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Back Propagation Approach for Image Contrast Enhancement

Shavneet Kaur[1], Jaspreet Kaur[2], Sukhmanpreet Singh[3]

M. Tech Student, Department of Electronics and Communication Engg., Rayat Bhara University, Mohali, India[1]

Assistant Professor, Department of Electronics and Communication Engg., Rayat Bhara University, Mohali, India[2,3]

Abstract: In this research work, An adaptive contrast enhancement technique which is based on the adaptive histogram equalization is used. The back propagation algorithm is applied to select the smoothing factor dynamically and to calculate histogram equalization. The simulation of the proposed modal is performed in MATLAB. The performance of proposed modal is compared in terms of PSNR , SSIM and MSE.

Keywords: Back propagation, CLAHE

I. INTRODUCTION

The enhancement of the various images that are gathered from different sources like cameras or sensors that are placed within several applications is known as image processing. The obtained output can be generated in the form of an image or any set of parameters [1]. In order to enhance the visual quality, recognize the patterns and perform digital image processing, Contrast Enhancement plays a very important role .Thus, Histogram Equalization (HE) is one of the most commonly utilized approaches today [2-4].

Contrast Limited Adaptive Histogram Equalization (CLAHE): The CLAHE is a modification of adaptive histogram equalization in which the contrast amplification is limited, so that at the output, the over amplification problem can be reduced.

Back Propagation (BP) Algorithm: Back Propagation algorithm is considered as the most popular Neural Networks algorithms currently. The back propagation technique is the neural networks technique which learns from the experiences and drive new values. Back propagation algorithms are collection of methods used to efficiently train Artificial Neural Networks (ANNs).

II. LITERATURE REVIEW

Qiang Song, et.al (2018) proposed a single-image super-resolution scheme by introducing a gradient field sharpening transform that converts the blurry gradient field of upsampled Low Resolution (LR) image to a much sharper gradient field of original High-Resolution (HR) image [5]. Experimental results demonstrate that the proposed algorithm can generate more accurate gradient field and produce super-resolved images with better objective and visual qualities.

Pai-Hui Hsu, et.al (2018) proposed a novel pan-sharpening method for remote sensing images has been proposed with sparse representation over learned dictionaries [6]. The experiment results indicate that the proposed method not only preserve spectral and spatial details of the source images but overcoming the drawbacks of fusion distortion.

Partha Pratim Banik, et.al (2018) proposed o novel mechanism through which it is possible to identify that region of the image that as low light[7].Once several experiments have been conducted, the value of gamma for various low-light images is approximated here.

Bo-Hao Chen, et.al (2017) presented the image contrast is enhanced on an assumption of maximum entropy for which they proposed a new HE-based algorithm such that several other features that are included in defining the quality of an image can also be maintained[11]. The experimental results shows that the performance of proposed approach is better than the existing methods.

Jia Chen, et.al (2017) presented the enhancement of image contrast in this paper which has been utilized such that the contrast level of images can be enhanced with Artificial Bee Colony (ABC) algorithm [8]. The results show that the performance of proposed technique is better as compared to other already existing techniques.

III. RESEARCH METHODOLOGY

In figure, the input image I is converted into HSV representation. The proposed intrinsic decomposition model is used that decomposes the value (V) channel image into illumination (L) and reflectance (R) layers as secondary step.

