexposed containing indoor scene. By applying NDNE, brightness is sufficiently enhanced and the resulting image is more pleasing to the eyes as can be seen from Figure 4.6(b). The sample image in Figure 4.6(c) contains underexposed outdoor scene. The enhanced version of the vary image provides better visibility with greater detail. For instance, in the enhance image shown in Figure 4.6(d), objects such as the branches of the tree, the bird feeder, the green crane, etc are easily noticeable. Figures 4.6(f) and (h) provide more examples of enhancement achieved by the NDNE algorithm for images captured under dark lighting conditions indoors as well as outdoors.

4.2 Comparison with AINDANE, IRME, MWIS, and LTSN

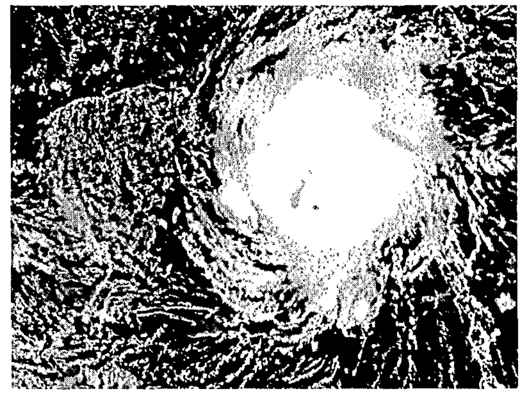
The NDNE algorithm has been applied to digital images captured under varying lighting conditions for comparison with other state of the art techniques. Results as well as detailed discussion about specific characteristics of this thesis' algorithm are presented in this section.

In Figure 4.7 the sample image is provided for comparison with the performance of IRME, AINDANE, MWIS, LTSNE, and NDNE. It can be observed that the images produced by NDNE possess more details with high visual quality in both the underexposed and over exposed regions than those processed by the above mentioned techniques. As can be seen in Figure 4.7(b), IRME enhances the dark areas properly however the highlighted regions look blurred. In the same way, AINDANE enhances the dark regions but over enhances the bright areas as shown in Figure 4.7(c). MWIS attempts to enhance the dark regions and compress the bright regions, however, the compression in the bright areas is not sufficient and the resulting image does not appear to have sufficient local contrast (Figure 4.7(d)). In the image processed by LTSNE (Figure 4.7(e)), the bright areas are compressed well, however, it creates dark halo around the bright areas. The resultant image (Figure 4.7(f)) of the proposed algorithm shows better balance in enhanced and compressed regions yielding more details.

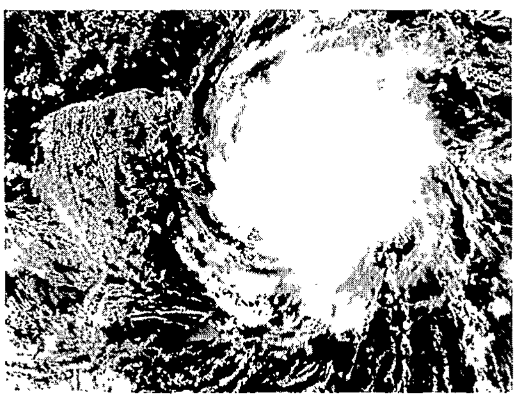
Figure 4.8 provides a sample image captured under complex lighting condition to demonstrate the functionality of the classical enhancement techniques as well as the proposed technique. From Figures 4.8(b) and (c), we can infer that IRME and AINDANE both enhance the dark regions well but AINDANE over-enhances the bright region around the lamp. From Figure 4.8(d), we can say that MWIS compresses the bright region but seems to have trouble with enhancement of the dark bricks in the bottom left corner. In the image processed by LTSNE (Figure 4.8(e)), the glare from the lamp is reduced, but it creates a ring with a relatively dark region around the lamp and the bright region in the center. Also, notice that the grid around the bricks is incorrectly lit making the overall image look dissimilar to the original image. From Figure 4.8(f), it is clear that the proposed algorithm enhances the dark background and gives finer details in the highlighted area around the lamp as well as the lamp itself. From both the examples, we can see that the proposed algorithm performs well where the other techniques lack.



