# LOW LIGHT ENHANCEMENT USING RETINEX BASED FAST ALGORITHM

Mini Project Progress Report

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#### **BACHELOR OF TECHNOLOGY**

in

#### **COMPUTER SCIENCE AND ENGINEERING**

By

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# **CERTIFICATE**

This is to certify that the project entitled "LOW LIGHT ENHANCEMENT USING RETINEX BASED FAST ALGORITHM" is a record of bonafide work carried out by BELLAMKONDA YASWANTH (N170612), CHEERAPA BANGARU RAJU (N170599), JAMANA PAVITRA (N170516), DHULIPUDI VAISHNAVI (N170367), ASARAPALLI DEVAKI (N170138) under my guidance and supervision for the Mini Project for the fulfillment for the Degree of Bachelor of Technology in Computer Science and Engineering during the academic session April 2022 – September 2022 at RGUKT-Nuzvid. To the best of my knowledge, the results embodied in this dissertation work have not been submitted to any university or institute for the award of any degree or diploma.

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# CERTIFICATE OF PROJECT COMPLETION

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# **DECLARATION**

We, BELLAMKONDA YASWANTH(ID NO: N170612), CHEERAPA BANGARU RAJU(N170599), JAMANA PAVITRA(N170516), DHULIPUDI DEVAKI(N170367), ASARAPALLI DEVAKI(N170138) hereby declare that the project report entitled "LOW LIGHT ENHANCEMENT USING RETINEX BASED FAST ALGORITHM" done by us under the guidance of Mrs. SAMINENI BHAVANI, Assistant Professor is submitted for the Mini Project for the Degree of Bachelor of Technology in Computer Science and Engineering during the academic session April 2022-June 2022 at RGUKT-Nuzvid.

We also declare that this project is a result of our own effort and has not been copied or imitated from any source. Citations from any websites are mentioned in the references. The results embodied in this project report have not been submitted to any other university or institute for the award of any degree or diploma.

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5

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We are extremely grateful for the confidence bestowed in us and entrusting our project entitled "LOW LIGHT ENHANCEMENT USING RETINEX BASED FAST ALGORITHM"

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# **Table of Contents**

	9
LIST OF TABLES	9
ABBREVIATIONS	9
ABSTRACT	10
CHAPTER 1	11
INTRODUCTION	11
1.1 Objective of Project	11
1.2 Current Low-Light Image Enhancement	11
1.3 Disadvantages of Histogram equalization	11
1.4 Related Works	11
CHAPTER 2	12
LITERATURE SURVEY	12
2.1 Histogram Equalization	12
2.1.1 Histogram	12
2.1.2 Histogram Equalization	12
2.2 Retinex Model	13
2.3 Non-linear Transformations	14
CHAPTER 3	16
PROPOSED MODEL	16
3.1 Retinex Model	16
3.2 Gamma Correction	16
3.3 HSV Color Space	17
3.4 Proposed Architecture	18
3.4.1 Brightness Enhancement	18
3.4.2 Dynamic Range Expansion	20
3.4.3 Saturation Adjustment	21
CHAPTER 4	23
RESULT	23
COMPARATIVE EXPERIMENTS	25

CHAPTER 5	27
CONCLUSION	27
BIBLIOGRAPHY	27

# LIST OF FIGURES

- Figure (1) Images Types and their corresponding histograms.
- Figure (2) Methods based on Retinex Algorithm.
- Figure (3) Effect of gamma correction on an image.
- Figure (4) Shapes of gamma functions with different γ values.
- Figure (5) The flowchart of the proposed method.
- Figure (6) Low light Enhancement process and corresponding grayscale histograms.

# LIST OF TABLES

- Table (1) Time Costs of Different Methods.
- Table (2) Quality Measure with Different Methods.