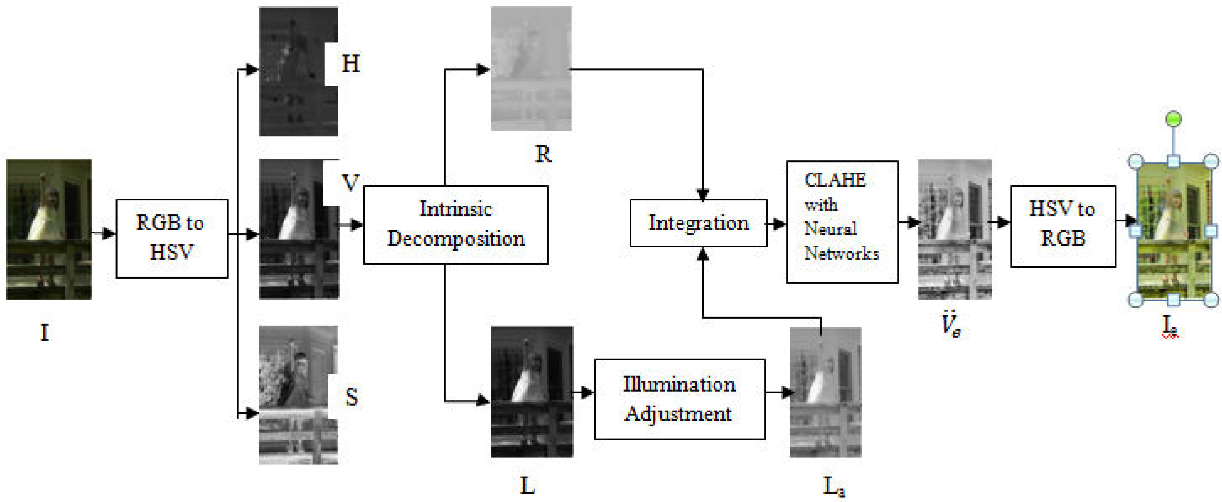

Fig 1: Framework of the Proposed Contrast enhancement method

An adjusted L layer which is represented as L_a is generated when L layer is adjusted using Gamma mapping function which is the third step. In order to generate the enhanced V channel image which is represented here as V_e, the adjusted L_a is multiplied by reflectance layer R. $\widehat{V}_e$ is used to denote the enhanced result. The formula is given in equation (1) to calculate actual value of equalization

Actual equalization value $=\sum_{\substack{x=0\\ w=0}}^{\substack{x=n\\ w=n}} x_n w_n$+bias –(1)

The final equalization will be at which error is least. The error will be calculated with the equation (2)

Error=Desired Equalization value- Actual equalization value (2)

At the end, the final result I_e is generated by transforming the enhanced HSV image into RGB space. Intrinsic decomposition and illumination adjustment are the two major modules of this proposed mechanism which are explained further.

a. Intrinsic Image Decomposition: In order to compute the equation $V = L.R$, the intrinsic decomposition issue is formulated here within Equation (3), as a minimization problem of the energy function. Here, vector form of V, L and R are used which are v, l, and r.

$$\min_{l,r} E(l,r)=E_r(r)+\mu E_l(l)+\theta E_d(v;l,r)+\beta E_\circ(l,l_\circ), \quad \text{s.t. } 0\le r\le 1, \ldots (3)$$

Here, the weighting parameters are denoted by $\mu, \theta,$ and β. Upon the reflectance and illumination layers, μ and θ are regularizer. In order to ensure the reliability of decomposition, β terms is used. l_2 norm penalty which is $(\|v - l.r\|_2^2)$ is utilized instead of previous equality constraint which was $v = l.r$ within the intrinsic decomposition such that the noise can be tolerated. In order to constrain the scale of l, the final term $E_\circ = (\|l - l_\circ\|_2^2)$ is used. The chromatic normalization value which is $\sqrt{I_r^2 + I_g^2 + I_b^2}$ is set for $l_\circ$ here.

The reflectance later is constrained to be piecewise constant as per the similarity of color by the $E_r(r)$ term. For instance, at pixel i, the reflectance value is denoted by r_i. The representation of this constraint is shown in Equation (4).

$$E_r(r) = \sum_i \sum_{j\in N(i)} w_{ij}\left\|r_i - r_j\right\| 1 \qquad .. (4)$$

Here, for pixel i, the neighborhood is $N(i)$. For pixel i and j, the similarity of chromatic value is measured by w_{ij}. The weight values are increased here such that the different amongst r_i and r_j can be penalized for the pixels that have similar colors. Thus, the weighting function is defined in equation (5) as:

$$w_{ij} = \exp\left(-\frac{\|f_i - f_j\|_2^2}{2\sigma^2}\right) \qquad \ldots (5)$$

Here, the value of pixel i is represented by f_i which can be denoted as $f_i = [\tau l_i, a_i, b_i]^T$. The values of τ and σ are constant. It is to be ensured that $\tau < 1$ in order to minimize the impact of illumination variations on the color similarity measurement.

The isotropic total variation is utilized in order to enforce that the illumination is smooth with the application of $E_l(l)$, and is defined by Equation (6) as:

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$E_l(l) = \|D_x l\|_2^2 + \|D_y l\|_2^2$ … (6)

Here, along the horizontal and vertical directions, D_x and D_y represent the matrix representation of derivative operators respectively.