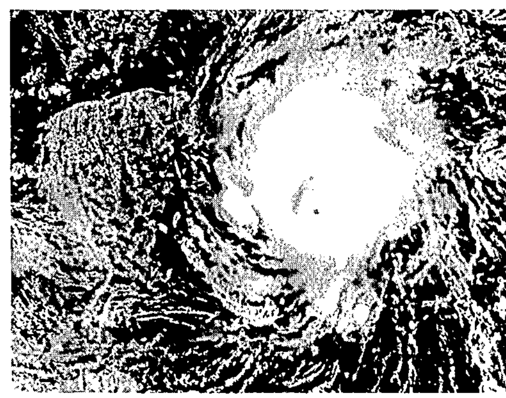
(a) Original Image



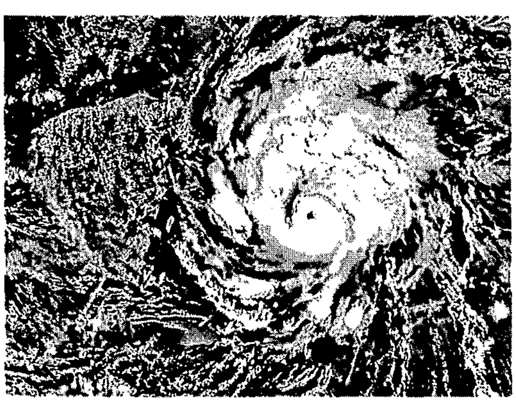
(b) IRME



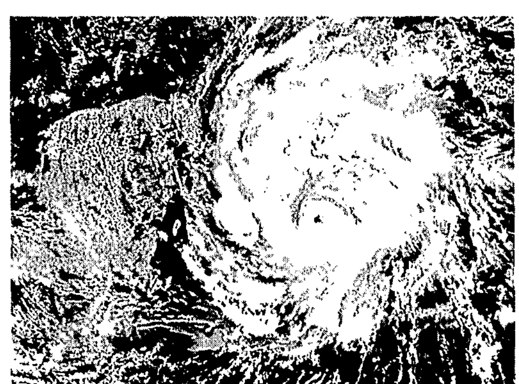
(c) AINDANE



(d) MWIS

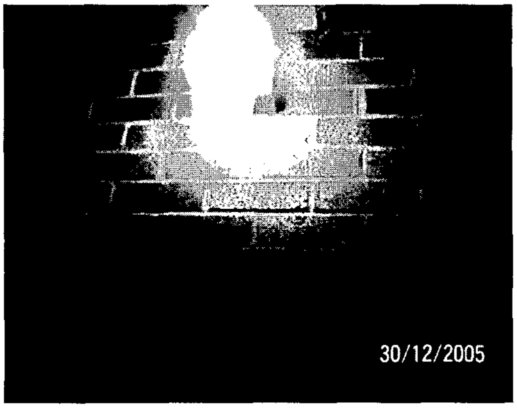


(e) LTSN



(f) NDNE

Figure 4.7 Comparison of the performance of NDNE algorithm with classical enhancement techniques IRME, AINDANE, MWIS and LTSN.



(a) Original Image

(b) IRME

(c) AINDANE

(d) MWIS

(e) LTSN

(f) NDNE

Figure 4.8 Performance comparison of NDNE algorithm with classical enhancement techniques.

4.3 Statistical Evaluation

When we look at an image, we assess the quality based on our perception of brightness, contrast, and sharpness instantly. To numerically assess the quality of image, the same metrics could be computed. The most common numerical measure of global image brightness is the image mean. Image contrast relates to the global amount of image gray level dispersion (variation about the mean gray level) and could be well presented by image standard deviation.

