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Low light image Enhancement

Under the supervision of
Abdessattar Ghemougui

Composition of the jury

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Mr.Chatra Mohammed	University of M'sila	Examiner

Dedication

We dedicate this work to our parents, without whom we are not worth anything, may God bless them and all the virtuous family of Saadi We also dedicate this work to everyone who stood with us throughout the academic journey. To everyone who encouraged us to continue, To all our friends and relatives

Acknowledgments

First and foremost, we thank ALLAH, the Almighty, for giving us the bravery and patience to do this small task; may it be blessed and honored. We also like to express our gratitude to Ghemougui abdessettar for agreeing to be our supervisor. We also appreciate his suggestions, revisions, and counsel. We'd also like to offer our heartfelt gratitude to the members of the jury. Thanks

abstract

Images taken in low light suffer from poor visibility and noise. A low-light image enhancing strategy based on Retinex and histogram equalization is presented in this study. Retinex employs two algorithms: single scale Retinex (SSR) and Multi Scale Retinex (MSR), both of which are based on experimental data and has no a unived mathematical model. Brightness preserving bi-histogram equalization (BBHE) and dualistic sub-image histogram equalization are two algorithms for histogram equalization (DSIHE). Finally, we used Retinex-based algorithms since they boost contrast while also improving visibility.

Keywords :

Image enhancement, Retinax, histogram equalization .

Résumé

Les images prises en basse lumière souffrent d'une mauvaise visibilité et de bruit. Une stratégie d'amélioration d'image à faible luminosité basée sur Retinex et l'égalisation d'histogramme est présentée dans cette étude. Retinex utilise deux algorithmes : le Retinex à échelle unique (SSR) et le Retinex multi-échelles (MSR), qui sont tous deux basés sur des données expérimentales et n'ont pas de modèle mathématique unique. L'égalisation de bi-histogramme préservant la luminosité (BBHE) et l'égalisation d'histogramme de sous-image dualiste sont deux algorithmes d'égalisation d'histogramme (DSIHE). Enfin, nous avons utilisé des algorithmes basés sur Retinex car ils augmentent le contraste tout en améliorant la visibilité.

Mots clés :

Amélioration de l'image, Retinax, égalisation de l'histogramme

الصور الملتقطة في الإضاءة المنخفضة تعاني من ضعف الرؤية والضوضاء. تم تقديم إستراتيجية تحسين الصورة في الإضاءة المنخفضة بناءً على غتنش ومعادلة الرسم البياني في هذه الدراسة. تستخدم غتنش خوارزميتين: غتنش (صصغ) و بلت صحًل غتنش (بصغ) ، وكلاهما يعتمد على البيانات التجريبية وليس لهما نموذج رياضي موحد. السطوع الذي يحافظ على معادلة الرسم البياني الثنائي (ـحي) ومعادلة الرسم البياني للصورة الفرعية المزدوجة هما خوارزميتان لمعادلة الرسم البياني (ضصيحي). أخيرًا ، استخدمنا خوارزميات قائمة على غتنش لأنها تعزز التباين مع تحسين الرؤية أيضًا.

الكلمات المفتاحية:

الكلمات المفتاحية: تحسين الصورة ، غتنش ، معادلة الرسم البياني

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General Introduction

Low-light image enhancement is one of the most difficult challenges in computer vision, and it is currently being explored and applied to a variety of issues. Under normal lighting circumstances, image processing achieves substantial performance most of the time.The reflectance image of the target surface can be obtained by comparing one pixel to its neighboring pixels. The "gray world" assumption was used to analyse the images. In low-light situations, however, an image becomes chaotic and black, making future computer vision tasks challenging. A lot of studies have been carried out to investigate the augmentation of contrast and lightness in color images in various methods, with some of these in suggesting an algorithm to improve the brightness, contrast, and sharpness of an image. It performs a non-linear spatial/spectral transition that compresses the dynamic range at the same time. In this research, At first we talked about 7 ways that can improve image quality, then we relied on two methods Histogram Equalization (HE) and Retinex These two algorithms are two more advanced picture improvement algorithms . In Retinex, we relied on two algorithms ,single scale Retinex (SSR) and Multi Scale Retinex (MSR) , As for the histogram equalization , we relied on Brightness preserving bi-histogram equalization (BBHE) ,dualistic sub-image histogram equalization (DSIHE) . finally , we combined the two equations and chose the best equation capable of image processing and color stability .

Chapter 1

Introduction to image processing and computer vision

1.1 introduction

Computer vision has been used in a variety of engineering fields as a result of advancements in computer technology and camera sensors, such as object detection in autonomous vehicles[1]and harvesting robots [2], detection and monitoring in civil engineering [3,4], video surveillance [5,6], 3D reconstruction [7], and so on. Because visual duties are so crucial in so many industries, dependable work performance is necessary. The tasks, however, rely on scene illumination, and any camera-sensor-based perception task's performance suffers greatly under bad lighting situations, such as low-light scenarios [7]. When a camera cannot get enough light or the camera sensor is not sensitive enough in low-light situations, the collected pictures may have issues such as poor visualization and bad image quality, disrupting the image's valid information and restricting its usage in computer vision tasks [8]. As we all know, low-light photos acquired in a non-uniform lighting situation suffer from significant object information loss, making object recognition more difficult [9]. Although the camera's night mode can occasionally prevent this deterioration, a minor tremor might cause additional issues such as blurring. In other cases, improving the lighting of the scene or replacing the camera sensor is not possible [10].

1.2 Computer vision

1.2.1 Definitions

There are many definitions of a computer vision according to many authors:

definition 1

is the study of extracting information and knowledge from photos and films using image and video analysis. We work with genuine photographs the majority of the time (Street with cars). Comprehending video and images is the ultimate aim; understanding entails categorizing distinct aspects of a picture and following them as they move.[11]

definition 2

is a branch of artificial intelligence (AI) that allows computers and systems to extract useful information from digital photos, videos, and other visual inputs, as well as conduct actions or make suggestions based on that data.[11]

definition 3

is the study of how computers see and comprehend digital pictures and movies. Computer vision encompasses all functions carried out by biological vision systems, such as "seeing" or perceiving a visual stimuli, comprehending what is seen, and extracting complicated information into a format that can be utilized in other processes.[12]

1.2.2 Applications of computer vision

The success of computer vision applications has been enormous, and some of the most noteworthy use cases are included here :

Defect Inspection

industrial hase benefited from image recognition. Image recognition has traditionally been used to identify damaged objects throughout the production process. The capacity to check thousands of problematic products on the production line dramatically speeds up the whole process and improves operational efficiency [13]

Image Classification

Picture categorization is perhaps the most important aspect of image recognition that has been studied in a variety of ways. Several studies in recent years have looked into the prospect of aiding doctors in locating a region of interest for diagnosing and forecasting a certain disease. In the e-commerce industry, image categorization has been a key contribution to improving the customer experience by providing rapid search options. Image classification allows you to categorize photographs based on their content. It is included in the majority of today's recommendation systems and image retrieval engines.[13]

Robotics

Many robotics-based projects have utilized image recognition to train them to recognize items for improved navigation and detect anything that may be encountered in their route.[13]

e-Commerce

Shoppers may now submit photographs of existing items or things they want to discover complimentary styles to in order to identify similar products. This necessitates the conversion of the image into a visual embedding, with the suggestions consisting of goods that are either identical to the one that was uploaded or those that are recognized to be complimentary.[13]

1.3 Image processing basics

1.3.1 Definitions of Image

definition 1

is a binary representation of visual data such as drawings, photographs, graphs, logos, or single video frames. Digital photos can be stored on any type of storage medium.[14]

definition 2

is a visual artifact that resembles a topic and hence gives a representation of it, such as a photograph or other two-dimensional picture. An image is a color distribution with a dispersed amplitude in signal processing (s).[15]

1.3.2 types of images

Real images

An image is the projection onto a plane of a 3D scene. mathimathicly, it can be viewd as a function of two variables . I (x, y) The location of a point in space on the projection plane is (x, y). The intensity (or brightness) at the coordinate point (x,y)is the value of I(x, y). An picture is a real-world analog plane with real-world intensities.

Digital images

is made up of single-colored dots called pixels that are arranged in a mosaic. The more pixels it has, the more well defined it is. When you enlarge pixels a picture on the screen, you don't modify the number of dots; instead, you make them bigger or smaller and therefore visible.[16] One is a two-dimensional descent function, f (x, y), with x and y being the spatial (plane) coordinates for each pixel. [17]

1.3.3 Image file formats

types of image formats

A quick summary of the most common file formats is given in the list below
:

- **TIFF image format**

  TIFF or Tagged Image File Format are lossless picture files, which means they don't have to compress or lose any image quality or information (though compression options are available), allowing for extremely high-quality photos but bigger file sizes.[18]

  BMP image format

  BMP or Bitmap Image File is a Windows format created by Microsoft. BMP files contain no compression or information loss, allowing for images of extremely high quality but also very large file sizes. TIFF files are often preferred over BMP files since BMP is a proprietary format.[18]

  JPEG image format

  JPEG stands for Joint Photographic Experts Groups is a "lossy" format, which means it compresses the picture to generate a smaller file. There is a quality reduction as a result of compression, although it is usually not visible. JPEG files are widely used on the Internet, and JPEG is a popular digital camera format, making it excellent for web usage and non-professional printing.[18]

  GIF image format

  GIF or Graphics Interchange Format file because they are limited to just 256 colors, they can allow for transparency, and they may be animated, they are commonly used for online graphics. GIF files are often tiny and easy to transport.[18]

PNG image format

PNG or Portable Network Graphics files are a proprietary image format that was created to replace and improve on the gif format. Unlike GIF, which only supports 256 colors, PNG files can hold up to 16 million colors.[18]

1.3.4 Pixel

is the smallest unit of a digital picture or graphic that may be represented and shown on a digital display device. In computer graphics, a pixel is the most fundamental logical unit. Pixels are used to create a complete picture, video, text, or any other visible object on a computer screen. [19] The pixel size, i.e. the grid's thinness, determines the resolution in comparison to the original analog picture. The lower the resolution, the fewer pixels there are in the image, and the worse the quality of the digital image. [20]

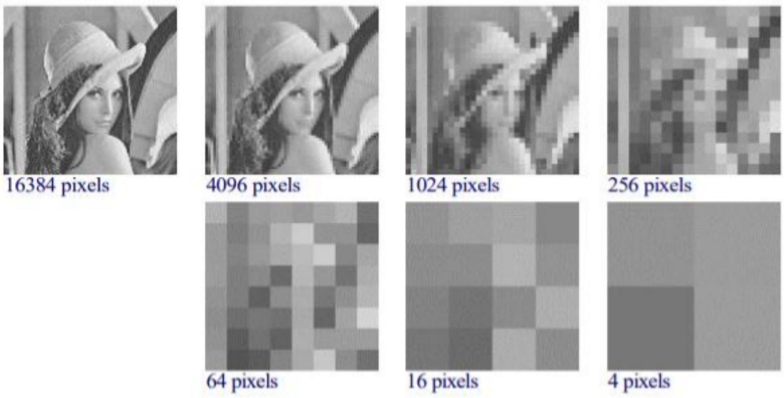


Figure 1.1: variation in the number of pixels. In fact, when viewing the screen, the size is divided by 4 at each step. [20]

1.3.5 Matrix Size

the width and height in pixels of a digital image; commonly described in terms of the image's width and height. The matrix size also determines the picture aspect ratio for an image with square pixels.[21]

1.3.6 Spatial Resolution

a metric for how much spatial detail there is in a digital image. Resolution is measured in pixels per centimeter or dots per inch, and is expressed as a ratio of physical to sampled dimensions. Whether the application is for acquisition or output determines the physical size.

1.3.7 Color Space

The mechanism for representing color is called color space or color specification system. A single intensity gradient is frequently used in greyscale or monochrome pictures. Color pictures, on the other hand, frequently encode color in numerous channels and combine them to represent a single color. Red-Green-Blue (RGB) and Cyan-Magenta-Yellow-Black (CMYK) are two common examples .[21]

1.3.8 Bit Depth

Color resolution, also known as bit or color depth, is a measurement of the amount of color detail in a digital image. The amount of computer storage units (bits) needed to describe the color of each particular pixel in a picture is referred to as bit depth. For RGB color pictures (8 bits per channel), the most common values are 24 bits per pixel (bpp) and 8 bits per pixel (bpp) for greyscale images. Medical greyscale photographs frequently surpass 8 bits per pixel, with 10 bits per pixel and 12 bits per pixel being the most prevalent.[21]

1.4 Image Processing

image processing is the use of a digital computer to run an algorithm on digital images. [21,22] Digital image processing, provides a number of benefits over analog image processing :

- Any format of the digital image can be made available (improved image, X-Ray, photo negative, etc)

- It aids in the enhancement of pictures for human understanding.
- Images may be analyzed and information retrieved for machine interpretation.
- The density and contrast of the pixels in the image may be adjusted to any desired level.
- Images can be simply stored and accessed.