B. Illumination Adjustment: Through the results obtained it is seen that the by preserving the lightness order, all the dark areas are darkened. Gamma function is utilized here for adjusting the illuminations which is represented in Equation (7).

$L_a = 255 \times (L/255)^{1/\gamma}$ … (7)

Here, for conducting experiments, the value of γ is set as 2.2.

IV. EXPERIMENTAL RESULTS

The proposed approach is implemented in MATLAB and the results are evaluated in proposed and existing approaches based on certain parameters.

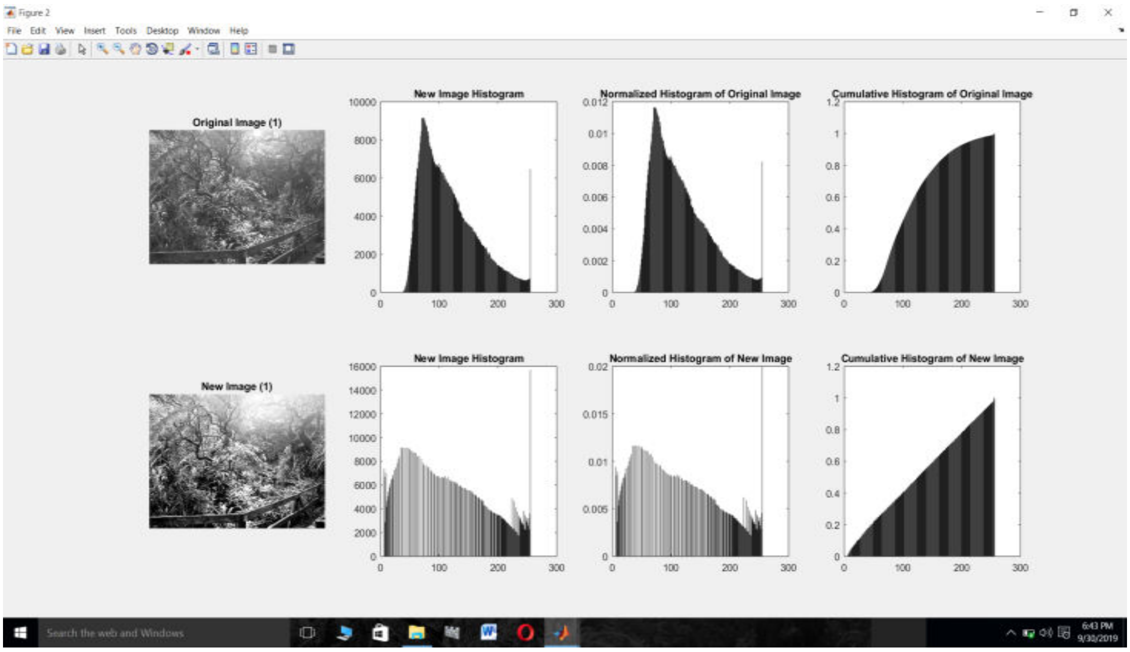

Fig 9: Histogram Equalizer with back propagation algorithm

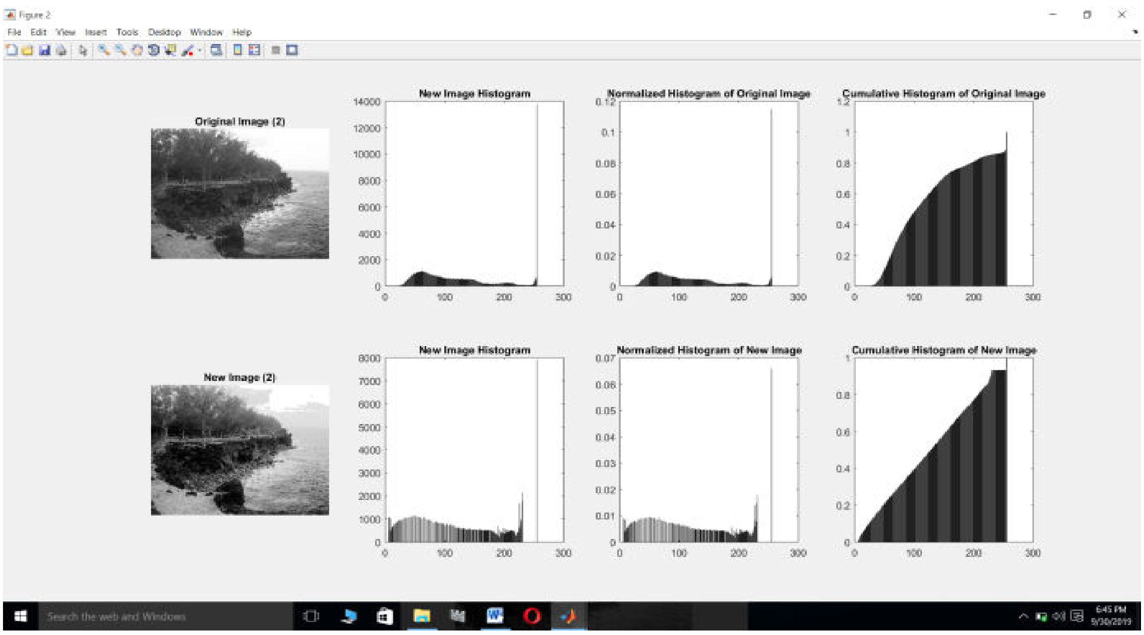

Fig 10: Histogram Equalizer with back propagation algorithm

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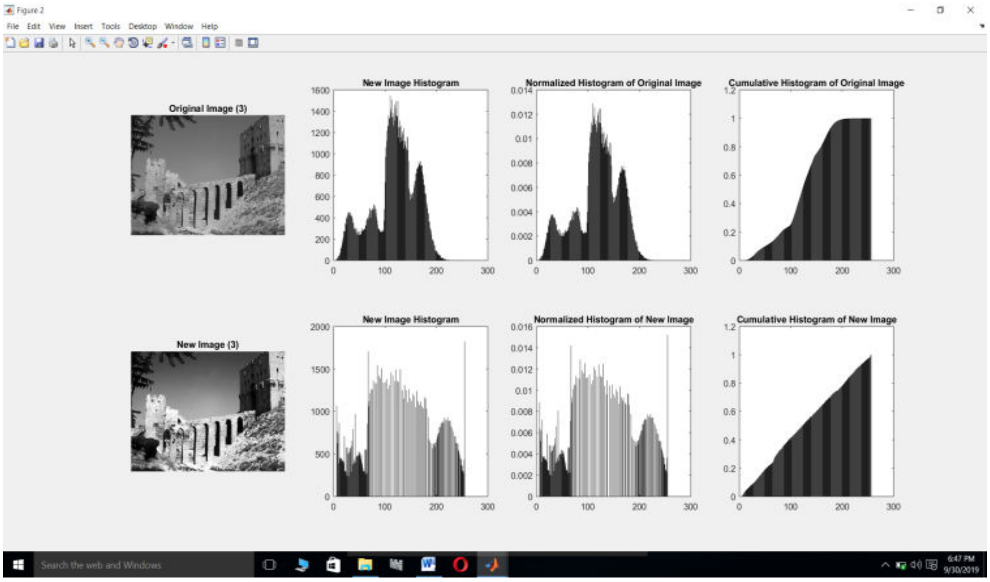

