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Low-Light Image Enhancement Based on Fast Fourier Transform and Gamma Correction

Zinah S. Abduljabbar

Department of Computer Science, College of Science,
Mustansiriyah University, Baghdad, Iraq

Abstract

Image processing is vital in many areas of human endeavor today. Images often suffer from poor illumination due to poor lighting, poor backlighting, or other conditions, resulting in low-light images, which are difficult to process in computer vision and human recognition. Therefore, processing to improve these low-light images becomes important in computer vision applications. This work aims to use the Retinex algorithm to improve low-light images through a two-stage process. First, dynamic range scaling is applied to each input channel, followed by transforming the result to the frequency domain using a fast Fourier transform (FFT). Multiscale Retinex is applied in the frequency domain before returning the image to the spatial domain. The second stage consists of improving the visual appearance of details by using nonlinear gamma correction of the reflectance component. Four metrics are used to evaluate and compare the experimental results of the proposed method when implemented on the MEF dataset. The results indicate good performance of the proposed method.

Keywords: Low illumination images, Retinex, FFT, Gamma correction.

Introduction

The efficiency of any system depends on the accuracy and clarity of the source data supplied to it. Low light is the main problem associated with image capture. This problem results from many factors, including poor lighting, backlighting and a dark area in the foreground. Equipment also affects the illumination of the image along with all the environmental conditions mentioned. Therefore, image enhancement technology is an important and interesting field for visually enhancing images in various ways. Many algorithms have emerged and these algorithms are classified into three main categories: the histogram equalization (HE) algorithm, the retinex algorithm and the nonlinear transformation [1].

Histogram equalization (HE) is a simple, fast and popular algorithm for contrast enhancement by expanding the grayscale of the original image and adjusting the image intensity. However, there are several limitations associated with this method such as loss of enhanced image details due to noise of the enhanced processed image, loss of information details due to gray level merging, and

HE enhances contrast without considering the real lighting conditions [2,3,4]. To overcome these problems, several histogram adjustment methods are emerging such as contrast limited equalization (CLAHE) [5], Bi-histogram equalization (BBHE) [6], dualistic sub-image histogram equalization (DSIHE) [7], exposure-based sub-image histogram equalization (ESIHE)[8] and exposure-based multi-histogram equalization contrast enhancement for non-uniform illumination images (EMHE) [9].

Retinex, a combination of the words retina and cortex, is an image enhancement theory proposed by Edward Land as a model of human brightness and color perception. It aims to provide computers with a way to make color images more closely match the color perceived by the human eye under different lighting conditions. According to this theory, images can be viewed as a product of reflectance and illumination [10]. Various algorithms have subsequently been proposed as improvements to the Retinex algorithm, such as the single-scale Retinex (SSR) algorithm [11], the multi-scale Retinex (MSR) algorithm [12], and the multi-scale Retinex with color restoration (MSRCR) algorithm [13]. Several studies have found that using the transform reduces computational complexity and improves enhancement quality [14, 15, 16]. Therefore, in this work, Fast Fourier Transforms (FFTs) are used with the MSR algorithm.

A nonlinear function is a pixel-wise operation performed to enhance low-light images. Gamma correction, logarithmic transfer and sigma function [17,18,19] are the most common types.

The Proposed System

Retinex technology is one of the popular methods used to enhance the image and as mentioned earlier, the image can be viewed as a result of reflection and illumination and this model can be obtained as follows [20]:

$$I(x,y) = R(x,y) \cdot L(x,y) \cdots\cdots (1)$$

where I(x,y) is the original input image, R(x,y) and L(x,y) are the reflectance and luminance of the observed image, respectively, and the (.) operation between R and L represents the multiplication.

According to the color constancy theory, light does not affect an object's intrinsic properties, while an object's color is determined by its ability to reflect different light waves. [21] Therefore, following this concept, only the reflectance component is extracted and optimized in this work.

Figure 1 illustrates the proposed improvement approach flowchart, which consists of two main stages as shown below:

Stage 1: This stage starts only after the low-light (RGB) images are loaded as inputs to the system. Images are usually represented by a wide range of pixel values but a narrow range of these values can represent certain features. Therefore, applying a logarithmic transformation to each channel can enhance the dynamic range of the image by spreading the narrow band. This transformation is obtained by this equation [22]:

$$S = C + \log(1 + I) \cdots\cdots (2)$$

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S: The resulting transformed image.

C: the constant value for scaling to adjust the contrast.

I: The original input image.