1.4.1 Components of the Image Processing System

Different computer algorithms are used to conduct image processing on digital images in digital image processing. [23] It is made up of the following elements:

Image Sensors

The intensity, amplitude, co-ordinates, and other properties of the pictures are sensed by image sensors, which then transfer the information to the image processing hardware.

Image Processing Hardware

Is the specialised hardware that processes the commands received from the image sensors. The result is sent to a general-purpose computer.

Computer

The image processing system's computer is a general-purpose computer that we all utilize on a regular basis.

Image Processing Software

Is the software that contains all of the image processing system's methods and algorithms.

Mass Storage device

During processing, the pixels of the photos are stored in mass storage device.

Image Display

It includes the monitor or display screen on which the processed pictures are shown.

Network

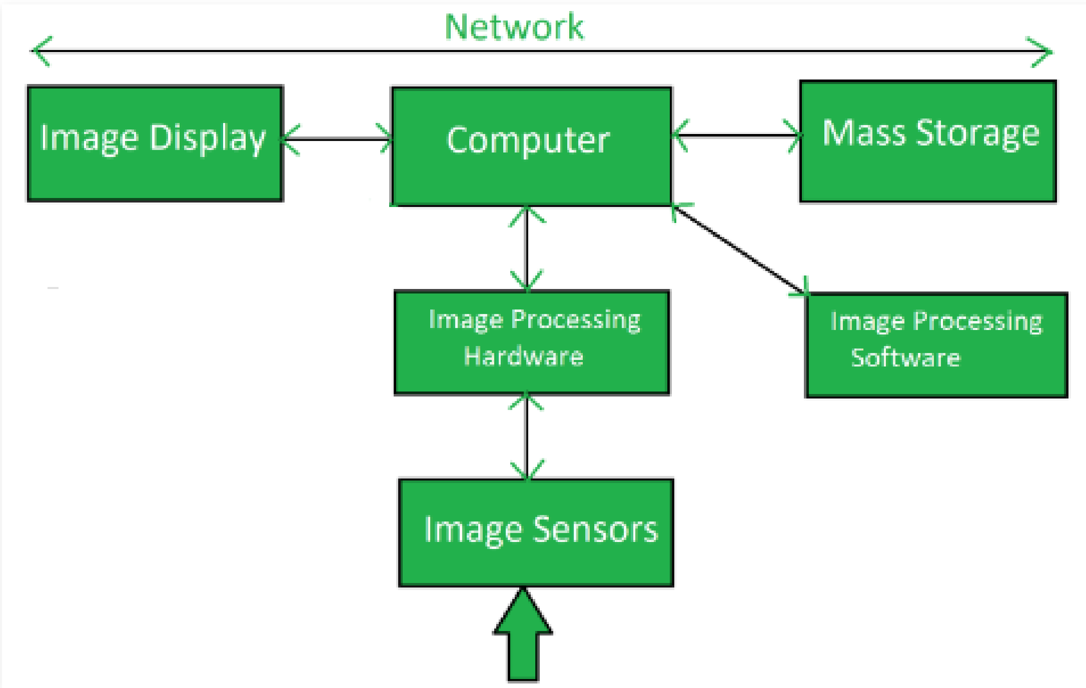


Figure 1.2: Components of Image Processing System [23]

is the link between all of the image processing system's above pieces.

1.4.2 Image processing tasks

- description
- Visualization Look for items that aren't visible in the photo.
- Recognition Identify or locate things in the image.
- Sharpening and restoration From the original photograph, create an upgraded image.
- Pattern recognition Calculate the different patterns that surround the things in the picture.
- Retrieval Browse and find photos comparable to the original image from a big library of digital images.

1.4.3 Image processing stages

Acquisition

It may be anything as basic as being handed a digital image. The major task entails:

1. Sizing up
2. Color transformation (RGB to Gray or vice-versa)

Image enhancement

It is one of the most basic and attractive image processing techniques. It is also used to extract certain hidden information from a picture and is subjective.

Image restoration

It similarly deals with visual appeal, but it is objective (Restoration is based on mathematical or probabilistic model or image degradation).

Color image processing

It is applied to digital image processing and works with pseudocolor and full color image processing color models.

Wavelets and multi-resolution processing

It is the foundation for varying degrees of visual representation.

Image compression

It entails creating certain functions to carry out this task. It mostly concerns picture size or resolution.

Morphological processing

It is concerned with picture component extraction technologies that are useful in the representation and description of form.

Segmentation

It entails breaking down a picture into its component elements or objects. The most demanding problem in Image Processing is autonomous segmentation.

Representation and description

It is based on the segmentation stage's output; selecting a representation is only one part of the solution for converting raw data into processed data.

Object detection and recognition

It's a method of giving an object a label depending on its description.[23]

1.4.4 Examples of image processing

Enhancement : improve the quality of the visual impression of a picture that we have.

Restoration : compensate for the loss of quality (noise, blurring, etc.).

Compression : Effortlessly store and transmit data.

Segmentation : Separate the "objects".

3D reconstruction : Obtain a volume from a set of plans (images).

Analysis : transform images into information .

Recognition / Understanding : Determine the content of an image. [24]

1.5 coclusion

In this chapter we introduced some of the basic concepts of computer vision and image processing. Computer vision as a field of a wide range of discipline has been closely linked to the discipline of image processing, The

Image processing, itself has brought benefits in different areas of technology especially to analyze images to obtain the necessary information and improve it.

Chapter 2

State-of-the-art of low-light image enhancement

2.1 Introduction

This chapter reviews the main techniques of low-light image enhancement . First, we present a classification of these algorithms, dividing them into seven categories: gray transformation methods, histogram equalization methods, Retinex methods, frequency-domain methods, image fusion methods, defogging model methods and machine learning methods. Then, all the categories of methods, including subcategories, are introduced in accordance with their principles and characteristics.

2.2 Classification of low-light image enhancement algorithms

Many image improvement methods for photos acquired in low-illumination settings have been proposed by scholars all over the world to improve low-light films and photographs from various angles [25,26,27]. We have seven kinds of processing techniques based on the algorithms used for brightness enhancement: gray transformation methods, histogram equalization (HE) methods, Retinex methods, frequency-domain methods, image fusion methods, defogging model methods, and machine learning approaches. According to the variations in their principles, these techniques can be further separated into subclasses. Figure 2.1 shows the total classification.

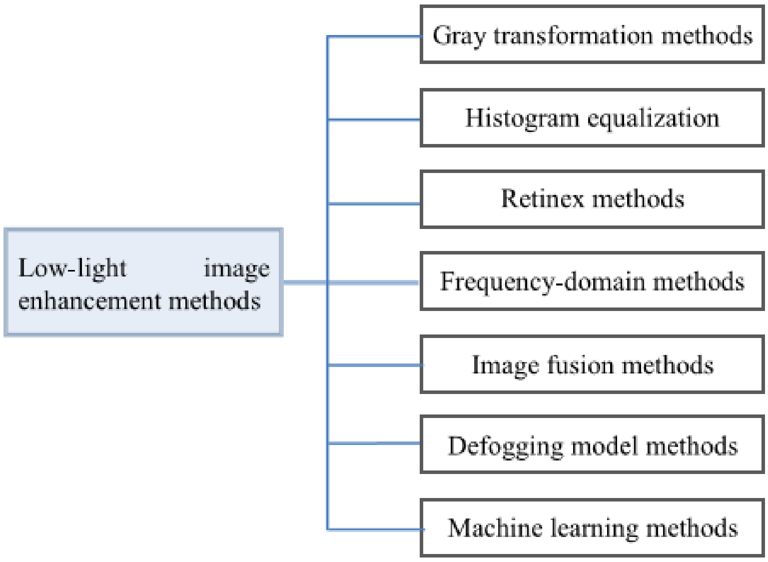


Figure 2.1: Classification of low-light image enhancement algorithms.

2.2.1 Gray transformation methods

A gray transformation technique, also known as a mapping-based approach, is a spatial-domain picture enhancement procedure based on the notion of changing the gray values of single pixels into other gray values using a mathematical function [28]. This approach improves a picture by changing the gray value distribution and dynamic range of the pixels [25,27] Linear and nonlinear transformations are the two primary subcategories of this class of methodes.

Linear gray transformations

A linear transformation of gray values is a linear function of the gray values of the input image [25], commonly known as linear stretching, it's givn by the following formula :

$$g(x, y) = C.f(x, y) + R \tag{2.1}$$

where $f(x, y)$ and $g(x, y)$ are the input and output images, respectively, while C and R are the linear transformation coefficients. The values of the coefficients in the following formula can be adjusted to enhance a picture to various degrees. Figure 2.2 depicts the relevant transformation curve (a).

$$g(x, y) = \frac{f(x, y) - f_{\min}}{f_{\max} - f_{\min}} (g_{\max} - g_{\min}) + g_{\min} \tag{2.2}$$

where $f\,\max$ and $f\,\min$ are the input image's maximum and minimum gray values, respectively, and $g\,\max$ and $g\,\min$ are the output image's maximum and minimum gray values, respectively [27]. To improve the brightness and contrast, the image's dynamic range is changed from $[f\,\min, f\,\max]$ to $[g\,\min, g\,\max]$. Only the gray values in a specific section of the image may need to be stretched at times.

Colored polylines in the coordinate system corresponding to the transformation represent the various functions in the piecewise formula. Figure 2.2 shows an example of a piecewise linear transformation curve (b).

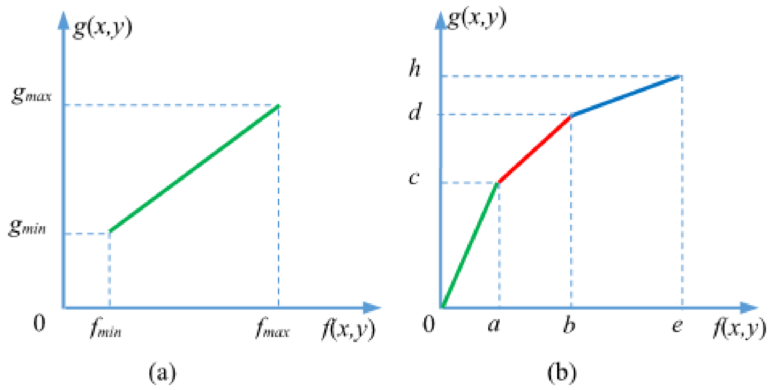


Figure 2.2: Linear transformation curves.

The piecewise linear transformation approach lacks an adaptive mechanism since parameter tuning can only be done based on experience or with significant human involvement. Although the theory of linear image enhancement is easy and quick to implement, the result is unsatisfactory, as certain picture features are often lost owing to unequal image enhancement.[29]

NonLinear gray transformations

The main idea behind a nonlinear gray transformation is to alter an image's gray values using a nonlinear function [30]. Logarithmic functions, gamma functions, and several other enhanced functions are often used nonlinear transformation functions .[31,32] A logarithmic transformation function indicates that the value of each pixel in the output picture is proportional to the value of the corresponding pixel in the input image. Because it may lengthen the picture's lower gray values while compressing the dynamic range of the pixels with higher gray values, this sort of modification is appropriate for an extremely dark image [33]. The following is a common formula:

$$g(x, y) = log(1 + cf(x, y)) \tag{2.3}$$

where $f(x, y)$ and $g(x, y)$ are the input and output pictures and$c$ is a control parameter.

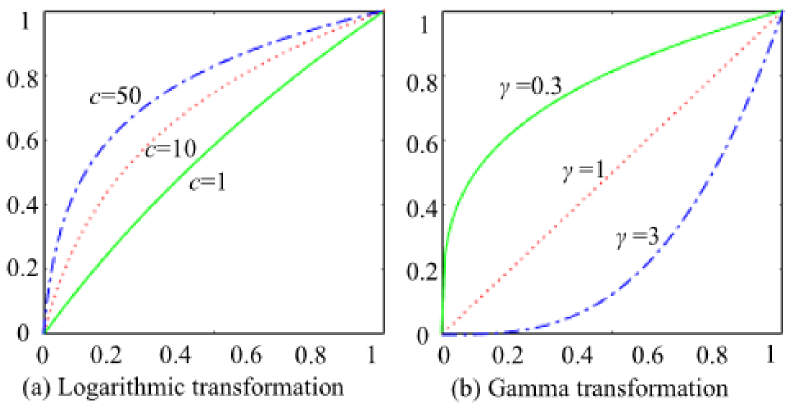


Figure 2.3: Nonlinear transformation curves.

Figure 2.3 depicts the forms of many logarithmic transformation functions (a). The gray values of pixels in low-gray-value areas are stretched, while the values of pixels in high-gray-value areas are compressed, using a logarithmic transformation function.