Fig 11: Histogram Equalizer with back propagation algorithm

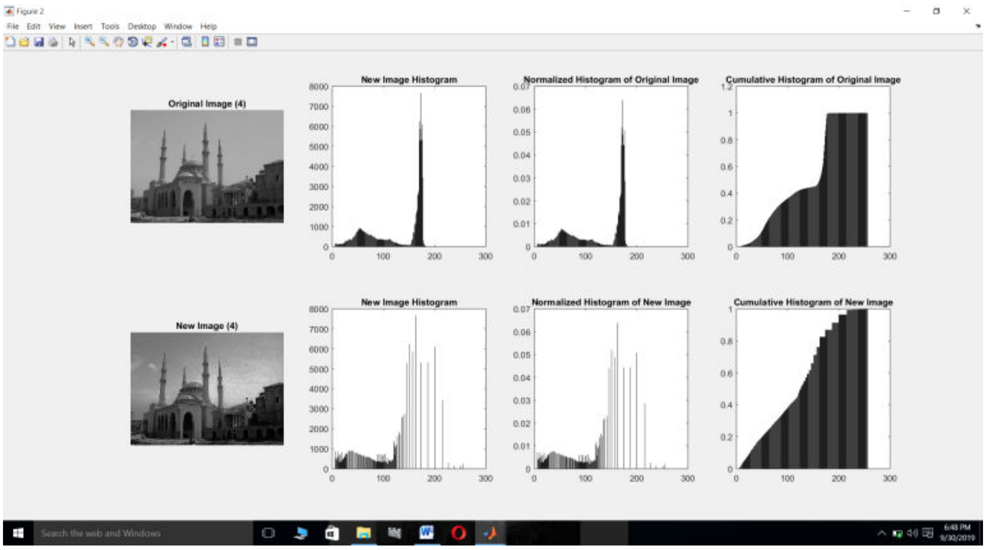

Fig 12: Histogram Equalizer with back propagation algorithm

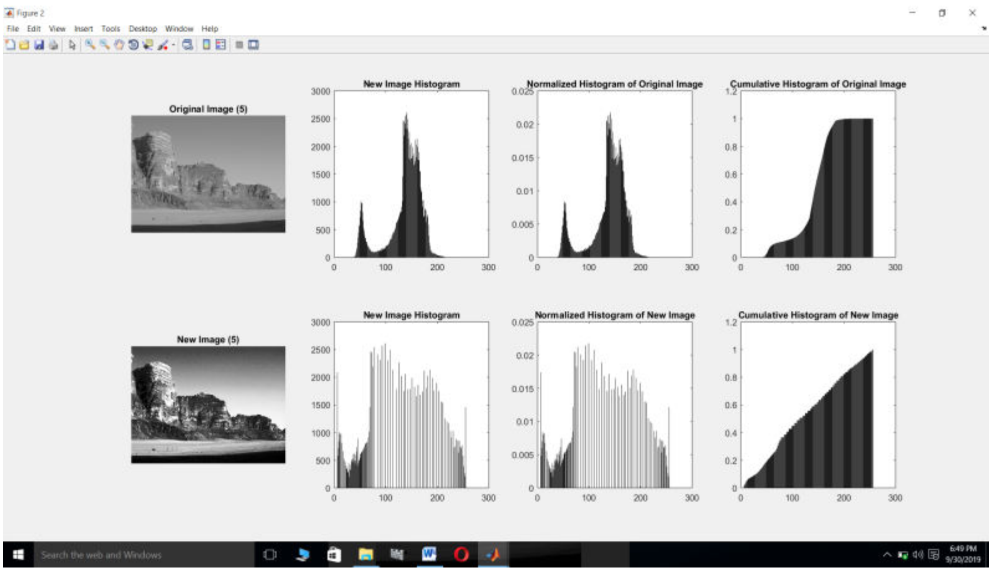

Fig 13: Histogram Equalizer with back propagation algorithm

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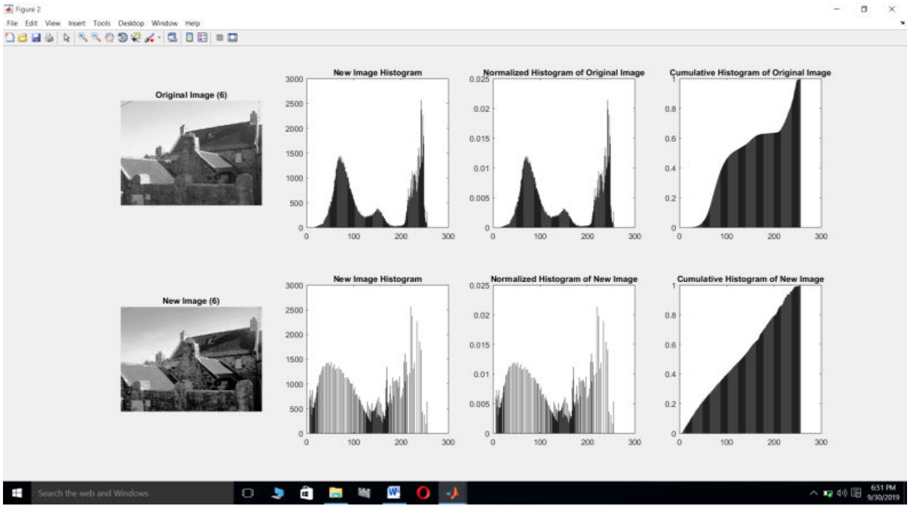