A study conducted in [38] investigated the connection between numerical and visual phenomena. The study indicates that global mean and global standard deviation does not reveal enough information to evaluate the quality accurately. The authors proposed a method which first computes regional mean and standard deviations and then compute mean of the regional standard deviations by dividing image into block of 50x50 pixels. The image is then classified based on its mean and mean of standard deviation into four categories: insufficient contrast, insufficient lightness, insufficient contrast and lightness, and visually optimal region. Figure 4.9 shows the regions corresponding to these categories.

The quality of large number of images processed by NDNE is assessed using this method. Figure 4.10 shows the quantitative evaluation of the original images and their corresponding enhanced images in terms of their location on the graph. In the figure, numbers from 1 to 16 indicate original images; their corresponding figures are listed in Table 1. The figure clearly shows the effectiveness of the NDNE algorithm, the images are transformed closer to the visually optimal regions.

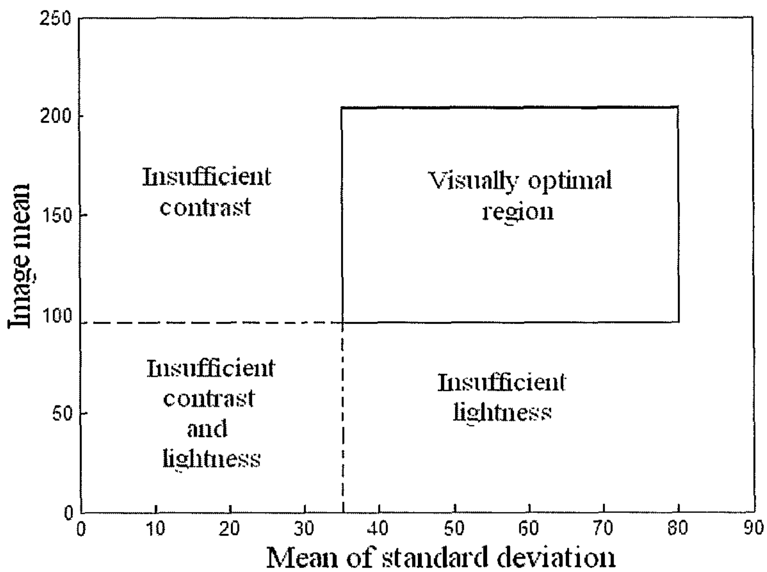


Figure 4.9 Image quality regions.