The gamma function is a nonlinear transformation having a wide range of applications, and its formula is:

Figure 2.4: (a)original image, (b)results of Gray transformation methods

$$g(x, y) = f(x, y)^{\gamma} \tag{2.4}$$

The gamma correction parameter, which is normally a constant, is denoted by Fig 2.3 depicts many gamma transformation curves (b).

By altering the parameter γ, as illustrated in Fig. 2.3(b), numerous distinct transformation curves may be generated. When $\gamma > 1$, the transformation will lengthen the low-gray-value parts of the image's dynamic range while compressing the high-gray-value areas. When γ <1, on the other hand, the transformation compresses low gray values while stretching high gray values. When $\gamma = 1$, the output is unchanged [34]. As a result, by altering this parameter, distinct gray portions of a picture may be selectively stretched or compressed for a greater enhancing effect.

Gray transformation may be used to emphasize gray regions of interest and has the advantages of being easy to use and quick. However, because such approaches do not take into account an image's general gray distribution, their enhancing potential is restricted, and their flexibility is weak.

Exemple

2.2.2 Histogram Equalization (HE) Methods

When an image's pixel values are uniformly spread throughout all potential gray levels, it has a strong contrast and a wide dynamic range. Based on this property, the HE algorithm adjusts the output gray levels to have a probability density function that corresponds to a uniform distribution, allowing hidden information in dark areas to reemerge and the visual impression of the input picture to be successfully improved [35,36].

Principale of HE

The CDF is utilized as the transformation curve for the picture gray values in the HE method [37]–[41]. Let's use the letters I and L to represent a picture and its gray levels, respectively. N represents the total number of pixels in the picture, and nk indicates the number of pixels of gray level k. $I(i,j)$ represents the gray value at the coordinates (i,j), N represents the total number of pixels in the image, and nk represents the number of pixels of gray level After that, picture I's gray-level probability density function is defined as

$$p(k) = \frac{n_k}{N}, (k = 1, 2, 3, ..., L - 1) \tag{2.5}$$

The CDF of the gray levels of image I is

$$c(k) = \sum_{r=0}^{k} p(r), \quad k = 0, 1, 2, \ldots, L - 1 \tag{2.6}$$

The conventional HE technique uses the CDF to convert the original image to an improved image with a nearly uniform gray-level distribution. The following is the mapping relationship:

$$f(k) = (L - 1)c(k) \tag{2.7}$$

In Fig.2.4, (a) the input low-light picture is displayed, (b) the histogram of the input low-light image is displayed, (c) the improved image after HE is displayed, and (d) the histogram of the enhanced image is displayed. The typical HE method has a basic premise that can be implemented in real time. However, owing to gray-level merging, the brightness of the improved image will be uneven, and some features may be lost.

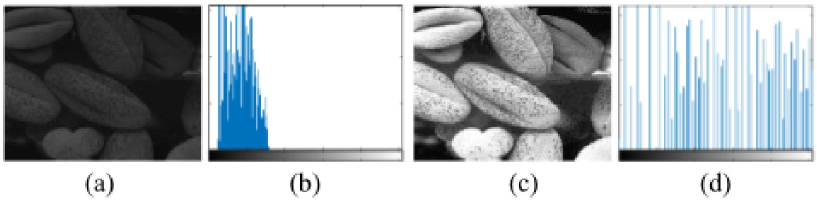


Figure 2.5: Example of HE on a grayscale image.

Basic models of HE methodes

HE approaches are classified as global histogram equalization (GHE) or local histogram equalization (LHE) based on the regions included in the computation [42].

- global histogram equalization (GHE) : The model shown in Fig. 2.5 illustrates the general concept of a GHE algorithm, in which X represents the original image,Y represents the enhanced image generated by theHE algorithm, $Y = f(X)$ represents the traditional HE process or an improved version, and $X1, X2, X3, ..., Xn$represent n sub images composed of pixels in the original image that satisfy certain conditions according to a given property, which is defined as $Q.(x)$. The picture Y after equalization is created by merging the sub images in accordance with the pixel coordinates, and the parameter x denotes the magnitude of the image gray value. $Y1, Y2, Y3, ..., Yn$ signify the equalized images corresponding to the n sub images.

  The GHE model has several advantages, such as relatively few calculations and high efficiency, and it is especially suitable for the enhancement of overall darker or brighter images [44]. However, it is difficult for a global algorithm, which conducts statistica loperations based on the gray values of the whole image, to obtain the optimal recovered values for each local region. Such an algorithm is unable to adapt to the local brightness characteristics of the input image, and consequently, the sense of depth in the image will be decreased after processing.

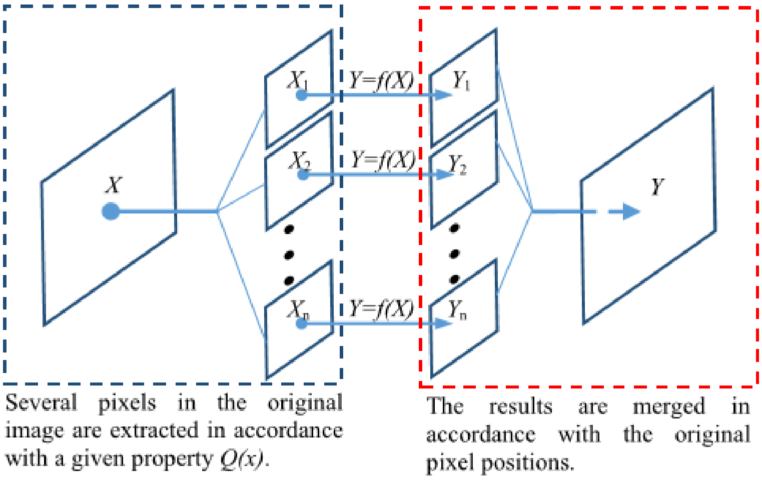


Figure 2.6: Basic model of GHE algorithms.

- local histogram equalization (LHE) : The primary concept behind LHE is to apply the HE operation to numerous local areas in the form of a picture. The original picture is broken into several sub blocks, and equalization is applied to each sub block independently to adaptively improve the image's local information to produce the desired enhancement result. As illustrated in Fig. 2.6, LHE methods may be further separated into three approaches: LHE with nonoverlapping subblocks, LHE with overlapping subblocks, and LHE with partially overlapping subblocks. The following is the procedure for implementing these algorithms.

  1. A subblock with dimensions of MN is defined in the upper left corner of an input picture of a particular size, MN, and other subblocks are defined by advancing along the horizontal and vertical axes with step sizes of h and w, respectively.
  2. Each subblock is subjected to HE processing in the same way as a GHE algorithm is. The findings are then combined with the output image, and the total number of subblock processing rounds for each pixel is kept track of.
  3. Moving horizontally with the horizontal step size h and vertically with the vertical step size w defines the following subblocks. Phase

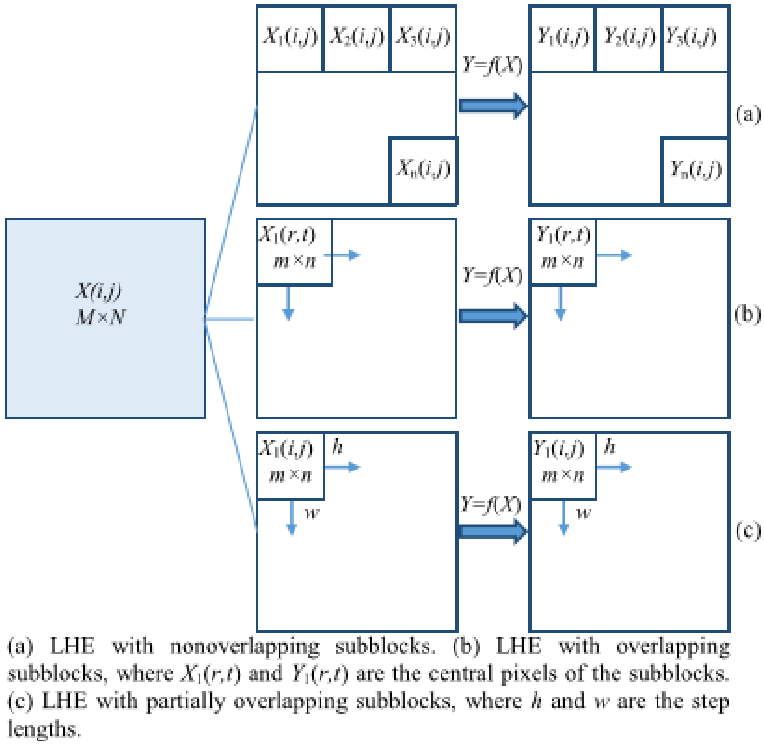


Figure 2.7: Basic model of LHE algorithms.

(2) is repeated for each subblock that does not exceed the picture border; if no such unprocessed subblocks remain, the procedure moves on to the next step.

4. Divide the gray value of each pixel in the output picture by the corresponding cumulative number of subblock processing rounds to get the output image. The local block effects and the enormous number of computations are also downsides of this technique.

HE Alghorithms

Many algorithms have been proposed created using the traditional HE method. For example :

- Kim [44] developed the equal-area dualistic subimage histogram equalization (DSIHE) technique [45],
- while Wang et al [44]. proposed the brightness-preserving bi-histogram equalization (BBHE) approach to retain image brightness [46].To max-

imize the image's entropy value, this approach utilizes the original image's median gray value as a threshold to divide it into two pieces of equal size.

Similarly, Tian et al. [47] suggested a :

- BBHE method that maintains color information. As explained in [48,49], this technique not only keeps the color information of the input image but also enhances the visual features. [50]
- The HE approaches outlined above, on the other hand, frequently fail to successfully reduce the potentially severe interference of noise in poorly lighted pictures; in fact, they may significantly exacerbate such noise.

Interpolation-based HE techniques, in which linear interpolation methods are employed to derive the transformation function for the current pixels, have been developed by researchers.

The AMHE [99], BBHE [46], CLAHE [51], DSIHE [45], HE [37], RMSHE [50], RSIHE [52], and WHE [53] algorithms are examined in both the RGB and HSI color spaces to demonstrate the performance of HE techniques on color photographs. Figures 2.7-2.9 show test image and its HE processing results.

- If the final image is obtained by simply equalizing and merging the three R, G, and B subimages after equalization, equalization and merging of the three R, G, and B subimages is observed. The fundamental reason for this is that the typical HE algorithm brightens the image too much. If one of the three R, G, and B subimages of a color picture has a mean brightness that is too dark or too bright, the mean brightness of that subimage after equalization will be close to the component's median gray value. As a result, following enhancement, the color associated with this subimage will be either enhanced or diminished, resulting in visible color distortion and inconsistencies in the final color image.

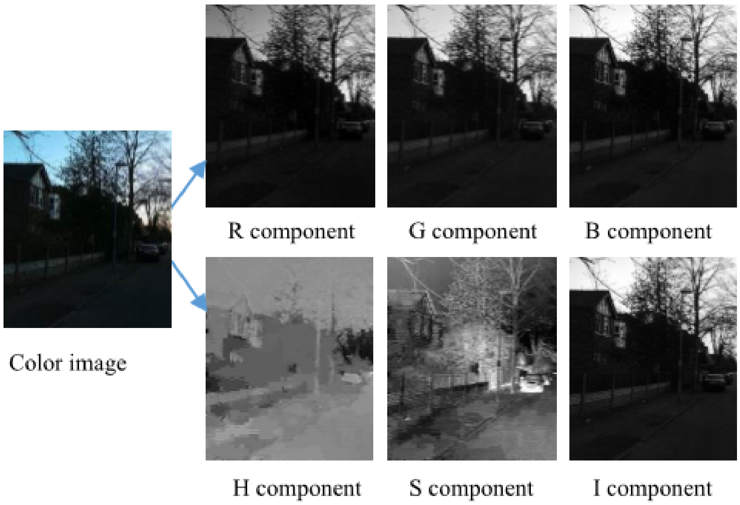


Figure 2.8: Image decomposition (into RGB and HSV subimages).

- Only the brightness component is equalized in the HSI model. The input color image is first transformed from RGB to HSI color space, and then HE enhancement is applied to the brightness component I in this approach. Finally, the RGB space is applied to the color picture. The number of equalizations is decreased from three to one in this method. However, certain computations are still required for the color space transition, and there is still a risk of over-enhancing images.

HE algorithms can improve low-light photos and are frequently used in conjunction with other techniques. The contrast and detail enhancement given by a HE algorithm can increase the visual impression of such a picture. However, these techniques can easily result in color fidelity loss and noise creation, resulting in picture distortion.