Fig 14: Histogram Equalizer with back propagation algorithm

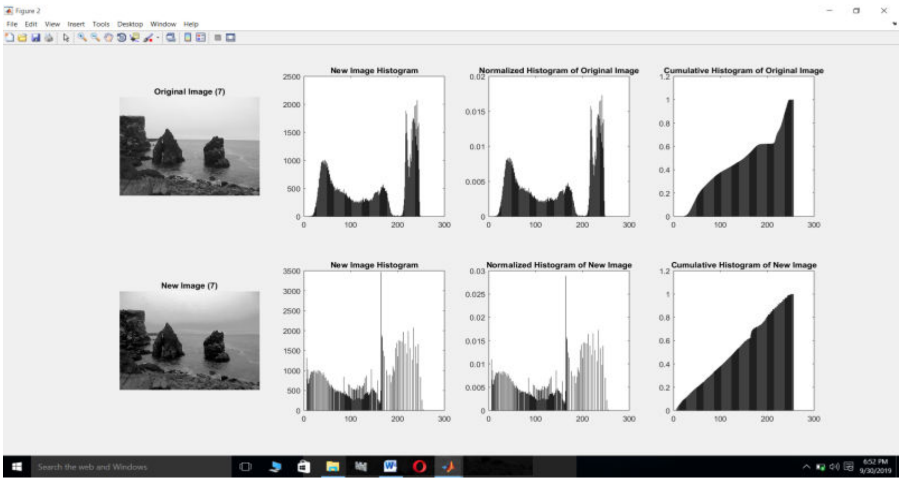

Fig 15: Histogram Equalizer with back propagation algorithm

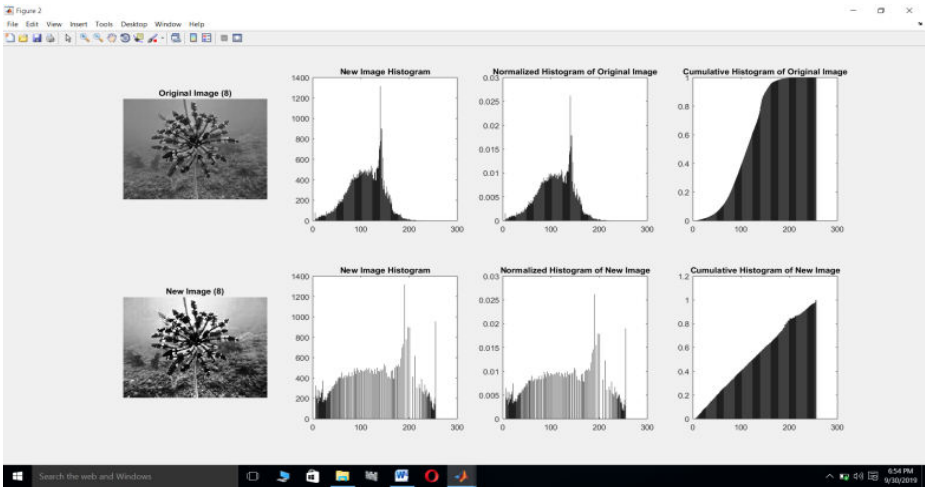

Fig 16: Histogram Equalizer with back propagation algorithm

As shown in figure 9-17, the technique of back propagation is applied with the histogram equalizer technique and results are shown from figure 9-16. The 8 figures are taken and the comparison is shown in terms of PSNR, SSIM and MSE. The technique of histogram equalizer is applied with back propagation algorithm which calculates average of color intensity and also used to increase the contrast of the image. The back propagation technique is the neural networks technique which learns from the experiences and drive new values.