# LIST OF ABBREVIATIONS

- **RBFA** Retinex Based Fast Algorithm
- **AFEM** Adaptive Finite Element Method
- **LIME** Local Interpretable Model-agnostic Explanations
- **FFM** Friction Force Microscopy
- JIEP Joint Intrinsic-Extrinsic Prior Model
- **PIQE** Perception Based Image Quality Evaluator
- **LOE** Lightness Order Error
- **MSE** Mean Squared Error
- **PSNR** Peak signal-to-noise Ratio

# **ABSTRACT**

We propose the Retinex-based fast algorithm (RBFA) to achieve low-light image enhancement in this project, which can restore information that is covered by low illuminance. Firstly, we convert the low-light image from the RGB (red, green, blue) color space to the HSV (hue, saturation, value) color space and use the linear function to stretch the original gray level dynamic range of the V component. Then, we estimate the illumination image via adaptive gamma correction and use the Retinex model to achieve the brightness enhancement. After that, we further stretch the gray level dynamic range to avoid low image contrast. Finally, we design another mapping function to achieve color saturation correction and convert the enhanced image from the HSV color space to the RGB color space after which we can obtain the clear image.

## PROJECT INTRODUCTION

# 1.1 Objective of the Project

Main aim of the project is to achieve Low Light Image Enhancement from the proposed algorithms and to choose the best algorithms which provide better results for the low light images. Here we combinedly used Retinex-Based Algorithm and Gamma correction technique from non-liner transformation known as the Retinex-Based Fast Algorithm.

# 1.2 Currently low light Image Enhancement Techniques

Present there are 3 categories for the image Enhancement

- ➤ Histogram equalization-based algorithm follows the technique where it adjusts the illumination by equalizing the histogram of input low light image.
- > The Retinex-model is a colour perception model of human vision, which consists of illumination and reflectance.
- ➤ Nonlinear functions are types of methods are pixel-wise operations for natural low light images.

# 1.3 Disadvantages

HE-based methods neglect the noise hidden in the dark region of low-light images.

#### 1.4 Related Works

Few works and their limitations

- 1. Histogram Equalization Based Algorithm
- 2. Retinex Based Algorithm
- 3. Non-Linear transformations

#### LITERATURE SURVEY

# 2.1 Histogram Equalization

#### 2.1.1 Histogram

Histogram is a graphical representation of the intensity distribution of an image.

#### 2.1.2 Histogram Equalization

Technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e., stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast.

A color histogram of an image represents the number of pixels in each type of color component. Histogram equalization cannot be applied separately to the red, green and blue components of the image as it leads to dramatic changes in the image's color balance. However, if the image is first converted to another color space, like HSL/HSV color space, then the algorithm can be applied to the luminance or value channel without resulting in changes to the hue and saturation of the image. Some of the methods based on HE is -

- Adaptive histogram equalization
- Contrast-limited adaptive histogram equalization
- Bi-histogram equalization
- Exposure based sub image histogram equalization
- Exposure based multi histogram equalization
- Contrast enhancement for non-uniform illumination images

Though we have many methods based on histogram equalization due to the disadvantages mention in 1.3 we don't use this method much.

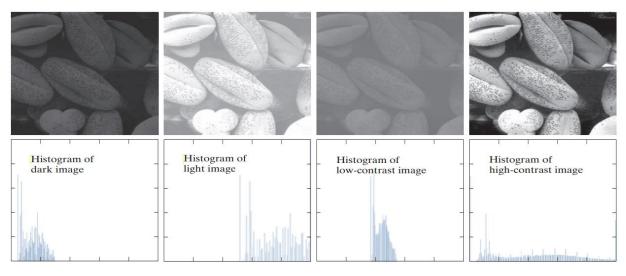


Figure (1)

Four image types and their corresponding histograms in Figure (1). (a) dark; (b) light; (c) low contrast; (d) high contrast.

#### 2.2 Retinex Model

Retinex is basically a concept of capturing an image in such a way in which a human being perceives it after looking at an object at the place with the help of their retina (Human Eye) and cortex (Mind).

Retinex theory based on the Physical Image Capturing Model. Retinex theory states an image as a multiplication of the illumination and the reflectance of the object. The characteristics of the illumination depend on the source of illumination. The characteristics of the reflectance depend on the nature of the object.