The image is then transformed into the frequency domain by applying a two-dimensional FFT on the log-transformed image and performing Multi-Scale Retinex by creating and multiplying a Gaussian filter in the frequency domain, which produces better results than applying the same filter in the spatial domain. The FFT is obtained by applying the following equation:

$$f(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} s(x,y) e^{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)} \cdots\cdots (3)$$

where f(u,v) is the image in the frequency domain and s(x,y) is the image in a special domain, both images have size M×N.

The image is returned to the spatial domain by performing an IFFT and then applying an exponent to the reflection image to undo the logarithmic transformation. The IFFT is performed by applying the following equation:

$$s(x,y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} f(u,v) e^{j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)} \cdots\cdots (4)$$

The reflectance image is considered an output of this stage.

Stage 2: In this stage, a non-linear gamma correction is applied to the reflection component to improve the visual appearance of the details. This is done by increasing the pixel intensity to the power called gamma γ. The general formula for this function is as shown in the following equation [13], where G_r is the gamma correction for the pixel intensity of the input image I(x,y):

$$G_r(x,y) = 255 \times \left(\frac{I(x,y)}{255}\right)^{\gamma} \cdots\cdots (5)$$

Local contrast stretching (LCS) is used to adjust each pixel in the image and enhance the perception of both the lightest and darkest parts of the image at the same time, and this is done as follows [14]:

$$I_s(x,y) = 255 \times \frac{I(x,y) - min}{max - min} \cdots\cdots (6)$$

where $I_s(x,y)$ is the color level pixel after the contrast stretching operation applied to the color level pixel of the input image $I(x,y)$

Min and max are the minimum and maximum color level values in the input image respectively.

Utilizing the two previous equations to improve the image visually, the following equation is adopted:

$$\bar{I}(x,y) = 255 \times \left(\frac{I(x,y) - min}{max - min}\right)^{\gamma} \cdots\cdots (7)$$

One of the most important factors is determining the value of gamma. In this work, the gamma value is calculated based on the average of each image. The average of each channel (red, green, and blue) is calculated, and then the average of the three values is divided by 100 and calculated as the gamma value according to the following equation. Therefore, the gamma value is not constant, but rather depends on the pixel values of the image.

$$\gamma = \left(\frac{M_R + M_G + M_B}{3}\right) \div 100 \cdots\cdots (8)$$

Where M_R, M_G and M_B are the mean values of red, green and blue bands respectively.