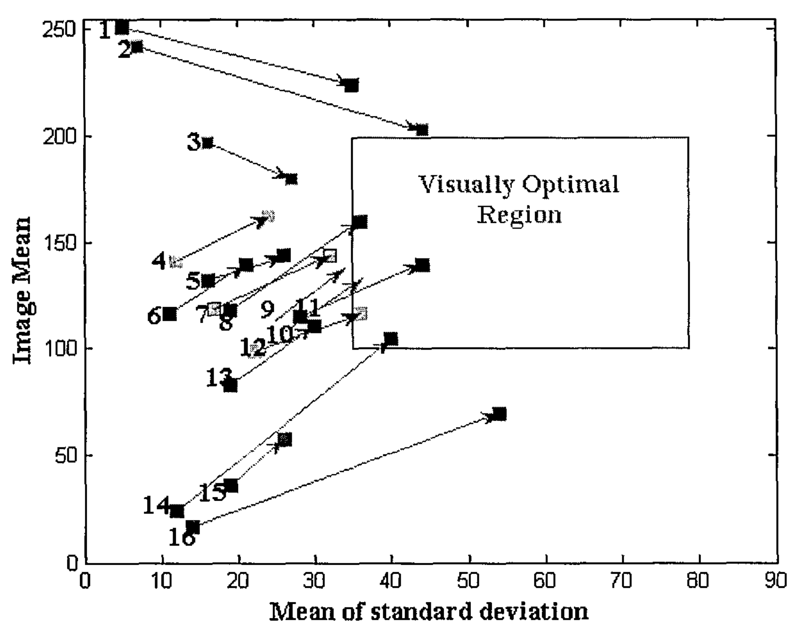


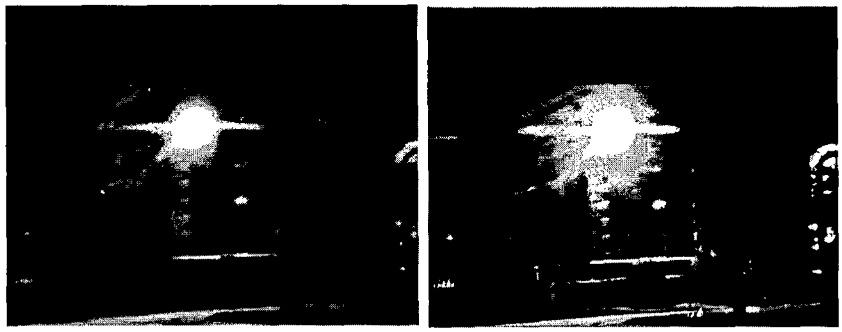
Figure 4.10 Statistical evaluation of image quality.

Table 1 List of figures and their corresponding image number shown in Figure 4.10.

Image Number	Corresponding Figure	Image Number	Corresponding Image
1	4.6(a)	9	4.3(c)
2	4.6(h)	10	4.3(g)
3	4.3(a)	11	4.3(e)
4	4.5(c)	12	4.2(c)
5	4.4(a)	13	4.6(c)
6	4.5(f)	14	4.2(a)
7	4.4(c)	15	4.5(a)
8	4.6(e)	16	4.2(e)

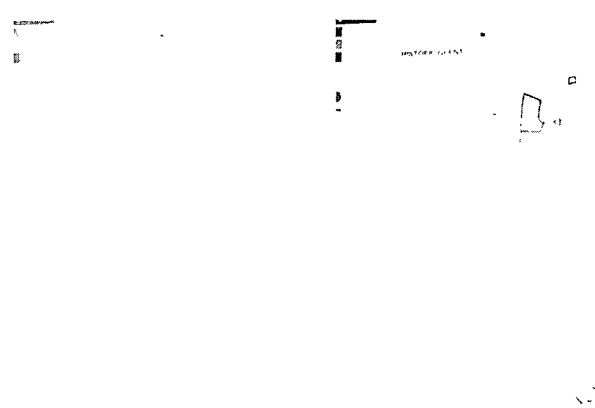
Furthermore, a set of images processed by NDNE and other state-of-the-art algorithms are evaluated using the same method in order to compare their performance. The mean and mean of standard deviations of the original images and the enhanced images are plotted in Figure 4.14. The diamonds, circles, and squares represent the images enhanced using the AINDANE, LTSNE, and NDNE algorithms, respectively. The numbers inside the shapes indicate the enhanced image corresponding to the original

(a) Original Image (b) AINDANE

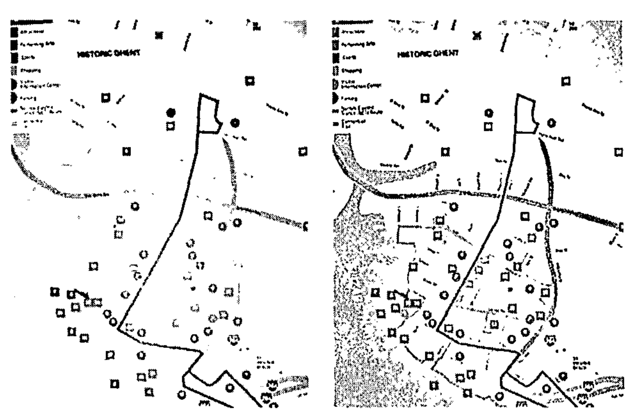


(c) LTSN (d) NDNE

Figure 4.11 Enhanced images with AINDANE, LTSN and NDNE algorithms.