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Comparison of Parameters:

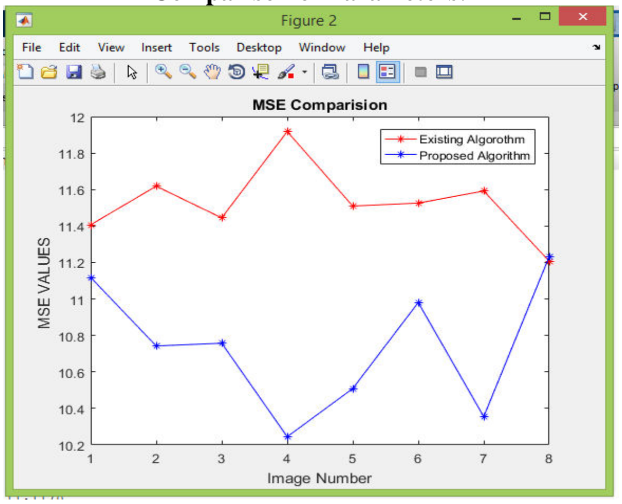

Fig 17: MSE

As shown in figure 17 and in table 1, the MSE value of the existing algorithm(Adaptive gradient sharpening transform) and proposed algorithm (Adaptive gradient sharpening transform with back propagation algorithm) is compared for the performance analysis and it is analyzed that the MSE value of the existing(Adaptive gradient sharpening transform) is less as compare to proposed algorithm (Adaptive gradient sharpening transform with back propagation algorithm).

Table 1: MSE Analysis

Image Number	Existing Algorithm(Adaptive gradient sharpening transform)	Proposed Algorithm(Adaptive gradient sharpening transform with back propagation algorithm)
New image 1	11.4	11.2
New image 2	11.7	10.8
New image 3	11.4	10.8
New image 4	12	10.4
New image 5	11.6	10.6
New image 6	11.1	10.42
New image 7	11.6	10.4
New image 8	11.2	11.3

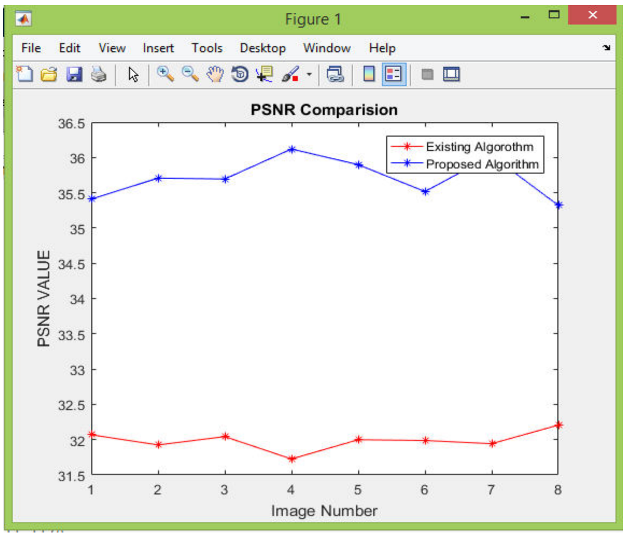

Fig 18: PSNR Analysis

As shown in Figure 18 and table 2 shows that the PSNR value of existing algorithm (Adaptive gradient sharpening transform) is high as compared to proposed algorithm (Adaptive gradient sharpening transform with back propagation algorithm) .

Table 2: PSNR Analysis

Image Number	Existing Algorithm(Adaptive gradient sharpening transform)	Proposed Algorithm(Adaptive gradient sharpening transform with back propagation algorithm)
New image 1	32.5	35.6
New image 2	33	36.2
New image 3	32.1	35.8
New image 4	31.5	36.5
New image 5	32	35.8
New image 6	32.1	35.5
New image 7	32.3	36
New image 8	32.4	35.6

Fig 19: SSIM Analysis

As shown in figure 19 and in table 3, the SSIM value of the existing (Adaptive gradient sharpening transform) is less as compared to proposed algorithm (Adaptive gradient sharpening transform with back propagation algorithm).

Table 3:SSIM Analysis

Image Number	Existing Algorithm(Adaptive gradient sharpening transform)	Proposed Algorithm(Adaptive gradient sharpening transform with back propagation algorithm)
New image 1	0.99	0.97
New image 2	0.99	0.98
New image 3	0.98	0.96
New image 4	0.98	0.96
New image 5	0.99	0.87
New image 6	0.98	0.96
New image 7	0.98	0.85
New image 8	0.98	0.96

V. CONCLUSION

In this paper, improvement in the intrinsic image decomposition technique is proposed. The intrinsic image decomposition technique is based on the illumination layer in which histogram equalization is calculated to image contrast. In this research work, the improvement in the intrinsic image decomposition technique is proposed based on back propagation technique. The simulation results shows that proposed technique performs well in terms of PSNR,SSIM,MSE than existing technique.

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