Some of the methods based on Retinex algorithm are –

- Single scale Retinex.
- Multi scale Retinex.
- Multi scale Retinex with color restoration.
- Multi scale Retinex with color preservation.

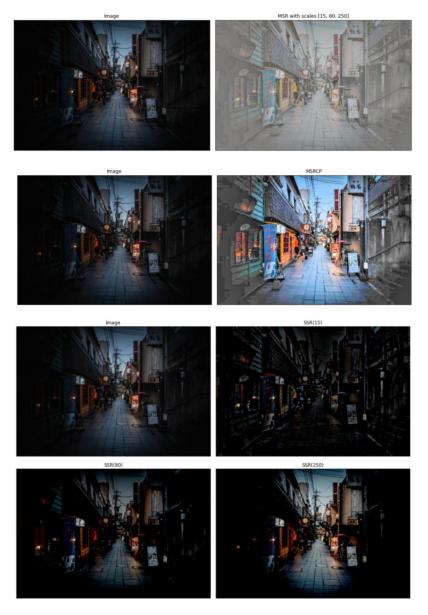


Figure (2)

## 2.3 Non-Linear Transformation

Non-Linear Methods effectively preserve edges and details of images while methods using linear operators tend to blur and distort them. The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application.

Common Non-Linear Functions are

- Gamma Corrections
- Sigmoid Transfer Functions

#### • Logarithmic Transfer Functions

These types of methods are pixel wise operations for natural low light images compared with other nonlinear function the gamma transfer function is widely used in the field of image processing, but the limitation of gamma correction is that if the parameter gamma is too small it will amplify the noise of the target image; by contrast, if the parameter gamma is close to 1, satisfactory enhanced results will not be obtained. Therefore, estimating a suitable gamma value is the key to obtain the satisfactory enhanced results.

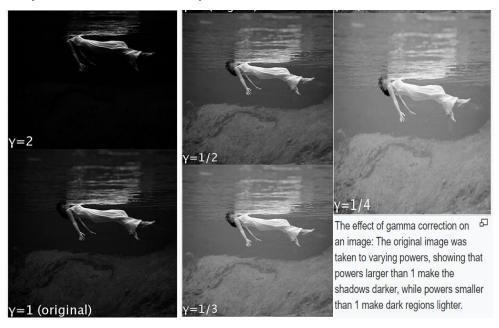


Figure (3)

Here we utilize the gamma transfer function to estimate the illumination and achieve brightness enhancement via the Retinex model. The enhanced image achieves satisfactory light enhancement and global brightness equalization; thus, our method can restore more information than other methods. The final experimental results show that compared with other state-of-the-art methods, the enhanced images through our algorithm have better qualitative and quantitative evaluations.

#### PROPOSED MODEL

Here we introduce the HSV colour space, Retinex model and gamma correction, which are foundation of our method.

#### 3.1 Retinex Model

The classical Retinex model assumes that the observed image consists of reflectance and illumination. Expression for the Retinex model is

$$\mathbf{H} = \mathbf{R} \cdot \mathbf{L} \tag{1}$$

where H is the observed image, R and L represent the reflectance and the illumination of the image, respectively. The operator '•' denotes the multiplication. In this paper, we utilize the logarithmic transformation to reduce computational complexity. We can obtain the following expression.

$$\log(\mathbf{H}) = \log(\mathbf{R} \cdot \mathbf{L}) \tag{2}$$

Finally, we can obtain Equation (3) to estimate the reflectance in the HSV color space.

$$\log(R) = \log(V) - \log(L) \tag{3}$$

#### 3.2 Gamma Correction

The Gamma Transfer Function is wildly used in the field of image processing, and the corresponding gamma transfer function can be expressed as follows.

$$g(x,y) = u(x,y)^{\gamma} \tag{4}$$

Where g(x,y) denotes the gray level of the enhanced image at pixel location (x,y), u(x,y) is the gray level of the input low-light image at pixel location (x,y), and  $\gamma$  represents the parameter of the gamma transfer function. The shape of the gamma transfer function can be affected by parameter  $\gamma$ ; the influence of different values of  $\gamma$  is shown in Figure 2.