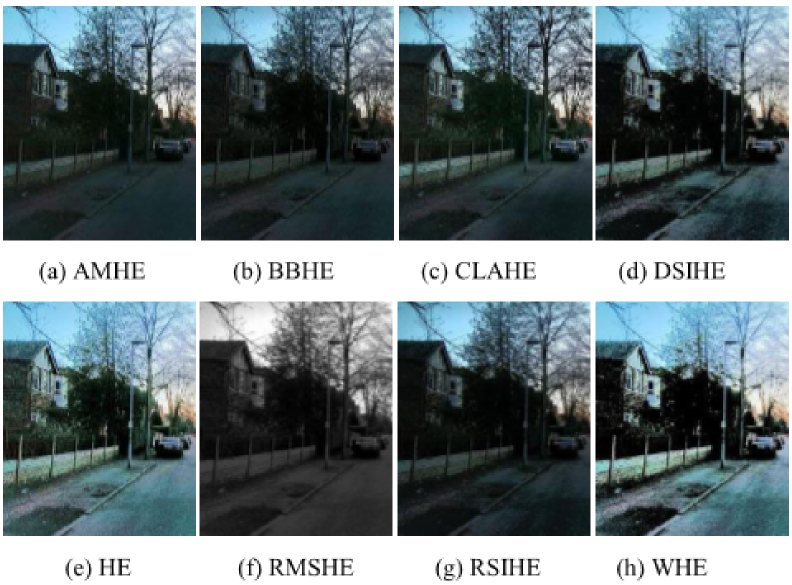
2.2.3 Retinex methods

The Retinex hypothesis, also known as the retinal cortex theory, was developed by Land and McCann [54]and is based on human color perception and color invariance modeling [54]. The goal of this theory is to determine an object's reflective nature by eliminating the illuminating light's effects from the picture. According to Retinex theory, during the transmission

(a) AMHE (b) BBHE (c) CLAHE (d) DSIHE

(e) HE (f) RMSHE (g) RSIHE (h) WHE

Figure 2.9: Image enhancement using RGB model .



(a) AMHE (b) BBHE (c) CLAHE (d) DSIHE

(e) HE (f) RMSHE (g) RSIHE (h) WHE

Figure 2.10: Image enhancement using HSI model.

of visual information, the human visual system processes information in a certain way, eliminating a number of unknown elements such as light intensity and unevenness. As a result, only the information that reflects the object's key features, such as the reflection coefficient, is kept [55]–[59]. An image may be described as the product of a reflection component and an illumination component [60] using the illumination-reflection model (as illustrated in Fig.2.10):

$$I(x, y) = R(x, y)L(x, y) \tag{2.8}$$

where R(x,y) is the reflection component, which reflects the object surface's reflective properties; $L(x, y)$ is the illumination component, which is dependent on the ambient light characteristics; and $I(x, y)$ is the perceived image.

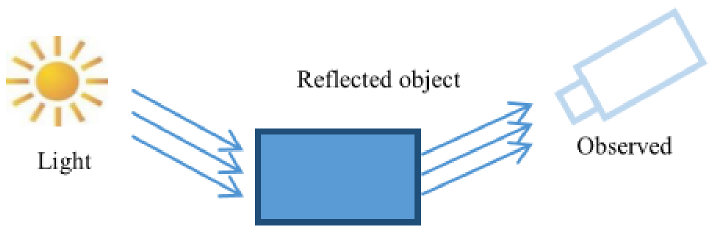


Figure 2.11: Light reflection model.

The dynamic range of the picture is determined by L(x,y), whereas the intrinsic character of the image is determined by R(x,y). If L(x,y) can be calculated from I(x,y), the reflection component may be isolated from the overall quantity of light, and the illumination component's influence on the picture can be minimized to improve the image [60].

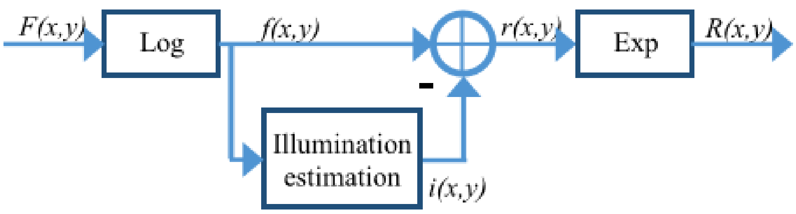


Figure 2.12: General process of the Retinex algorithm.

Sharpening, color stability, huge dynamic range compression, and good color fidelity are all aspects of the Retinex algorithm. The Retinex algorithm's overall process is depicted in Figure 2.11 , where Log signifies a logarithmic operation and Exp denotes an exponential operation.

Some algorithms suggested by researchers :

Single-Scale Retinex (SSR)

The SSR method produces a reflection picture by evaluating ambient brightness. The following is the formula:

$$logR_i(x,j) = logI_i(x,y) - log[G(x,y) * I_{i(x,y)}] \tag{2.9}$$

where $I(x,y)$ represents the input image, $R(x,y)$ represents the reflection image, i represents the various color channels, (x,y) represents the position of a pixel in the image, $G(x,y)$ represents the Gaussian surround function, and represents the convolution operator.

The Gaussian surround function's formula is :

$$G(x,y) = k \exp^{-\frac{x^2+y^2}{\sigma^2}} \tag{2.10}$$

where $\sigma$is the scaling factor. The smaller this parameter's value, the greater the image's dynamic range compression and the clearer the local values. K is a normalizing factor that ensures the Gaussian function meets the requirements.

$$\int\int G(x,y)dxdy = 1 \tag{2.11}$$

However, the SSR algorithm has some limitations. It is difficult to maintain a balance between detailed information enhancement and color fidelity in image sprocessed with this algorithm due to the use of a single scale parameter.

Multiscale Retinex (MSR)

Jobson, Rahman, and colleagues [61] modified the single-scale technique to a multiscale approach, the MSR algorithm [61], to maintain a balance between dynamic range compression and color constancy:

$$MSR = \log R_i(x,y) = \sum_{N}^{k=1} \omega_k \left\{ \log I_i(x,y) - \log \left[G_k(x,y)^* I_i(x,y) \right] \right\} \tag{2.12}$$

$$\sum_{k=1}^{N} \omega_k = 1 \tag{2.13}$$

where I stands for the three color channels, k for the Gaussian surround scales, $N$for the number of scales, and the parameters for the scale weights. The MSR method, as opposed to the SSR algorithm, may take advantage of the advantages of numerous scales. The MSR algorithm improves picture details and contrast while also producing upgraded photos with increased color consistenxe and aesthetic effect.

Multiscale Retinex with color resroration (MSRCR)

During the process of image enhancement, the SSR or MSR algorithm is applied separately to the three color channels, R, G and B. Therefore, compared with the original image, the relative proportions of the three color channels may change after enhancement, thus resulting in color distortion. To overcome this problem, MSRCR has been proposed. This algorithm includes a color recovery factor C for each channel, which is calculated based on the proportional relationship among the three color channels in the input image and is then used to correct the color of the output image to eliminate color distortion.

The color recovery factor is calculated as follows:

$$C_i(x,y) = f\left(\frac{I_i(x,y)}{\sum_{i=1}^{3} I_i(x,y)}\right) \tag{2.14}$$

where $C(x,y)$ is the color recovery factor and f is the mapping function. Jobson et al. discovered that when the mapping function is a logarithmic function, the best color recovery result is obtained.

$$C_i(x, y) = \beta \times \log \left(\alpha \times \frac{I_i(x, y)}{\sum_i^3 I_i(x, y)} \right) \tag{2.15}$$

The convolution operation with Gaussian functions is used in the method. At large, medium, and small scales, dynamic range compression and color constancy are accomplished, resulting in a visually perfect appearance. Figure 2.12 depicts experimental results produced using the SSR, MSR, and MSRCR algorithms.

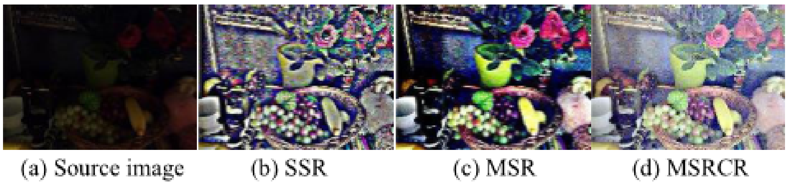


Figure 2.13: Enhancement with different Retinex algorithms.

2.2.4 Frequency-domain methods

Image enhancement methods have been extended from the spatial domain to the frequency domain as a result of the development of multiscale image analysis technology [62]. Picture enhancement methods that use the frequency domain convert an image into the frequency domain for filtering using Fourier analysis, and then inversely transform the final image back into the spatial domain. Homomorphic filtering (HF) and wavelet transform (WT) are two common frequency-domain approaches.

Homomorphic filtering (HF)

The properties of the illumination-reflection model are used in HF-based enhancement approaches to turn the illumination and reflection components into a sum in the logarithmic domain rather than a product [29].

The following are the specific steps in the HF process :

1. The illumination component is multiplied by the reflection component in the illumination-reflection model, which cannot be converted into

the frequency domain. As a result, the logarithmic transformation needs be used to convert these multiplicative components into additive components before they may be treated independently. Taking the logarithm of both sides of equation (2.16) gives us:

$$lnI(x,y) = lnL(x,y) + lnR(x,y) \tag{2.16}$$

2. The Fourier transform is used to transform the picture from the spatial domain to the frequency domain, i.e. the Fourier transform is applied to both sides of the given equation :

$$F[lnI(x,y)] = F[lnL(x,y) + lnR(x,y)] \tag{2.17}$$

3. A suitable high-pass filter is chosen for contrast enhancement, and the transfer function H enhances the $R(u,v)$ component in the frequency domain (u,v). The following is the resultant expression:

$$S(u,v) = H(u,v)I(u,v) = H(u,v)L(u,v) + H(u,v)R(u,v) \tag{2.18}$$

4. The image is transformed from the frequency domain to the spatial domain using the inverse Fourier transform. Let $s(u,v)$ indicate the inverse Fourier transform corresponding to $S(u,v)$; then equation (2.16)'s inverse Fourier transform is

$$s(u,v) = F^{-1}(H(u,v)L(u,v)) + F^{-1}(H(u,v)R(u,v)) = h_L(x,y) + h_R(u,v) \tag{2.19}$$

5. The inverse logarithmic transform $G(x,y) = exp[s(x,y)]$ is applied to 2.19 to obtain the final corrected image. Thus, by taking the exponent of both sides of equation, the image after frequency-domain

correctionis obtained as follows:

$$G(x, y) = exp|h_L(x, y)|exp|h_R(x, y)| \tag{2.20}$$

The primary goal of the HF technique is to reduce the dynamic range and improve contrast by designing an appropriate filter H(u,v) based on the image properties defined by the illumination component and the reflection component. This filter is then combined with a frequency filter and a gray transformation. The general form of a homomorphic filter is as follows:

$$H(u, v) = (\gamma_H - \gamma_L)H_{hp}(u, v) + \gamma_L \tag{2.21}$$

where γ_L 1 and γ_H 1; these parameters are used to regulate the filter's amplitude's range. H_{hp} is typically a high-pass filter, such as a Laplacian, Butterworth, or Gaussian high-pass filter. If Hhp is a Gaussian filter, then :

$$H_{hp} = 1 - \exp[-c * (D^2(u, v)/D_0^2)] \tag{2.22}$$

where c is a constant that controls the form of the filter.

According to Fig.2.13, the slope gets steeper the higher the value of the gradient separating low frequency from high frequency.

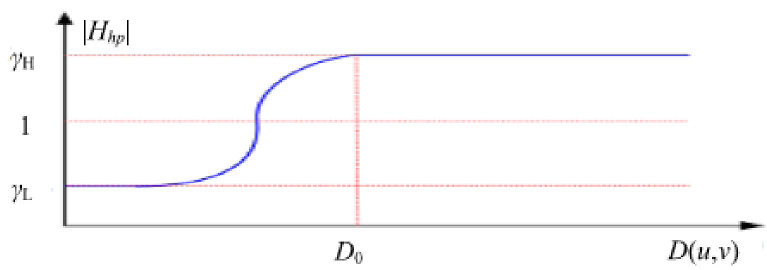


Figure 2.14: Amplitude-frequency curve of a homomorphic filter.

Figure 2.14 depicts the HF method's particular algorithm flow. Log represents the logarithmic transform, FFT represents the fast Fourier transform, H(u,v) represents the frequency filtering function, IFFT represents the inverse FFT, and Exp represents the exponential operation in this diagram.

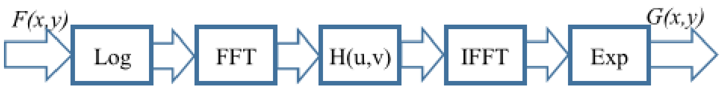


Figure 2.15: Flowchart of the HF process.

Wavelet transform

The WT is a mathematical transform that represents or approximates a signal using a combination of functions termed a wavelet function basis[63].

The WT may be used to describe the local properties of signals in the time and frequency domains, as well as to undertake a multiscale analysis of functions or signals using scaling and translating procedures. WT techniques have so made significant progress in image contrast enhancement.