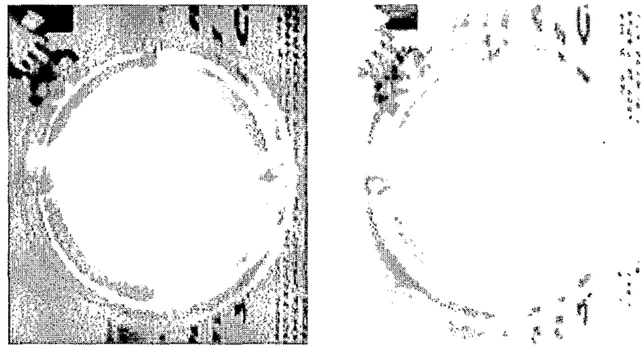


(a) Original Image (b) AINDANE

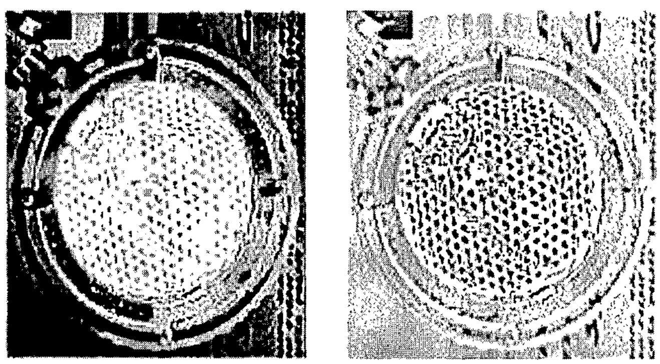


(c) LTSN (d) NDNE

Figure 4.12 Enhanced images with AINDANE, LTSN and NDNE algorithms.



(a) Original Image (b) AINDANE



(c) LTSN (d) NDNE

Figure 4.13 Enhanced images with AINDANE, LTSN and NDNE algorithms.

image number. The first image (Figure 4.11(a)) was captured under very dark lighting condition with a bright object in the center. All three techniques increase the luminance as well as contrast and the image mean and standard deviation are moved closer to the visually optimal regions by all three techniques as shown in Figure 4.11(b), (c) and (d). Though LTSN and NDNE both aim for compression of bright regions and enhancement of the darker regions, the image processed by NDNE is more consistent as it does not incorrectly generate dark halo around the bright light source. The second image (Figure 4.12(a)) is captured under extremely bright lighting conditions and has a very low contrast. NDNE and LTSNE compress the bright regions well. The difference is that instead NDNE brings out more details instead of making the entire image darker. Also, the transfer function in AINDANE does not compress the bright regions but we see a decrease in the intensity. This is mainly due to the contrast enhancement step and does not brighten the details in the washed out regions. The third image (Figure 4.13(a)) is very bright for which AINDANE enhances the extremely brighter pixels whereas LTSNE and NDNE compresses them. As can be seen in Figure 4.14, the resultant image of NDNE falls in the visually optimal region, LTSNE closer to the visually optimal and AINDANE, showing the opposite behavior.

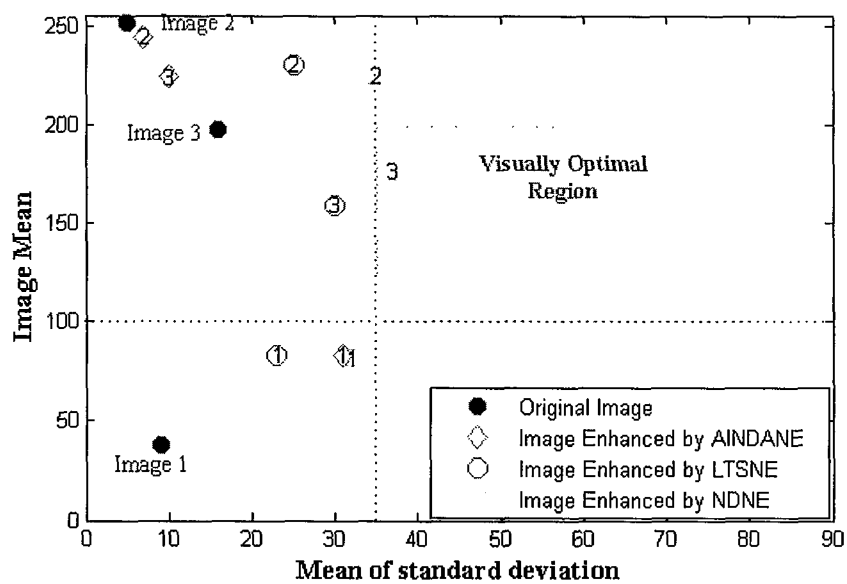


Figure 4.14 Comparison of visual quality of images enhanced by AINDANE, LTSNE, and NDNE.