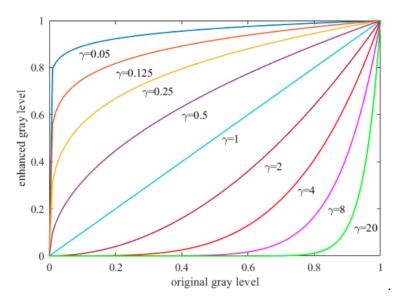


Figure (4) The shapes of gamma functions with different  $\gamma$  values.

Gamma curves with fractional values of  $\gamma$  map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input levels. Note also in Figure (4) that a family of transformations can be obtained simply by varying  $\gamma$ . Curves generated with values of  $\gamma > 1$  have exactly the opposite effect as those generated with values of  $\gamma < 1$ . If we can make the size of parameter  $\gamma$  fall within the range from 0 to 1, then we can achieve a higher value of the gray level.

# **3.3 HSV Colour Space**

The HSV color space consists of a hue component (H), saturation component (S) and value component (V). The value component represents the brightness intensity of the image. The advantage of the HSV color space is that any component can be adjusted without affecting each other, more specifically, the input image is transferred from the RGB (red, green, blue) color space to the HSV color space, which can eliminate the strong color correlation of the image in the RGB color space. Therefore, this work is based on the HSV color space. Commonly, image enhancement in RGB color space need to process R, G and B, three components, but we only need to process the V component in this work. Therefore, this will greatly reduce the image processing time.

# 3.4 Proposed Architecture

The detailed information of our algorithm is given in this section. Based on the descriptions in Section 3.2, here we only concentrate on the V component to adjust the brightness of the low-light image and the flowchart of the proposed method is given in Figure (5). We choose an image named "Arno" to demonstrate the enhancement process of the proposed method, the processing of image enhancement and corresponding histograms are shown in Figure (6).

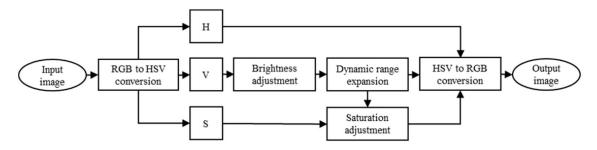


Figure (5) The flowchart of the proposed method.

Here we use Retinex model to achieve brightness enhancement and Gamma correction to estimate the illumination. Using gamma correction to estimate the illumination is far better than using filters. This is because using gamma correction greatly reduces computational time. The key to gamma correction is to compute the value of gamma parameter.

#### 3.4.1. Brightness Enhancement

For low light image, Gray levels mainly depend upon low Gray level area, and the dynamic range for low Gray levels is very narrow. By seeing Figure 2, we can understand that higher the Gray level dynamic range of the input image, the higher the Gray level dynamic range of the output image.so before gamma correction we use linear enhancement to stretch the Gray level dynamic range, and to prevent over-enhancement we make sure that the value of the stretched Gray level falls within the range of (0,1)

$$V_{\text{max}} = \max(V(x, y)) \tag{5}$$

$$V1(x,y) = \frac{1}{V_{\text{max}}} \times V(x,y)$$
 (6)

here  $V_{max}$  denotes the maximum pixel value of gray image, max( . ) denotes take the maximum value of V(x,y), V(x,y) is the pixel value of the original gray image at location (x,y), V1(x,y) is the enhanced pixel value at location (x,y) and '×' represents the multiplication. Linear

Enhancement is performed on the pixel values which are greater than 5 and less than 220 of the gray image. The maximum value of the low-light image is usually lower than 1; we can infer that  $\frac{1}{V_{max}} > 1$ , so this linear function can stretch the dynamic range of the low-light image, and we also can obtain that  $V1(x,y) \le 1$ .