The following is the fundamental procedure for WT-based picture enhancement.

$$WT_x(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^* \left(\frac{t-\tau}{a}\right) dt \quad (a > 0) \tag{2.23}$$

The displacement τ is processed for the function ψ(t) representing the fundamental wavelet (parent wavelet); subsequently, the inner product between the processed ψ(t) and the signal x(t) to be studied at various scales yields a wavelet sequence :

$$WT_x(a,\tau) = \frac{\sqrt{a}}{2\pi} \int_{-\infty}^{+\infty} X(\omega)\psi^*(a\omega)e^{j\omega\tau} d\omega \tag{2.24}$$

The steps of WT-based image enhancement are as follows [163], [164] :

1. The source image is used.
2. Wavelet decomposition is used to extract the low- and high-frequency components of the source image.
3. With a functional relationship that satisfies, the wavelet coefficients are nonlinearly increased.

4. To obtain the reconstructed improved picture, the enhanced wavelet coefficients are inversely converted.

Figure 2.15 depicts the basic flow of the WT-based picture enhancing technique.

Figure 2.16: Flowchart of WT-based image enhancement.

2.2.5 Methods based on image fusion

Methods based on picture fusion techniques [64] are another area of research in low-light image improvement.

Many photos of the same scene are collected with separate sensors in these approaches, or additional images of the same sensor are obtained using different imaging methods or at different times. Finally, as much valuable information as possible is retrieved from each image in order to synthesize a high-quality image, increasing the image information's usage rate. The synthesized picture can reflect multilayer information from the source photographs to fully characterize the scene, allowing available image information to better fulfill the needs of both human observers and computer vision systems.

Multispectral image fusion

By fusing a visible picture with an infrared image, multispectral image fusion improves the process of acquiring the details of a low-light imaged scene. Because near-infrared (NIR) light has a longer wavelength and greater penetrating capabilities than visible light, it may be used to filter out redundant information from an infrared picture. Additionally, a low-light viewable picture can give rich background information, allowing image fusion to produce superior images [65]–[67].

Some algorithms proposed by researchers :

1. Toet et al. introduced a pseudocolor fusion technique for infrared and visible pictures [68], which improves image clarity while preserving the unique information recorded by different sensors. Furthermore, [69].

2. Night vision context enhancement (FNCE) [70] is a fusion framework suggested by Zhu et al. for night vision applications, in which the fused output is achieved by integrating deconstructed pictures using three separate principles.

Image fusion based on background highlighting

In general, backdrop highlighting image fusion approaches rely on the integration of low-light photographs with daytime images to increase image details, hence boosting the visual impression of the low-light images [71].

The following is a description of the overall procedure.

To begin, an image is captured during the day under reasonable lighting circumstances to serve as the background for the fused image.

The backdrop of this image is then deleted, and another photograph is taken in the same spot under low illumination. The foreground of the fused picture is made up of the remainder of the latter image.

Finally, an appropriate algorithm is used to combine the backdrop and foreground into a single image.

Fusion based on multiple exposures

The technique of integrating many photographs of the same scene into a single high-quality image with more information than any single input image is known as image fusion.

Low-light photos can be significantly enhanced by combining many photographs taken from the same scene. Because high-quality picture data from the same scene is required, these approaches have severe image acquisition criteria; in particular, the camera equipment must be reliable. This technology cannot be used for real-time image or video enhancement since it requires a significant shooting time. Furthermore, for photographs with a low overall brightness, the enhancing impact is minimal.

Fusion based on a singal image

The primary principle behind image fusion approaches is that meaningful information about the same target acquired from numerous sources may be combined using image processing and computer technology to produce a final high-quality image without the usage of a physical model.

These fusion-based approaches are straightforward and effective. However, they necessitate two or more different photos of the same scene; as a result, it is difficult to achieve image enhancement in a short period of time, as is required in real-time monitoring scenarios, and these approaches are difficult to use and popularize in reality.

2.2.6 Methods based on defogging models

Algorithms based on defogging models provide high performance while requiring little computing effort. Their physical interpretation, on the other hand, is a little shaky, and they're still prone to over-enhancement in several particular areas. Inverted low-light photographs have their own set of features, and applying defogging algorithms directly to them is still not the best way to improve them.

2.2.7 Methods based on machine learning

Deep-learning-based approaches can generate good results in low-light image improvement, and they're also a hot topic in image processing research . However, such approaches require big datasets, and increasing the complexity of a model increases the time complexity of the related algorithm dramatically. With the steady growth of low-light image enhancement research, not only is some low-light data available from widely used public benchmark datasets like PASCAL VOC [72], ImageNet [73], and Microsoft COCO [283], but researchers are also creating public datasets specifically designed for low-light image processing, such as SID [74] and EDD (Exclusively Dark Dataset) [75].

2.3 conclusion

This chapter outlines and analyzes the basic principles of seven frequently used classes of low-light image enhancement techniques, as well as their upgraded versions. Low-light image enhancement's main goal is to improve image contrast both globally and locally in a certain region of gray space, in accordance with the gray value distribution of the original image pixels. Simultaneously, guarantee that the improved image has good image quality in terms of human visual perception features, noise suppression, image entropy maximization, brightness maintenance, and so on.

Chapter 3

Implementation of low light image enhancement methods

3.1 Introduction

In this chapter we present the implementation of some state-of-the-art low light image enhancement methods, Namely we focus on the Retinex and histogram equalization algorithms.

3.2 Retinex methods

In this method it is assumed that the input image $I(x, y)$ is regarded as the product $I(x, y) = R(x, y)L(x, y)$ where $R(x, y)$ is the reflectance and $L(x, y)$ is the illumination at each pixel (x, y).

3.2.1 single scale Retinex (SSR)

we input the image to enhance it, then we Follow us following steps :

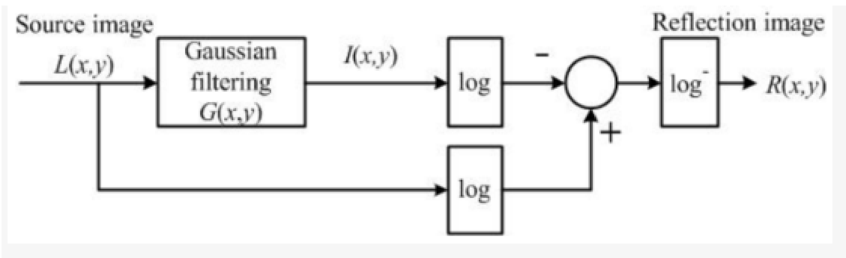


Figure 3.1: Schematic diagram of a single-scale Retinex (SSR) algorithm.

- step 1 :We chose that the Gaussian function because can effectively estimate the illumination image from the source image as Figure 3.1.As may be seen in formula :

$$G(x, y) = k \exp^{-\frac{x^2+y^2}{\sigma^2}} \tag{3.1}$$

- step 2 :the transformation of a picture into the logarithmic domain As may be seen in formula :

$$logS = logR + logL \tag{3.2}$$

- step 3 : The logarithm of the reflectance is derived by subtracting the logarithm of the illumination from the logarithm of the picture. As may be seen in formula :

$$logR = logS - logL \tag{3.3}$$

- step 4 : The reflectance may then be calculated using the index form, as illustrated in formula :

$$R = exp(logS - logL) \tag{3.4}$$

3.2.2 Multi Scale Retinex (MSR) :

The multi scale retinex (MSR) algorithm is a variant of the single scale retinex method . The MSR proficiency is represented by the functions listed below :

$$MSR = logR_i(x, y) \tag{3.5}$$

method of algorithm works :

for processing :

1. Utilizing spatial filters, two functions for multiscale(MSR) and single scale retinex algorithms (SSR) are created. If the source image is grayscale, each pixel's gray value is changed from an integer (int) to a

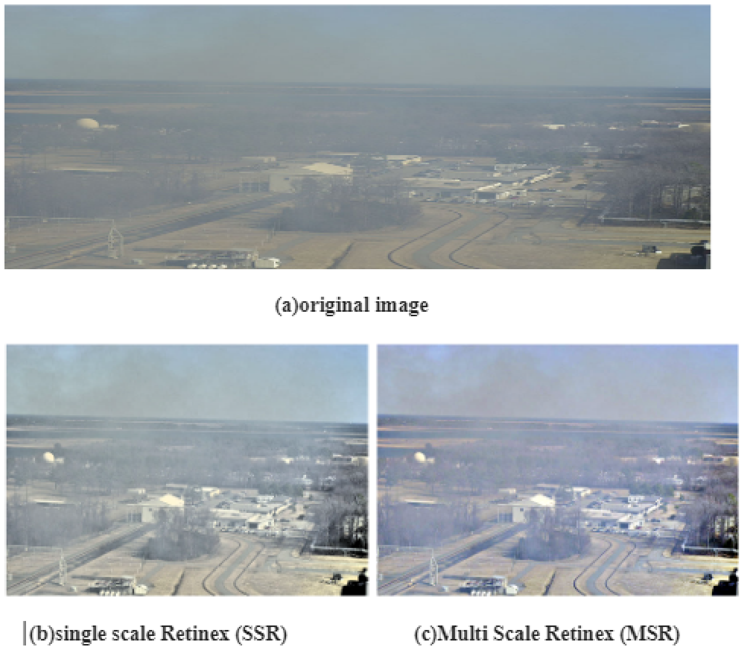


Figure 3.2: results of Retinex MSR and SSR algorithms

floating point (float) and then to a logarithmic domain. If the original image is a color map, each component pixel value is changed from an integer (int) to a floating point (float) and then to a logarithmic domain.

2. finally The image is displayed after the log domain has been translated to the real domain for additional image processing.

3.2.3 Results of Retinex methods

Figure 3.2 shows an image of both MSR and SSR algorithms enhancement results.

3.2.4 histogram equalization methods

Because of its high efficiency and simplicity, histogram equalization is a widely used contrast-enhancement technique in image processing. It is one of the more advanced methods for manipulating an image's dynamic range and contrast by changing the image's intensity histogram to the desired shape.