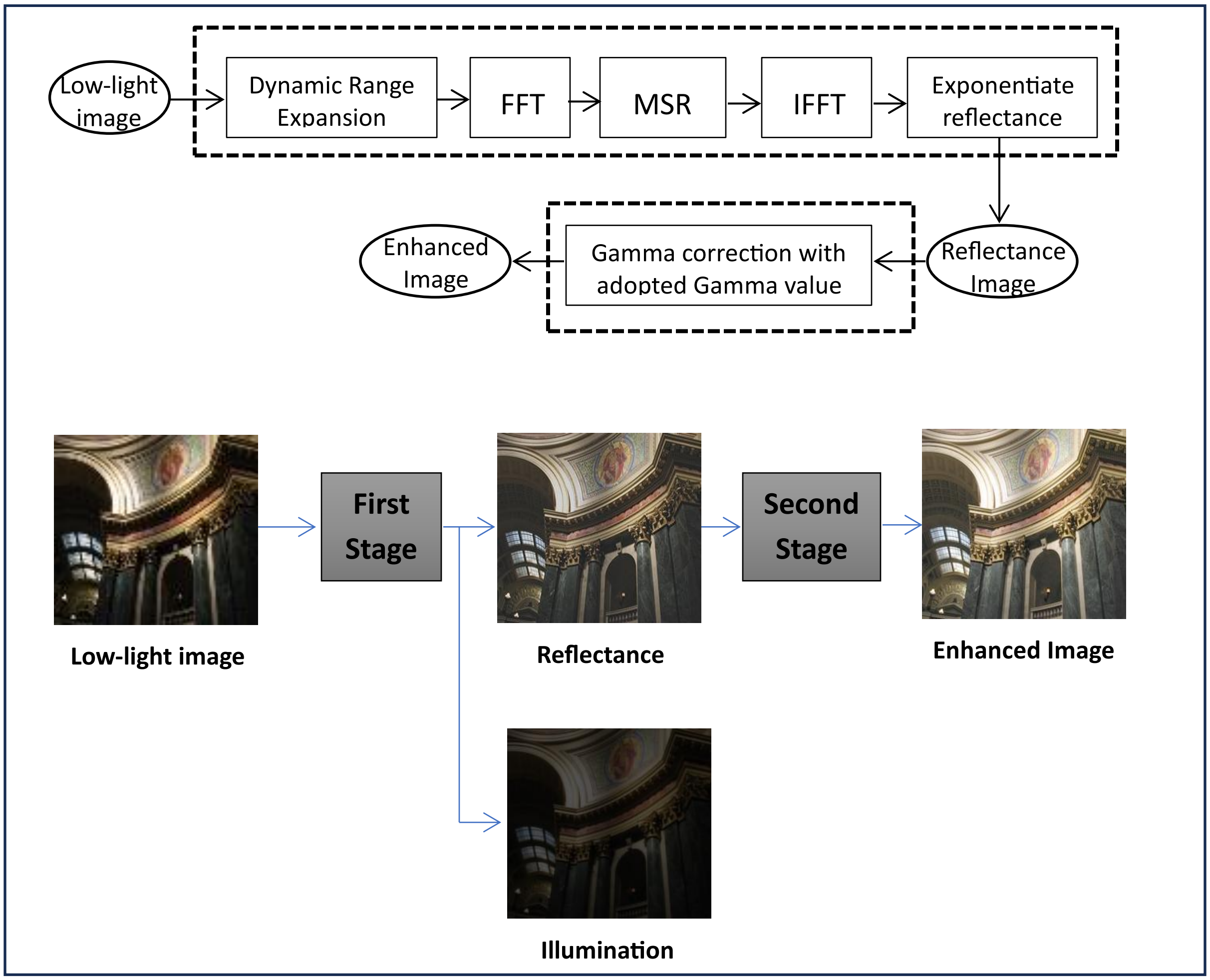

Figure 1: the layout of suggested enhancement approach

Results

This section presents the results of the proposed method and compares them with other methods. This method was applied to 24 low-light images from a public dataset called MEF [24]. The results of the proposed method were implemented using MATLAB R2018b on a Windows 10 computer with an Intel(R) Core (TM) i5-8250U processor at 1.60 GHz and 8 GB of RAM.

The results obtained from this work were compared with RBEA [1], which was previously compared with six methods [25, 26, 4, 27, 28, 29, 1], so based on the results in [1], a comparison is made with seven methods.

To evaluate performance, an objective evaluation is used. There are many types of image quality assessment (IQA) metrics, some of which are fully referenced [30]. In this type, an image is given as a full reference; however, in many practical applications, a reference image is not available, and in this type, “blind” IQA can be used without a reference [31,32].

The Perceptual-Based Image Quality Evaluator (PIQE) is used as a blind image quality evaluator, and three types of full reference image quality evaluators are also used, including the mean square error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity (SSIM). The equations for the three types of full reference evaluators are shown as follows:

The difference between the original and enhanced images is measured using MSE [30]:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - E(i,j)]^2 \cdots\cdots (9)$$

$I(i,j)$ is the original image and $E(i,j)$ is the enhanced image.

m and n are image dimensions.

To measure the peak error between original and enhanced images, PSNR is used [30]:

$$PSNR = 10\ log_{10}\left(\frac{max_I^2}{MSE}\right) \cdots\cdots (10)$$

Where the numerator in the equation above represents the maximum possible value of the image pixels.

SSIM is used to measure the similarity between the two images taking into account luminance, contrast and structure as follows [30]:

$$SSIM(I,E) = \frac{(2\mu_I\mu_E + C_1)(2\sigma_{IE} + C_2)}{(\mu_I^2 + \mu_E^2 + C_1)(\sigma_I^2 + \sigma_E^2 + C_2)} \cdots\cdots (11)$$

$\mu_I\ and\ \mu_E$ are the mean values for I and E respectively.

$\sigma_I^2\ and\ \sigma_E^2$ are the variances of I and E respectively.

σ_{IE} is the covariance of I and E respectively.

To evaluate how the human visual system perceives an image, four metrics were calculated and recorded in the table below. The number in red indicates the best value obtained among the methods. PIQE was used, and better results were obtained than the proposed method using AFEM and RBEA, with the difference from the best result being only 1.213.

MSE gives a numerical representation of how different the two images (reference/enhanced) are. A lower value indicates higher similarity, and the result of the proposed method is 1.67 higher than the previous best method. PSNR represents a measure of quality in decibels through a numerical representation and the PSNR result of the proposed method is the highest. SSIM is a comprehensive metric and provides a meaningful assessment of quality represented by luminance, contrast, and structure. A higher SSIM value is desirable, and the result of the proposed method is 0.006 higher than the highest recorded value.