After the gray level dynamic range is stretched, we adopt gamma correction to estimate illumination. For a low-light image, the lower the brightness intensity, the lower the gray level. Therefore, we take this feature into consideration. First, based on the global histogram, we compute the mean gray level value, which can reflect the overall brightness level to a certain extent. The corresponding computational formula is expressed as Equation (7), and we can obtain the mean gray level value via this equation.

$$\mathbf{m} = \frac{\sum_{i=0}^{L} P(i) * i}{\sum_{i=0}^{L} P(i)}$$
 (7)

where is the mean value of gray levels, denotes the maximum value of gray levels of an image and is the histogram of gray level.

In this paper, we assume that the gray levels more than zero and less than m+1 are the extreme low gray levels. In fact, this part of the gray level is the key to determine the mean gray level of the low-light image. Based on the above descriptions, we design a formula to convert the gray level of this part into a constant, and use this constant to compute the gamma value. The corresponding transfer formula is expressed as Equation (8).

$$c = \frac{\sum_{i=1}^{m} P(i)*i}{128*\sum_{i=1}^{m} P(i)}$$
 (8)

where c is the value of conversion result and c is a positive number. Low-light images may have similar mean values, which will lead to similar c values. In order to enlarge the difference of c values among different images, we use the following expression to enlarge c values.

$$c1 = \frac{1}{1 + e^{-c}} \tag{9}$$

where c1represents the enlarged c value. In addition, we also think that the focus of brightness enhancement lies in the low gray level area rather than the high gray level area. Therefore, we take the distribution of the low gray level as one of the important bases for estimating the gamma value. In order to calculate the distribution of the low gray level, the

cumulative distribution function (CDF) is used to calculate the distribution of the gray level in this part. In this paper, we consider the gray level less than 128 to be the low gray level area.

$$cdf(j) = \sum_{i=0}^{j} pdf(i)$$
 (10)

$$pdf(i) = \frac{p(i)}{M*N}$$
 (11)

where p(i) is the number of pixels that have gray level i, M and N are the length and width of the image, j is the threshold point of CDF and we set j equals to 128. Then we weigh the CDF value with the c1 value to obtain the gamma parameter value.

$$y = w * c1 + (1 - w) * cdf$$
 (12)

where  $\gamma$  represents the gamma parameter, w is the weighted value and equals to 0.48. Combining Equations (4), (6) and (12), we can get the final expression as follows.

$$VL(x,y) = V1(x,y)^{w*c1+(1-w)*cdf}$$
(13)

where VL(x,y) denotes the pixel location (x,y) of illumination image. Combing Equations (3) and (13), we can get the reflectance, and it is shown as follows. Gamma Correction is performed on the pixel values which are greater than 5 and less than 220 of the V components.

$$\log(R) = \log(V) - \log(VL) \tag{14}$$

We get the enhanced V component as follows:

$$VE = \exp(\log(V) - \log(VL)) \tag{15}$$

The enhanced V component and corresponding histogram are shown in Figure (6) c.

#### 3.4.2. Dynamic Range Expansion

After brightness enhancement, the pixel values are easily concentrated in the higher gray level range, which leads to the grayscale dynamic range becoming narrow with low contrast in the enhanced image. We can adjust the contrast of the image by enlarging the V component gray level. In order to avoid pixels values concentrated in the higher gray level range, we use a piece

wise function to further stretch the gray level dynamic range to achieve dynamic range expansion. The corresponding expression can be expressed as follows.

$$VE'(x,y) = \begin{cases} VE(x,y), VE(x,y) \ge 100 \\ 2.5 \times (VE(x,y))^2, VE(x,y) < 100 \end{cases}$$
 (16)

The dynamic range enlarged V component and corresponding histogram are shown in Figure (6) d.

#### 3.4.3. Saturation Adjustment

In addition to brightness, the color saturation also directly affects the visual experience. In the HSV color space, the mean value of the S component and V component of a clear image should be approximately equal. However, with the adjustment of brightness, the mean value of the V component changes greatly, which affects the image color. Based on the mean difference between the V component and the S component, Formula (20) is designed to adjust the S component. The details of our method are described as follows. Firstly, we use Equation (17) to compute the mean difference between the V component and S component.

$$VES = VE'_{mean} - S_{mean}$$
 (17)

Where VES is the mean difference,  $VE'_{mean}$  is the mean value of enhanced V component and  $S_{mean}$  is the mean value of S component. The expression used to compute  $VE'_{mean}$  is shown below.

$$VE'_{mean} \frac{\sum_{0}^{i} VE'(i)*i}{M*N}$$
 (18)

where i denotes the gray level, and VE'(i) is the number of pixels that have gray level i. M and N are the length and width of the image. Similarly, we can get Equation (19) to compute the  $S_{mean}$ .