Exemple

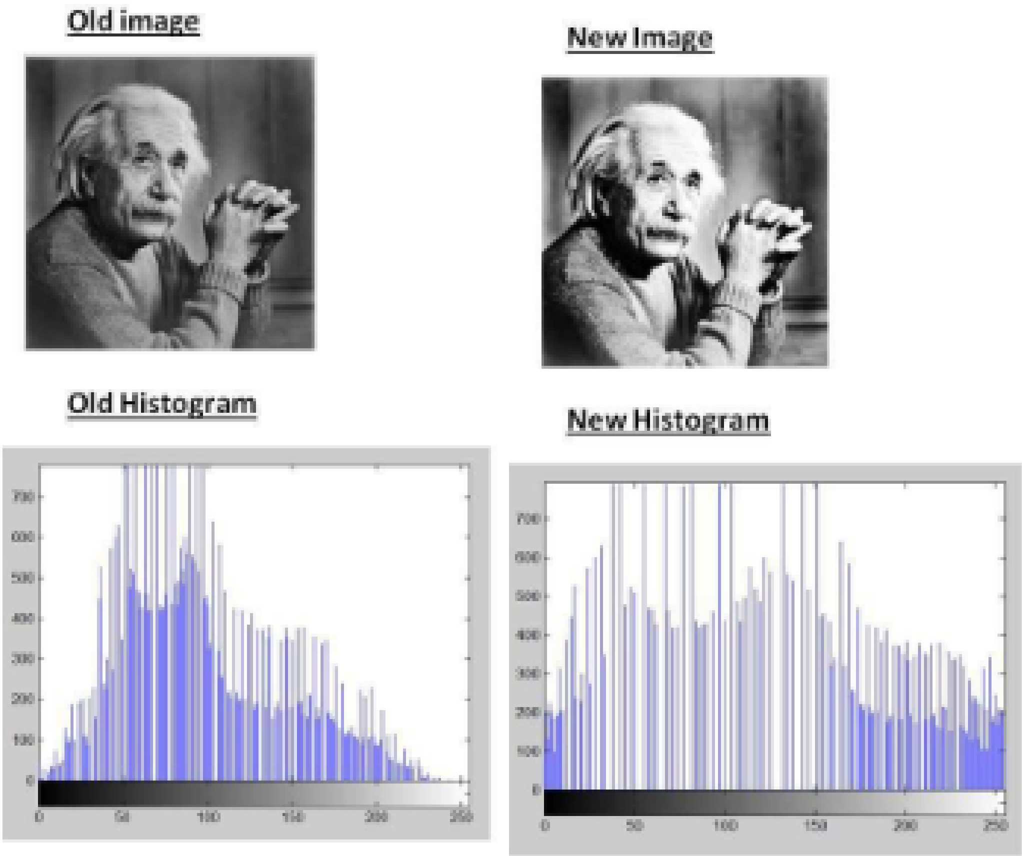


Figure 3.3: Example of the histogram equalization technique

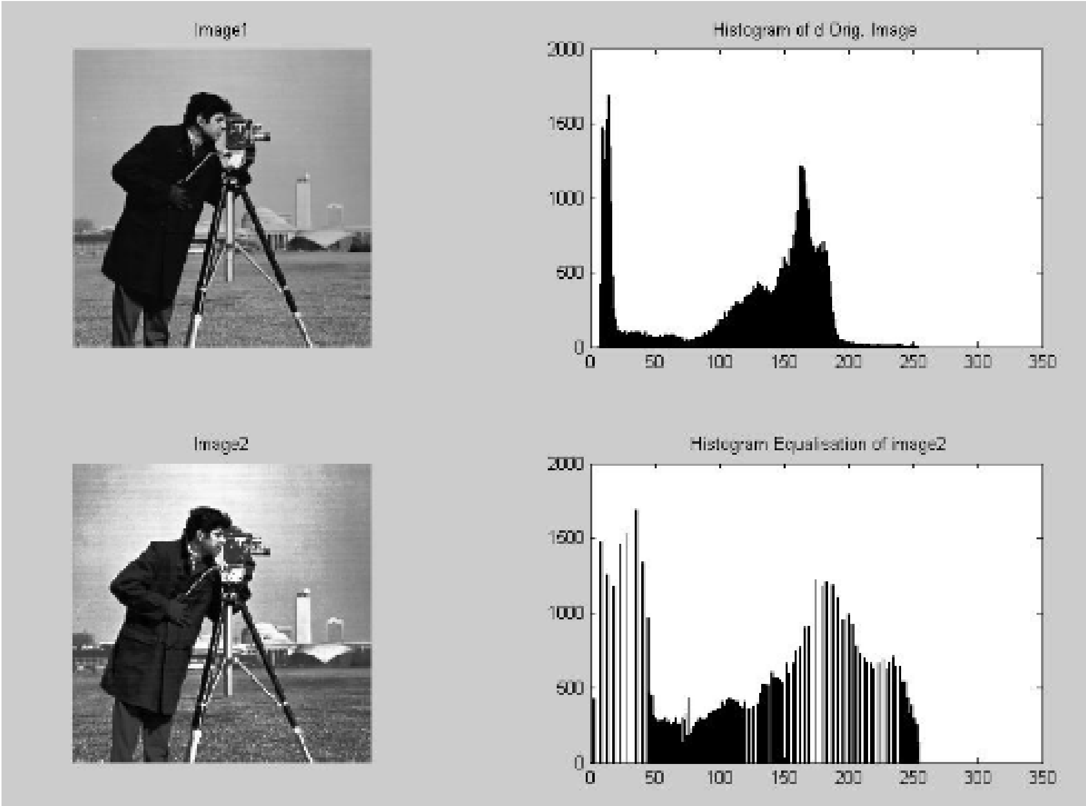


Figure 3.4: Exemple 2 of histogram equalization

Brightness preserving bi-histogram equalization (BBHE)

The BBHE divides an input image's histogram $H(X)$ into two sub-images based on the input image's mean. Using the input mean X_m, we can now deconstruct the input image X into two sub-images X_L and X_U,

$$X = X_L \cup X_U \tag{3.6}$$

Then, for the sub-images X_L and X_U, define their respective probability density functions as :

$$PL(X_K) = n_L^K / n_L where K = 0, 1, 2, \ldots\ldots .m \tag{3.7}$$

$$PU(X_K) = n_U^K / n_L where K = m + 1, \ldots\ldots ..L - 1 \tag{3.8}$$

Sub images are equalized independently using these transformation functions, and the result of BBHE is a composition of equalized sub images.

BBHE's output, Y, may now be expressed as :

$$Y = Y(i,j) = f_L(X_L) \cup f_U(X_U) \tag{3.9}$$

dualistic sub-image histogram equalization (DSIHE) :

RLBHE was proposed by Chao Zuo et al, and it is based on selecting a suitable threshold for histogram equalization and determining upper and lower bounds for the same [4]. The weighted sum of variances between the pixel classes is used to determine the best threshold for separating the two classes of pixels in an image :

$$\sigma^2(X_T) = W_L \Big(E(X_L - E(X))^2 + W_U (E(X_U) - E(X)) \tag{3.10}$$

The final image's mean brightness is essential, as it is not changed by the technique used. It is expressed as :

$$\approx E(X) = X_m = \sum_{j=0}^{L-1} X_j p(X_j) \tag{3.11}$$

3.2.5 Experimental results

We have processed many images to show the performance of different histogram equalization techniques discussed above. We have selected some standard images and apply HE, BBHE, DSIHE, methods to evaluate their performance. the performance is assessed on the basis of absolute mean brightness error (AMBE), peak signal to noise ratio (PSNR), and structure similarity index measure (SSIM).

- Absolute Mean Brightness Error (AMBE): The absolute mean brightness error (AMBE) is used to assess how well a processed image retains its brightness. AMBE is defined as :

$$(AMBE)(X,Y) = |X_M - Y_M| \tag{3.12}$$

Image	HE	BBHE	DSIHE
couple	96.88	32.07	40.97
einstein	20.67	17.23	9.98
f16	52.29	0.194	18/10
fighterplane	98.81	14.75	33.14
fruits	17.99	10.03	11.24
girl	6.70	22.60	12.89
house	10.13	3.300	14.28
lady	70.98	21.20	29.21
plene	37.09	1.463	23.75
tank	21.76	18.90	9.64
average	43.33	14.17	20.32

Table 3.1: For Mean Brightness Error (AMBE)

- Peak signal to noise ratio (PSNR) : Assume an input image X(i,j) with M*N pixels and a processed image Y for peak signal to noise ratio (PSNR) (i,j). We begin by calculating the Mean Squared Error (MSE) :

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}|X(i,j) - Y(i,j)|^2}{M \times N} \tag{3.13}$$

Now peak signal to noise ratio (PSNR) :

$$PSNR = 10 \log_{:0} \frac{(2-1)^2}{Msz} \tag{3.14}$$

Image	HE	BBHE	DSIHE
couple	7.56	13.43	12.14
einstein	15.05	15.22	16.06
f16	11.49	20.16	15.63
fighterplane	15.63	12.51	33.14
fruits	16.81	18.98	18.59
girl	13.31	13.60	14.41
house	17.70	17.83	17.46
lady	10.16	16.20	14.68
plene	10.97	13.32	11.66
tank	13.10	13.19	14.10
average	12.31	15.76	14.72

Table 3.2: For Peak Signal to Noise Ratio (PSNR)

- Structured Similarity index (SSI) : The structural similarity index is a tool for comparing two photographs' similarities. The SSIM index is a full reference metric, which means that it measures image quality using an uncompressed or distortion-free image as a starting point. The structural similarity index is defined as follows:

$$SSI(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{3.15}$$

Image	HE	BBHE	DSIHE
couple	0.29	0.68	0.61
einstein	0.68	0.67	0.68
f16	0.56	0.90	0.74
fighterplane	0.16	0.64	0.37
fruits	0.92	0.92	0.92
girl	0.30	0.38	0.35
house	0.57	0.62	0.59
lady	0.61	0.87	0.80
plene	0.34	0.48	0.37
tank	0.50	0.49	0.51
average	0.49	0.67	0.59

Table 3.3: For Structure Similarity Index (SSI)

- Entropy : The entropy is a useful tool for determining how rich the features in the output image are. is defined as follows:

$$Entropy[p] = -\sum_{k=0}^{1-1} p\left(X_k\right) \log_2 p\left(X_k\right) \tag{3.16}$$

Image	HE	BBHE	DSIHE
couple	6.42	6.25	6.19
einstein	6.89	6.75	6.75
f16	6.70	6.44	6.60
fighterplane	5.64	5.41	5.54
fruits	7.59	7.45	7.43
girl	5.59	5.28	5.28
house	6.50	6.26	6.25
lady	7.05	6.90	6.90
plene	4.00	3.88	3.93
tank	5.99	5.88	5.87
average	6.24	6.05	6.06

Table 3.4: For Entropy

this is some results and comparing booth the image and histograme :

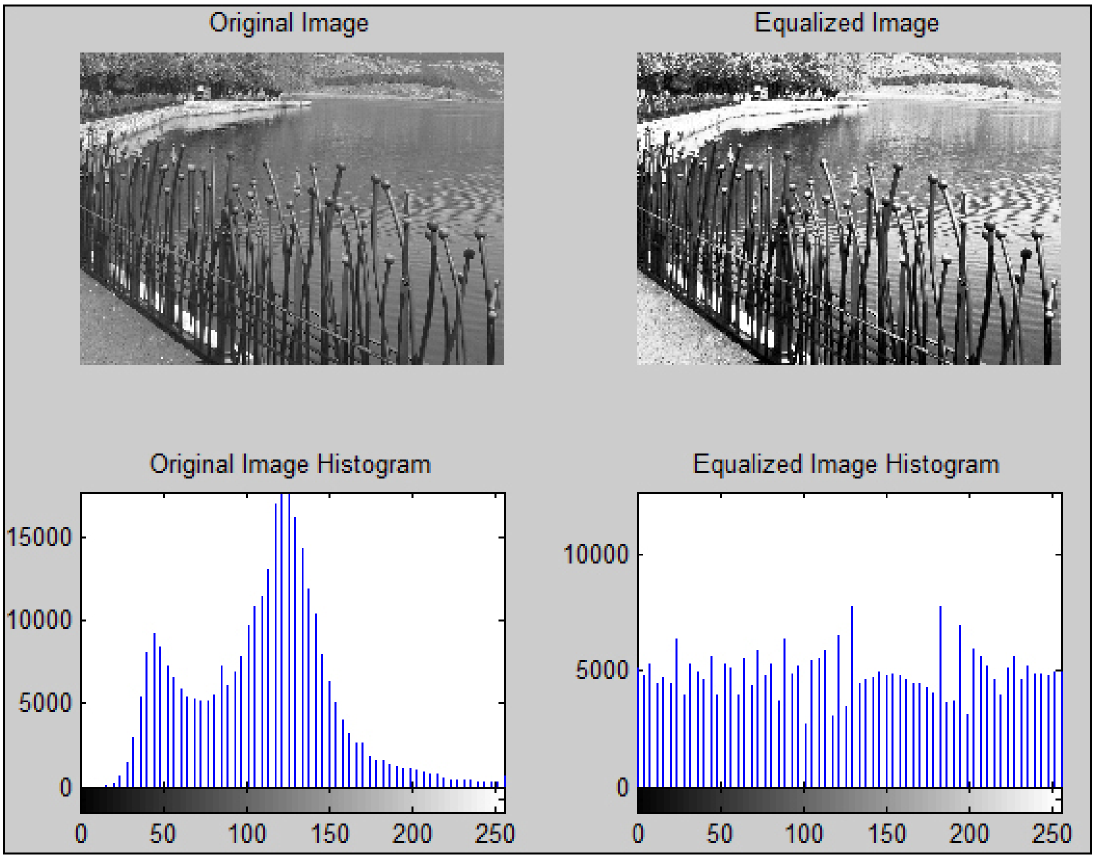
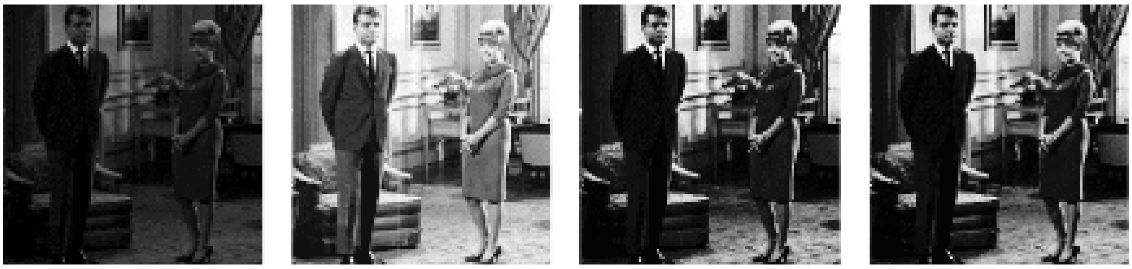


Figure 3.5: input and output of image using histogram equalization

we have tested images with the BBHE and DSIHE methods , in fg 3.6 and 3.7 shows the results of them

(a) Original Image (b) HE (c) BBHE (d) DSIHE

Figure 3.6: Results of methods tested on the image of ‘Einstein



(a) Original Image (b) HE (c) BBHE (d) DSIHE

Figure 3.7: Results of methods tested on the image of ‘Couple’.

3.3 implimentation and comparesion

The use of histogram equalization techniques and Retinex algorithm-based techniques for picture contrast enhancement has been completed, with sample image outputs presented in Figure 3.9/3.10/3.11.