Table 1: Metrics for measuring image quality results using different methods

Metrics	LECARM	AFEM	FFM	JIEP	LIME	SDD	RBEA	Proposed
PIQE	39.818	39.809	42.884	40.072	42.705	51.457	**38.601**	39.814
MSE	3777.2175	2021.305	2823.849	2241.768	1153.584	1617.479	1158.174	**1151.914**
PSNR	12.504	16.350	14.464	15.847	18.136	17.511	18.258	**18.517**
SSIM	0.531	0.747	0.709	0.732	0.739	0.751	0.753	**0.759**

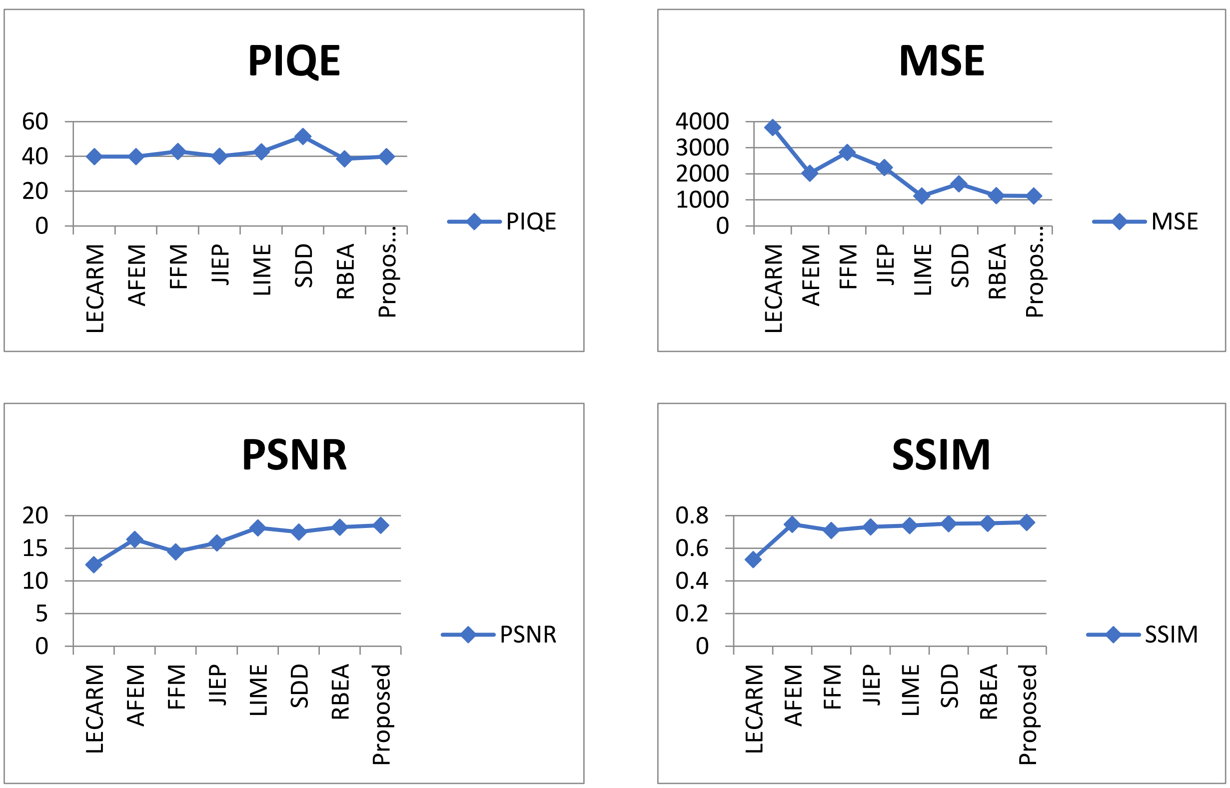

Figure 2: The Results of different metrics (PIQE, MSE, PSNR and SSIM)

The figures below represent the effect of the proposed method on the image, where Figure 3 shows the images before the enhancement process while Figure 4 shows the results of the enhancement process.