4.4 Computational Speed

The processing time needed for enhancing images of different sizes is compared between AINDANE, LTSNE, and NDNE. The computing platform is an Intel Pentium 4 system, processor running at 3.06 GHz, 1GB memory, and using the Windows XP® Professional Edition operating system. AINDANE, LTSNE, and NDNE implemented in C++ are applied to process the same set of images. The processing time needed to enhance images of various sizes is provided in Table 2 for comparison between AINDANE, LTSNE, and NDNE. Table 1 showed that the time required to process an image using NDNE is less than that of LTSNE and AINDANE. NDNE requires less processing time due to the fact that the intensity enhancement process requires fewer and simpler functions. In LTSNE, the computation of image dependent parameter involves computationally expensive logarithm and tangent functions. Whereas in NDNE, these functions are replaced with a division operation in order to reduce processing time.

Table 2 Comparison of processing time of AINDANE, LTSNE and NDNE.

Image size (pixels)	Processing time by AINDANE (seconds)	Processing time by LTSNE (seconds)	Processing time by NDNE (seconds)
360 × 240	0.25	0.19	0.173
640 × 480	1.4	0.687	0.527
1024 × 768	2.8	1.716	1.28
2000 × 1312	6.7	4.572	3.438

4.5 Summary

In this chapter, simulation results of the NDNE algorithm are presented. Images captured under non-uniform lighting conditions are processed with NDNE algorithm and the performance is evaluated both visually and quantitatively. From the experimental results, it is clear that NDNE algorithm performs well on underexposed regions as well as overexposed regions. The adaptive calculation of parameters makes the algorithm flexible and more effective. The simplification of the transfer function and parameter calculation makes the algorithm fast and suitable for video enhancement. This algorithm can be applied to many image processing applications such as face detection processes to identify the faces in extreme dark and bright environment. The algorithm can also be applied to video stabilization for accurate feature selection invariant of poor illumination.

CHAPTER 5

CONCLUSIONS AND FUTUREWORK

In this thesis, a new nonlinear image enhancement algorithm NDNE to improve the visual quality of digital images captured under complex lighting conditions is presented. The method performs adaptive luminance enhancement, contrast enhancement, and color restoration steps. Dividing the enhancement process in three steps increases the flexibility and provided more control for fine tuning. This method allows for corrections of non uniform illumination, shadows, and other traditionally difficult lighting issues. Effectiveness of the algorithm depending on the statistical information (mean and mean of standard deviation) of the original and enhanced images has been evaluated based on its capability to automatically refine the image quality. The algorithm has been tested on a large dataset and the performance has been verified. The images enhanced by NDNE possess improved visual quality compared with those produced by other techniques in terms of better contrast and luminance enhancement of images containing underexposed and overexposed regions. The algorithm has been optimized to reduce computational complexity. The processing speed of NDNE is faster than LTSNE, and AINDANE. A NDNE algorithm would be a more efficient and fast image enhancement technique that could be useful in many applications.

Future work will concentrate on converting empirical constants used in computation of control parameter q into adaptive parameters to make the algorithm fully adaptive. A number of improvements in the color restoration step to produce color constant images are envisioned. Currently adapted methods use a linear combination of the chromatic information contained in the original image. In the development of a new method for color restoration, the ratio between each color channel in the original image will play an important role.