The original photographs taken are shown in figure 3.9/3.10/3.11 (a). With respect to the algorithms used, the resulting photographs clearly exhibit the contrast increases. With the limitation of poorly visible features on photographs, the outputs of histogram equalization algorithms boost the contrast of the image. This is depicted in figure 3.9/3.10/3.11 images (b), (c), and (d).

Retinex-based algorithms, on the other hand, increase contrast with better visible characteristics. Figure 3.9/3.10/3.11's images (e) and (f) demonstrate the use of retinex algorithms.

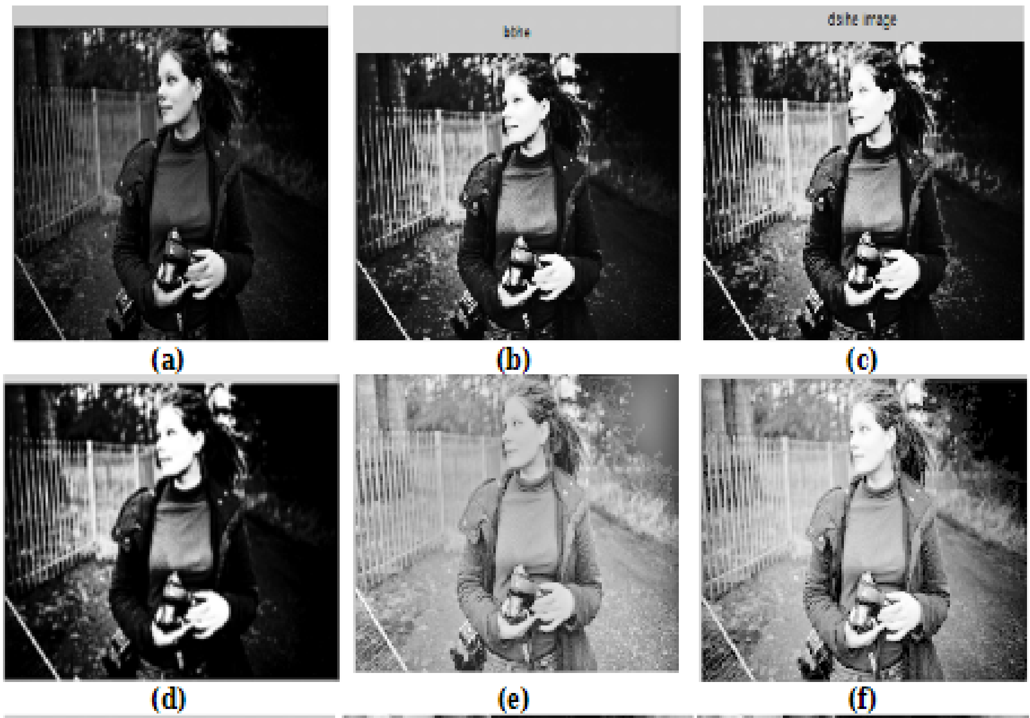


Figure 3.8: (a) Original Image (b) BBHE (c) DSIHE (d) SSR (e) MSR

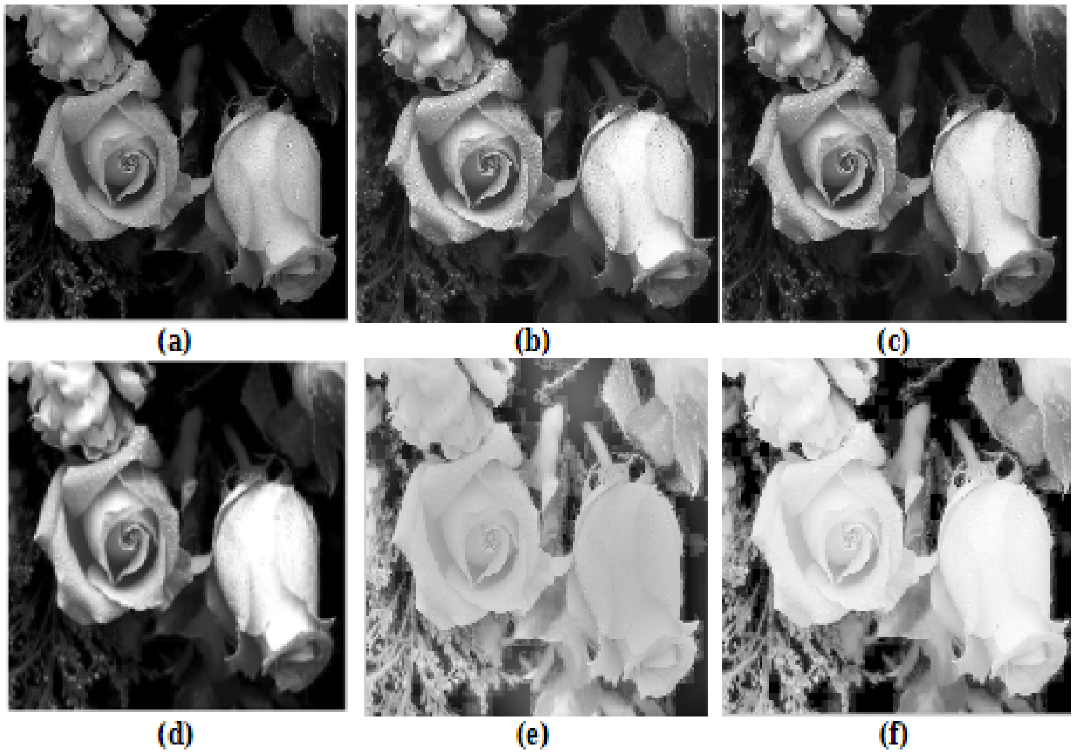


Figure 3.9: (a) Original Image (b) BBHE (c) DSIHE (d) SSR (e) MSR

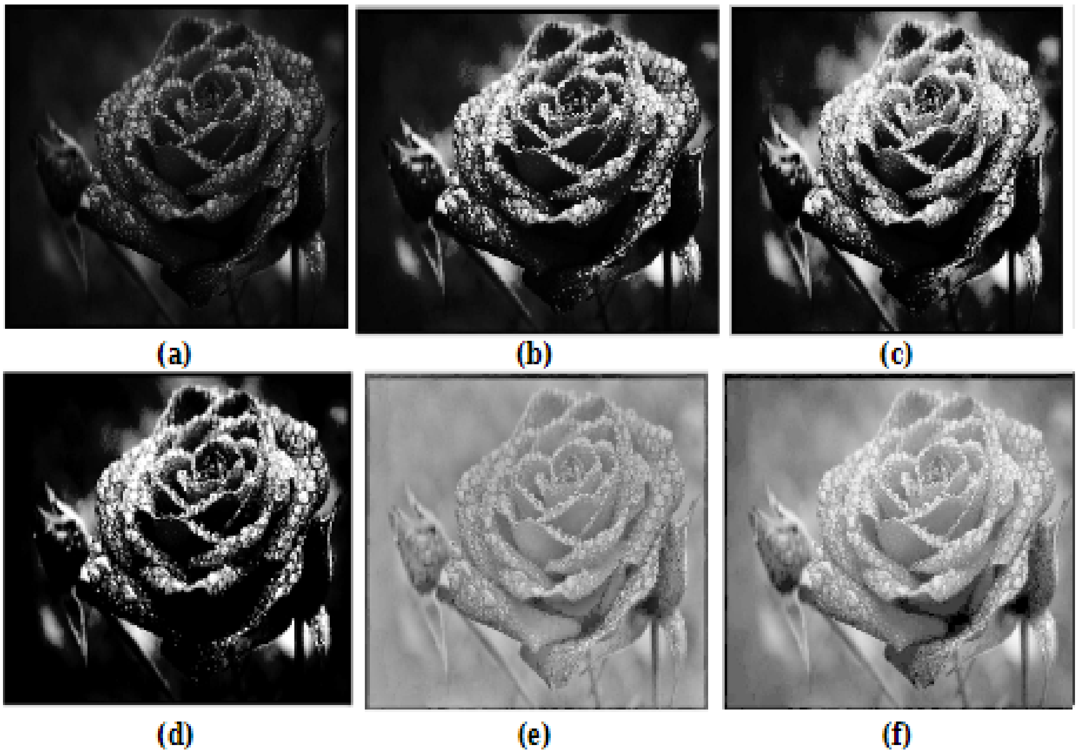


Figure 3.10: (a) Original Image (b) BBHE (c) DSIHE (d) SSR (e) MSR

3.4 implementation environment

3.4.1 Hardware

The experements was carried out in DELL DESKTOP-UB5DHK5 machine with the following specifications :

- Memory: 4 GB RAM
- Processor: Intel(R) Core (TM) i5-4310U CPU @ 2.00 GHz, 2.60 GHz, 2 Core(s),
- Operating system: Windows 10 Pro 64 bits

3.4.2 Programming language

For the development of our system, we used the Python programming language with Opencv,numpy,matplotlib frameworks.

3.5 conclusion

In this chapter, we implemented the two low-light image enhancing algorithms. Retinex and equalization of histograms, The use of histogram equalization and retinex algorithm-based techniques results in excellent contrast enhancement when retinex algorithms are used instead of other techniques. As a result, the output images shown above are the final product. The following are some of the disadvantages of past orderliness: Equalization procedure in BBHE and DSIHE diminishes pixel quality, Variation in grey-scale image during Histogram, and loses definition on the borders of objects. All of these flaws are overcome by Retinex algorithms, which provide improved image contrast augmentation.

General conclusion

Image Enhancement is one of the most important and complex techniques in image processing technology. The main aim of image enhancement is to improve the visual appearance on an image and to offer a better representation of the image for Computer Vision Algorithms. In this project,we is covered a few methods of image enhancement with various images like gray transformation methods, histogram equalization methods, Retinex methods, frequency-domain methods, image fusion methods, defogging model methods and machine learning methods. The main objective of this paper is It is a comparison between two methods and choosing the best method to low light image enhancement .

Bibliography

[1] Zhao X., Sun P., Xu Z., Min H., Yu H. Fusion of 3D LIDAR and camera dataforobject detection in autonomous vehicle applications. IEEE Sens. J. 2020;20:4901–4913. doi: 10.1109/JSEN.2020.2966034.

[2] Li J., Tang Y., Zou X., Lin G., Wang H. Detection of fruit-bearing branches and localization of litchi clusters for vision-based harvesting robots. IEEE Access. 2020;8:117746–117758. doi: 10.1109/ACCESS.2020.3005386.

[3] Tang Y., Li L., Wang C., Chen M., Feng W., Zou X., Huang K. Real-time detection of surface deformation and strain in recycled aggregateconcrete-filledsteeltubularcolumnsvia four-ocular vision. Robot. Comput. Integr. Manuf. 2019;59:36–46. doi: 10.1016/j.rcim.2019.03.001.

[4] Tang Y., Chen M., Lin Y., Huang X., Huang K., He Y., Li L. Vision-based three-dimensional reconstruction and monitoring of large-scale steel tubular structures. Adv. Civ. Eng.2020;2020:1236021. doi: 10.1155/2020/1236021.

[5] Zhang T., Chowdhery A., Bahl P., Jamieson K., Banerjee S. The design and implementation of a wireless video surveillance system; Proceedings of the Annual International Conference on Mobile Computing and Networking; Paris, France. 7–11 September 2015; pp. 426–438.

[6] Chen M., Tang Y., ZouX.,HuangZ.,ZhouH.,ChenS.3Dglobalmappingoflarge-scale unstructured orchard integrating eye-in-hand stereo vi-

sion and SLAM. Comput. Electron. Agric.2021;187:106237. doi: 10.1016/j.compag.2021.106237.

[7] Rashed H., Ramzy M., Vaquero V., El Sallab A., Sistu G., Yogamani S. FuseMODNet: Real-Time Camera and LiDAR Based Moving Object Detection for Robust Low-Light Autonomous Driving; Proceedings of theIEEEInternationalConferenceonComputerVision Workshop; Seoul, Korea. 27–28 October 2019; pp. 2393–2402.

[8] Wang R., Zhang Q., Fu C.W., Shen X., Zheng W.S., Jia J. Underexposed photo enhancement using deep illumination estimation; Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; Long Beach, CA, USA. 15–20 June 2019; pp. 6842–6850.

[9] Xu X., Wang S., Wang Z., Zhang X., Hu R. Exploring Image Enhancement for Salient Object Detection in Low Light Images. ACM Trans. Multimed. Comput. Commun. Appl. 2021;17:1–19.

[10] Ma S., Ma H., Xu Y., Li S., Lv C., Zhu M. A low-light sensor image enhancement algorithm based on HSI color model.Sensors.2018;18:3583.doi: 10.3390/s18103583.

[11] https://www.forbes.com/sites/bernardmarr/2019/04/08/7-amazing-examples-of-co mputer-and-machine-vision-in-practice/3dbb3f751018 (Link resides outside ibm.com)

[12] R. L. Gregory, The Intelligent Eye. New York: McGraw-Hill, 1970.