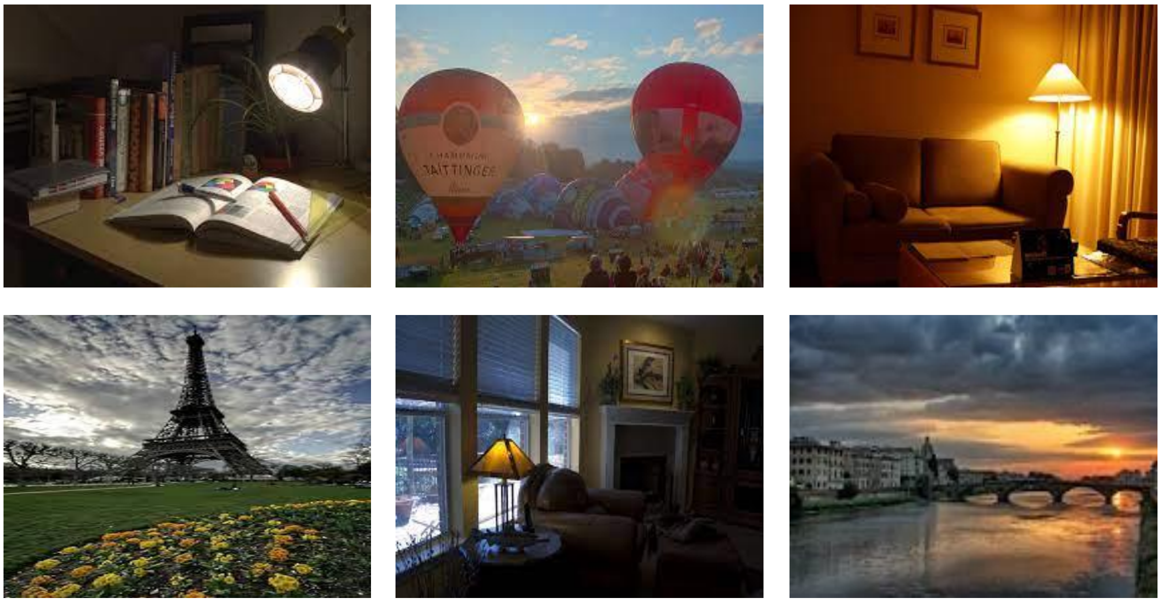

Figure 3: The Images before the Enhancement Process

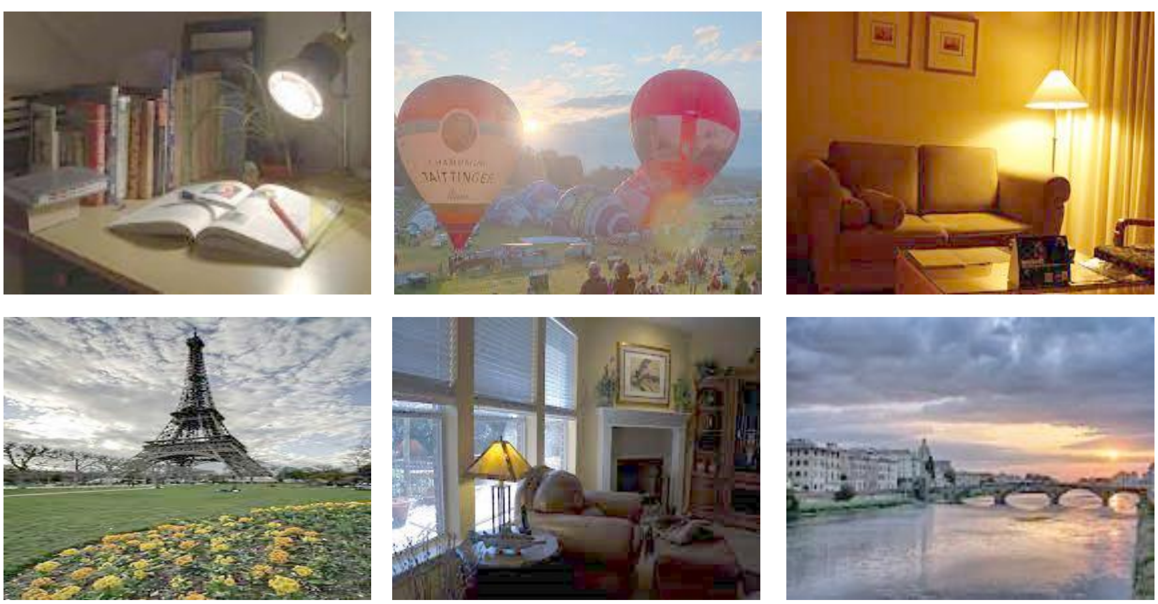

Figure 4: The Enhanced Images

Conclusion

This work presents an enhanced method for low-light images. The proposed methods have two stages: dynamic range expansion, FFS, and MSR. The reflectance image was the output for the second stage, and a nonlinear function representing gamma correction was applied to it. It was noted that the most crucial factor was calculating the gamma value using the proposed equation, which had a significant impact on the results. This method was applied to 24 low-light images, and the results were evaluated using four metrics, with all results demonstrating promising results compared to previous work.

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