REFERENCES

[1] *Digital Photography Color Management Basics*, International Color Consortium, April 2005, White Paper no. 20, http://www.color.org/ICC_white_paper_20_ Digital_ photography_color_management _basics.pdf. [Accessed: July 17, 2010].

[2] C. Bianco, "How Vision Works," 01 April 2000, HowStuffWorks.com. http://health.howstuffworks.com/human-body/systems/eye/eye.htm. [Accessed: July 20, 2010].

[3] H. Kolb, "How the Retina Works," *American Scientist*, vol. 91, pp. 28-35, 2003.

[4] J. O. Smith III, *Introduction to Digital Filters with Audio Applications*, Stanford, California, September 2007.

[5] R. Gonzalez and R. Woods, *Digital Image Processing,* Addition-Wesley Publishing Company, 1992, pp. 167-168.

[6] N. Bonnier and E.P. Simoncelli, "Locally Adaptive Multiscale Contrast Optimization," *Proc. 12th IEEE International Conference on Image Processing*, vol. 1, pp 949-952, 2005.

[7] S. M. Pizer and E. P. Amburn, "Adaptive histogram equalization and its variations," *SPIE Proceedings*, vol. 1092, pp. 290-300, 1989.

[8] B. Funt, F. Ciurea, and J. McCann, "Retinex in Matlab," *Proc. CIC'8 8th Color Imaging Conference*, Scottsdale, Arizona, pp. 112-121, 2000.

[9] E. Land and J. McCann, "Lightness and Retinex Theory," *Journal of the Optical Society of America*, vol. 61, pp. 1-11, 1971.

[10] Z. Rahman, D. Jobson, and G. Woodell, "Multiscale Retinex for Color Image Enhancement," *Proceedings of the IEEE International Conference on Image Processing*, Lausanne, Switzerland, vol.3, pp. 1003-1006, 1996.

[11] Z. Rahman, D. Jobson, and G. Woodell, "Multiscale Retinex for Color Rendition and Dynamic Range Compression," *Applications of Digital Image Processing XIX*, Denver, Colorado, pp. 9-17, 1996.

[12] Z. Rahman, D. Jobson, and G. Woodell, "Multiscale Retinex for Bridging the Gap between Color Images and Human Observations of the Scene," *IEEE Transactions on Image Processing: Special Issue on Color Processing*, vol.6, pp. 965-976, 1997.

[13] Z. Rahman, G. Woodell, and D. Jobson, "A Comparison of the Multiscale Retinex with Other Enhancement Techniques," *Proceeding of the IS&T 50th Anniversary Conference*, pp. 426-431, IS&T, 1997.

[14] Z. Rahman, G. Woodell, and D. Jobson, "Retinex Processing for Automatic Image Enhancement," *Journal of Electronic Imaging*, vol. 13, no.1, pp. 100-110, 2004.

[15] Z. Rahman, "Lecture Notes," *ECE 883: Digital Image Processing*, Old Dominion University, Spring 2010.

[16] L. Tao and K.V. Asari, "An integrated neighborhood dependent approach for nonlinear enhancement of color images," *Proceedings of the IEEE Computer Society International Conference on Information Technology: Coding and Computing – ITCC 2004*, vol. 2, pp.138-139, April 2004.

[17] L. Tao and K. V. Asari, "An Adaptive and Integrated Neighborhood Dependent Approach for Nonlinear Enhancement of Color Images," *SPIE Journal of Electronic Imaging*, vol. 14, no. 4, pp. 1.4 -1.14, 2005.

[18] L. Tao, R. C. Tompkins, and K. V. Asari, "An illuminance-reflectance model for nonlinear enhancement of video stream for homeland security applications," *IEEE International Workshop on Applied Imagery and Pattern Recognition, AIPR - 2005*, Washington DC, October 19 - 21, 2005.

[19] K.V. Asari, E. Oguslu, and S. Arigela, "Nonlinear enhancement of extremely high contrast images for visibility improvement," *Lecture Notes in Computer Science, Proc. of the 5th Indian Conference on Computer Vision, Graphics and Image Processing - ICVGIP 2006*: (ISBN: 3-540-29643-3), vol.4338/2006, pp.240-251, October 2006.