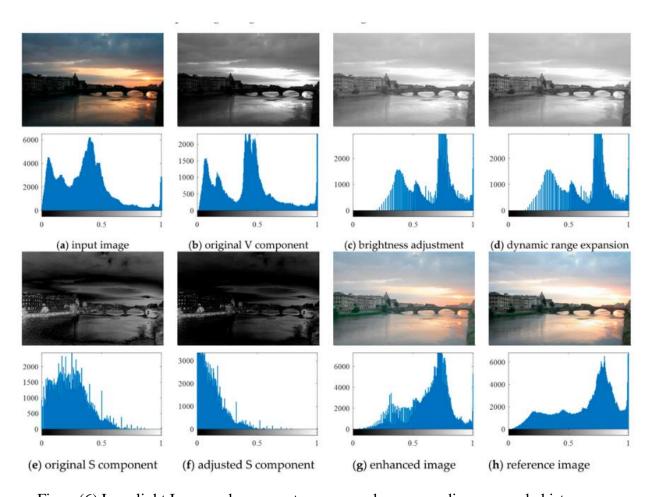
$$S_{\text{mean}} = \frac{\sum_{0}^{i} S(i) * i}{M * N}$$
 (19)

where i denotes the gray level, S(i) is the number of pixels that have gray level i. From the above description, we adjust the S component value to reduce the mean difference value between the VE' component and S component to achieve the purpose of color saturation adjustment. After

VES is obtained, we use it to adjust the S component. According to Section 2.2, if we want to enlarge the value of the S component, we must ensure that the gamma parameter lies in the range (0,1). On the contrary, we need to ensure that the parameter value is greater than 1 to reduce the value of the S component. Therefore, we use Equation (20) to achieve this step.

$$S1(x,y)=S(x,y)^{1+(-1)^{2-n}*(|VES|^2+|VES|)}, n = \begin{cases} 0 \text{ VES} < 0\\ 1 \text{ VES} \ge 0 \end{cases}$$
 (20)

where S1(x,y) denotes the pixel location (x,y) of the adjusted S component, and S1(x,y) is the pixel location (x,y) of the original S component. According to Equation (17), we can see that if VES < 0, we know that VE<sub>mean</sub> < S<sub>mean</sub>, so we need to reduce the value of the S component. Meanwhile, from Equation (20) we know that n=0 and  $1 + (-1)^{2-n} * (|VES|^2 + |VES| > 1$ , then we get S1(x,y)< S(x,y). Similarly, we can see that when VES> 0, we also can get S1(x,y)> S(x,y). The original S component and corresponding histogram are shown in Figure 4e and the adjusted S component and corresponding histogram are shown in Figure (6)f.



Figure(6) Low-light Image enhancement process and corresponding grayscale histograms.

# **RESULT**

By using Retinex Based Fast Algorithm, we achieved low light image enhancement for the following images.





(a)Input Image 1

(a)Output Image 1



(b)Input Image 2



(b)Output Image 2



(c)Input Image 3



(c)Output Image 3



(d)Input Image 4



(d)Output Image 4



(e)Input Image 5



(e)Output Image 5



(f)Input Image 6



(f)Output Image 6

# **COMPARATIVE EXPERIMENTS**

# **Time Costs of Different Methods (in Seconds):**

IMAGE SIZE	200×90	700×315	2000×900	2500×1125	3000×1500	4500×2024
AFEM	0.7187	0.8605	1.7605	2.3837	3.1532	5.9948
LIME	2.4580	6.1446	15.2291	32.3309	53.2626	124.2189
FFM	1.0225	5.7972	39.1736	61.2648	105.6805	226.8455
JIEP	0.72165	1.3991	9.8091	16.3103	29.9571	67.8563
RBFA	0.03695	0.1598	1.0372	1.5313	2.1498	4.2629
PROPOSED	0.03695	0.1598	1.0372	1.5313	2.1498	4.2629