[13] Gomes, J. F. S.,AND Leta, F. R. (2012). Applications of computer vision techniques in the agriculture and food industry: a review. European Food Research and Technology, 235(6), 989-1000.

[14] Chakravorty, Pragnan (September 2018). "What is a Signal? [Lecture Notes]". IEEE Signal Processing Magazine. 35 (5): 175–77.

[15] L.Grazide,L'imageélectronique,http://auch2.free.fr/Documents/Informatique/ronique.pdf,consulted on18-042018.

[16] Rafael C Gonzalez andRichardEWoods.Digitalimageprocessing3rdedition,Pears
Prentice Hall, Upper Saddle River, 2007.

[17] Numeriksciences, http://numeriksciences.fr/,consulted on 18-04-2018

[18] https://www.sites.univ-rennes2.fr/artsspectacle/cian/image.numFlash/pdf/ch

[19] Techopedia https://www.techopedia.com/definition/24012/pixel, consulted on July 26, 2016

[20] Foley, J. D.; Van Dam, A. (1982). Fundamentals of Interactive Computer Graphics. Reading, MA: Addison-Wesley. ISBN0201144689.

[21] Chakravorty, Pragnan (2018). "What is a Signal? [Lecture Notes]". IEEE Signal Processing Magazine. 35 (5): 175–177.

[22] Gonzalez, Rafael (2018).Digital image processing.New York, NY: Pearson.

[23] Digital Image Processing (Rafael c. gonzalez)

[24] Séverine Dubuisson, 'Introduction au traitement d'images', Fondements du Traitement d'Images, novembre, 2006

[25] H. Wang, Y. Zhang, and H. Shen, "Review of image enhancement algorithms," (in Chinese), Chin. Opt., vol. 10, no. 4, pp. 438–448, 2017.

[26] M.Fang,H.Li,andL.Lei, "Areview on low light video image enhancement algorithms, "(inChinese), J.ChangchunUniv.Sci.Technol.,vol.39, no. 3, pp. 56–64, 2016.

[27] S. Park, K. Kim, S. Yu, and J. Paik, "Contrast enhancement for low-light image enhancement: A survey," IEIE Trans. Smart Process. Comput., vol. 7, no. 1, pp. 36–48, Feb. 2018.

[28] Q. Xu, H. Jiang, R. Scopigno, and M. Sbert, “A novel approach for enhancing very dark image sequences,” Signal Process., vol. 103, pp. 309–330, Oct. 2014.

[29] J. Wang, “An enhancement algorithm for low-illumination color image withpreservingedge,”(inChinese),Comput.Technol.Develop.,vol.28, no. 1, pp. 116–120, 2018.

[30] K. Srinivas and A. K. Bhandari, “Low light image enhancement with adaptive sigmoid transfer function,” IET Image Process., vol. 14, no. 4, pp. 668–678, Mar. 2020.

[31] W. Kim, R. Lee, M. Park, and S.-H. Lee, “Low-light image enhancement based on maximal diffusion values,” IEEE Access, vol. 7, pp. 129150–129163, 2019.

[32] K. Panetta, S. Agaian, Y. Zhou, and E. J. Wharton, “Parameterized logarithmicframeworkforimageenhancement,”IEEETrans.Syst.,Man, Cybern. B, Cybern., vol. 41, no. 2, pp. 460–473, Apr. 2011.

[33] Z. Xiao, X. Zhang, F. Zhang, L. Geng, J. Wu, L. Su, and L. Chen, “Diabetic retinopathy retinal image enhancement based on gamma correction,” J. Med. Imag. Health Informat., vol. 7, no. 1, pp. 149–154, Feb. 2017.

[34] S.Lee,N.Kim,andJ.Paik,“Adaptivelypartitionedblock-basedcontrast enhancement and its application to low light-level video surveillance,” SpringerPlus, vol. 4, no. 1, Dec. 2015, Art. no. 431.

[35] L.Li,S.Sun,andC.Xia,“Surveyofhistogramequalizationtechnology,” Comput. Syst. Appl., vol. 23, no. 3, pp. 1–8, 2014.

[36] K. Singh, R. Kapoor, and S. K. Sinha, “Enhancement of low exposure imagesviarecursivehistogramequalizationalgorithms,”Optik,vol.126, no. 20, pp. 2619–2625, Oct. 2015.

[37] A.SinghandK.Gupta,“Acontrastenhancementtechniqueforlowlight images,” in Proc. Int. Conf. Commun. Syst., 2016, pp. 220–230.

[38] Q. Wang and R. Ward, “Fast image/video contrast enhancement based on weighted thresholded histogram equalization,” IEEE Trans. Consum. Electron., vol. 53, no. 2, pp. 757–764, Jul. 2007.

[39] R. Dale-Jones and T. Tjahjadi, “A study and modification of the local histogram equalization algorithm,” Pattern Recognit., vol. 26, no. 9, pp. 1373–1381, Sep. 1993.

[40] M. F. Khan, E. Khan, and Z. A. Abbasi, “Segment dependent dynamic multi-histogram equalization for image contrast enhancement,” Digit. Signal Process., vol. 25, pp. 198–223, Feb. 2014.

[41] L. Li, S. Sun, and C. Xia, “Survey of histogram equalization technology,” (in Chinese), Comput. Syst. Appl., vol. 23, no. 3, pp. 1–8, 2014.

[42] https://ieeexplore.ieee.org/author/37965059400

[43] X. Tian, X. Xu, and C. Wu, “Low illumination color image enhancement algorithm based on LIP model,” (in Chinese), J. Xian Univ. Posts Telecommun., vol. 20, no. 1, pp. 9–13, 2015.

[44] Y. Wang, Q. Chen, and B. Zhang, “Image enhancement based on equal area dualistic sub-image histogram equalization method,” IEEE Trans. Consum. Electron., vol. 45, no. 1, pp. 68–75, Feb. 1999.

[45] Y.-T. Kim, “Contrast enhancement using brightness preserving bi-histogram equalization,” IEEE Trans. Consum. Electron., vol. 43, no. 1, pp. 1–8, Feb. 1997.

[46] X. Tian, D. Qiao, and C. Wu, “Color image enhancement based on bi-histogram equalization,” (in Chinese), J. Xian Univ. Posts Telecommun., vol. 20, no. 2, pp. 58–63, 2015.

[47] M.F.Al-Sammaraie,"Contrastenhancementofroadsimageswithfoggy scenesbasedonhistogramequalization,"inProc.10thInt.Conf.Comput. Sci. Educ. (ICCSE), Jul. 2015, pp. 95–101.

[48] G. Yadav, S. Maheshwari, and A. Agarwal, "Foggy image enhancement usingcontrastlimitedadaptivehistogramequalizationofdigitallyfiltered image: Performance improvement," in Proc. Int. Conf. Adv. Comput., Commun. Informat., Sep. 2014, pp. 2225–2231.

[49] S.-D. Chen and A. R. Ramli, "Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation," IEEE Trans. Consum. Electron., vol. 49, no. 4, pp. 1301–1309, Nov. 2003.

[50] A. M. Reza, "Realization of the contrast limited adaptive histogram equalization(CLAHE)forreal-timeimageenhancement,"J.VLSISignal Process.-Syst. Signal, Image, Video Technol., vol. 38, no. 1, pp. 35–44, Aug. 2004.

[51] K. S. Sim, C. P. Tso, and Y. Y. Tan, "Recursive sub-image histogram equalization applied to gray scale images," Pattern Recognit. Lett., vol. 28, no. 10, pp. 1209–1221, Jul. 2007.

[52] M. Kim and M. Chung, "Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement," IEEE-Trans.Consum.Electron.,vol.54,no.3,pp.1389–1397,Aug.2008.

[53] E. H. Land and J. J. McCann, "Lightness and Retinex theory," J. Opt. Soc. Amer., vol. 61, no. 1, pp. 1–11, Jan. 1971.

[54] S. Park, S. Yu, B. Moon, S. Ko, and J. Paik, "Low-light image enhancement using variational optimization-based Retinex model," IEEE Trans. Consum. Electron., vol. 63, no. 2, pp. 178–184, May 2017.

[55] H. Tanaka, Y. Waizumi, and T. Kasezawa, “Retinex-based signal enhancement for image dark regions,” in Proc. IEEE Int. Conf. Signal Image Process. Appl., Sep. 2017, pp. 205–209.

[56] S. Liao, Y. Piao, and B. Li, “Low illumination color image enhancement based on improved retinex,” in Proc. LIDAR Imag. Detection Target Recognit., Nov. 2017, p. 160.

[57] M. Li, J. Liu, W. Yang, X. Sun, and Z. Guo, “Structure-revealing lowlight image enhancement via robust Retinex model,” IEEE Trans. Image Process., vol. 27, no. 6, pp. 2828–2841, Jun. 2018.

[58] H. Hu and G. Ni, “Color image enhancement based on the improved retinex,” in Proc. Int. Conf. Multimedia Technol., Oct. 2010, pp. 1–4.

[59] H.-G. Lee, S. Yang, and J.-Y. Sim, “Color preserving contrast enhancement for low light level images based on retinex,” in Proc. Asia–Pacific Signal-Inf.Process.Assoc.Annu.SummitConf.,Dec.2015,pp.884–887.

[60] D. J. Jobson, Z. Rahman, and G. A. Woodell, “A multiscale retinex for bridging the gap between color images and the human observation of scenes,” IEEE Trans. Image Process., vol. 6, no. 7, pp. 965–976, Jul. 2002.

[61] M. Wang, Z. Tian, W. Gui, X. Zhang, and W. Wang, “Low-light image enhancementbasedonnonsubsampledshearlettransform,”IEEEAccess, vol. 8, pp. 63162–63174, 2020.

[62] A. Loza, D. Bull, and A. Achim, “Automatic contrast enhancement of low-light images based on local statistics of wavelet coefficients,” in Proc. IEEE Int. Conf. Image Process., Sep. 2013, pp. 3553–3556.

[63] L.Wang,G.Fu,Z.Jiang,G.Ju,andA.Men,“Low-lightimageenhancement with attention and multi-level feature fusion,” in Proc. IEEE Int. Conf. Multimedia Expo Workshops, Jul. 2019, pp. 276–281.

[64] A. Toet, M. A. Hogervorst, R. van Son, and J. Dijk, “Augmenting full colour-fused multi-band night vision imagery with synthetic imagery in real-time,” Int. J. Image Data Fusion, vol. 2, no. 4, pp. 287–308, Dec. 2011.

[65] M. Aguilar, D. A. Fay, and A. M. Waxman, “Real-time fusion of lowlight CCD and uncooled IR imagery for color night vision,” Proc. SPIE, vol. 3364, pp. 124–135, Jul. 1998.

[66] B. Qi, G. Kun, Y.-X. Tian, and Z.-Y. Zhu, “A novel false color mapping model-based fusion method of visual and infrared images,” in Proc. Int. Conf. Opt. Instrum. Technol., Optoelectron. Imag. Process. Technol., Dec. 2013, Art. no. 904519.

[67] A. Toet, “Colorizing single band intensified nightvision images,” Displays, vol. 26, no. 1, pp. 15–21, Jan. 2005.

[68] W. Yang, J. Zhang, and H. Xu, “Study of infrared and LLL image fusion algorithm based on the target characteristics,” (in Chinese), Laser Infr., vol. 44, no. 1, pp. 56–60, 2014.

[69] J. Zhu, W. Jin, and L. Li, “Fusion of the low-light-level visible and infrared images for night-vision context enhancement,” (in Chinese), Chin. Opt. Lett., vol. 16, no. 1, pp. 94–99, 2018.

[70] J.Li,S.Z.Li,Q.Pan,andT.Yang,“Illuminationandmotion-basedvideo enhancement for night surveillance,” in Proc. IEEE Int. Workshop Vis. Surveill. Perform. Eval. Tracking Surveill., Jun. 2005, pp. 169–175.

[71] Y. P. Loh and C. S. Chan, “Getting to know low-light images with the exclusively dark dataset,” Comput. Vis. Image Understand., vol. 178, pp. 30–42, Jan. 2019.

[72] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, “The Pascal visual object classes (VOC) challenge,” Int. J. Comput. Vis., vol. 88, no. 2, pp. 303–338, Jun. 2010.

[73] C. Chen, Q. Chen, J. Xu, and V. Koltun, “Learning to see in the dark,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 3291–3300.

[74] T. Lin et al., “Microsoft COCO: Common objects in context,” in Proc. Eur. Conf. Comput. Vis., Zürich, Switzerland, Sep. 2014, pp. 740–755.

[75] Joshi, P., Hearty, J., Sjardin, B., Massaron, L., Boschetti, A. (2016). Python: Real world machine learning. Packt Publishing Ltd.