[20] S. Arigela and K. V. Asari, "A Locally Tuned Nonlinear Technique for Color Image Enhancement," *WSEAS Transactions on Signal Processing*, vol. 4, pp. 514-519, 2008.

[21] S. H. Park and E. D. Montag, "Evaluating Tone Mapping Algorithms for Rendering Non-Pictorial(Scientific) High-Dynamic-Range Images", *ACM Transactions on Applied Perception*, Vol. V, No. N, pp. 1-22, 20YY.

[22] J. Tumblin and H.E. Rushmeier, "Tone reproduction for realistic images," *IEEE Computer Graphics & Applications*, vol.13 (6), pp. 42-48, November 1993.

[23] S.S. Stevens and J.C. Stevens, "Brightness function: parametric effects of adaptation and contrast," *Journal of the Optical Society of America*, vol.50, no.11, pp.1139A, 1960.

[24] G.W. Larson, "Logluv encoding for full-gamut, high dynamic range images," *Journal of Graphics Tools*, vol.3, no.1, pp. 15-31, 1998.

[25] G.W. Larson, H. Rushmeier, and C. Piatko, "A visibility matching tone reproduction operator for high dynamic range scenes," *IEEE Transactions on Visualization and Computer Graphics,* vol.3 (4), pp. 291-306, 1997.

[26] K. Chiu, M. Herf, P. Shirley, S. Swamy, C. Wang, and K. Zimmerman, "Spatially nonuniform scaling functions for high contrast images," *Graphics Interface*, pp. 245-255, May 1993.

[27] P. Ledda, L.P. Santos, and A. Chalmers, "A local model of eye adaptation for high dynamic range images," *Proceedings of the 3rd International Conference on Computer Graphics, Virtual Reality, Visualisation,* AFRIGRAPH 2004, ACM Press, pp.151-160, November 2004.

[28] C. Schlick, "Quantization techniques for visualization of high dynamic range pictures," 5^{th} *Eurographics Workshop on Rendering*, Springer-Verlag, pp. 7-20, June 1994.

[29] S.N. Pattanaik and J.A. Ferwarda, M.D. Fairchild, and D.P. Greenberg, "A multiscale model of adaptation and spatial vision for realistic image display," *Proc. of SIGGRAPH 98, Computer Graphics Proceedings,* pp. 287-298, July 1998.

[30] J. Tumblin and G. Turk, "LCIS: A boundary hierarchy for detail-preserving contrast reduction," *SIGGRAPH 99 Conference Proceedings, Compute Graphics Annual Series*, pp. 83-90, 1999.

[31] B. K. P. Horn, "Determining lightness from an image," *Computer Graphics and Image Processing*, vol. 3, pp. 277-299, 1974.

[32] E. Land. "An alternative techniques for the computation of the designator in the retinex theory of color vision," *Proceedings of the National Academy of Sciences*, vol. 83, pp. 3078-3080, 1986.

[33] Moore, J. Allman, and R.M. Goodman, "A real-time neural system for color constancy," *IEEE Transactions on Neural Networks,* vol.2, pp. 237-247, March 1991.

[34] Moore, G. Fox, J. Allman, and R.M. Goodman, "A VLSI neural network for color constancy," *Advances in Neural Information Processing*, vol.3, pp. 370-376, 1991.

[35] A. Hulbert, "Formal connections between lightness algorithms," *Journal of the Optical Society of America A*, vol.3, pp. 1684-1692, 1986.

[36] D.J. Jobson and G.A. Woodell, "Properties of a center/surround Retinex, Part 2: Surround design," *NASA Tech. Memo*, 110188, 1995.

[37] G. Valensi, "Color Television System," US Patent 3,534,153. Oct 1970.

[38] D. J. Jobson, Z. Rahman, G. Woodell, "Statistics of Visual Representation," *SPIE Proceedings*, vol. 4736, pp. 25-35, 2002.

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