Table (1) Time Costs of Different Methods

# **Quality Measure Metrics with Different Methods:**

Metrics	FFM	JIEP	LIME	AFEM	RBFA	PROPOSED
PIQE	33.214	15.4431	15.4200	15.0383	28.2231	13.7150
LOE	238.5874	2709.9789	434.7973	971.5404	1111.2368	56.0708
MSE	416.2042	16747.2845	5438.4254	1906.2398	2395.8858	55.5773
SSIM	0.8760	0.4038	0.5620	0.7287	0.5849	0.9575
PSNR	21.9377	5.8914	10.7761	15.3290	14.3361	30.6818

Table (2) Quality Measure with Different Methods

**PIQE** (**Perception based Image Quality Evaluator**) is a no-reference algorithm that uses statistical features of the input image to evaluate the image quality. It estimates block-wise distortion (the straight lines of an image appear to be deformed or curved unnaturally) and measures the local variance of perceptibly distorted blocks to compute the quality score.

To evaluate this metric, we have the PIQE algorithm inbuilt in MATLAB. So, we use the function PIQE (image) which processes the image and returns the score. The smaller score indicates better perceptual quality.

**LOE** (**Lightness Order Error**) is a quantitative measure metric which measures the lightness distortion in the enhanced image. This metric is evaluated using the following formula

$$LOE = \frac{1}{m} \sum_{x=1}^{m} \sum_{y=1}^{m} (U(M(x), M(y)) \oplus U(M_e(x), M_e(y))$$
 (21)

m is the number of pixels in the image. M(x) and  $M_e(x)$  are the maximum values among the three-color channels at location x of the input image and the enhanced image, respectively.  $\bigoplus$  is the exclusive-or operator. The lower value of LOE indicates that the better lightness order is preserved.

**MSE** (**Mean Squared Error**) is the cumulative squared error between the compressed and the original image. The lower the value of MSE, the lower the error. This metric is calculated using the following formula.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M \times N}$$
 (22)

 $I_1$  (m, n) is the pixel value at m, n of image  $I_1$  and  $I_2$  (m, n) is the pixel value at m, n of image  $I_2$ ,  $M \times N$  is the image size.  $I_1$ ,  $I_2$  are original and enhanced images.

**SSIM** (**Structural Similarity Index**) is a perceptual metric that quantifies image quality degradation caused by processing such as data compression or by losses in data transmission. To evaluate this metric, following formula is used.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$
(23)

 $\mu_x$  is the pixel sample mean of x.

 $\mu_y$  is the pixel sample mean of y.

 $\sigma_x^2$  is the variance of x.

 $\sigma_{v}^{2}$  is the variance of y.

 $\sigma_{xy}$  is the covariance of x and y.

To evaluate this metric, we have the algorithm inbuilt in MATLAB so we use the function SSIM (image) which processes the image and returns the score. An SSIM score of 1.00 indicates perfect structural similarity, as is expected out of identical images.

**PSNR** (**Peak Signal-to-Noise Ratio**) computes the peak signal-to-noise ratio in decibels between two images. This ratio is used as a quality measurement between the original and a compressed image. The higher the score the better the quality of the compressed, or reconstructed image. To evaluate this metric following formula is used.

$$PSNR = 10\log_{10}(\frac{R^2}{MSE}) \tag{24}$$

*R* is the maximum fluctuation.

MSE is the mean squared error

# **CONCLUSION**

We proposed the Retinex-based fast enhancement method. This method can achieve uneven brightness and greatly improve the brightness of low-light areas. The proposed method is more efficient. In general, the proposed RBFA algorithm performance is better than other state-of-theart methods due to less Time Complexity and better score of Quality Metrics. In other words, the proposed RBFA method is simple and efficient low-light image-enhancement algorithm.

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