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DWT based historical image enhancement technique using adaptive gamma correction

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ABSTRACT

Historical Images are of great significance as they depict the social and cultural heritage of a country. The sculptures and murals have a unique way of expressing age-old traditions and diversities of art that existed for many centuries. Digital restoration of historical images may undergo several defects of low intensity lighting conditions, blurred and occluded images. Their preservation and reconstruction of damaged images are of prime importance. In this paper, an algorithm is proposed to enhance the image quality of digitally captured images of historical importance to illustrate the art and other image details clearly. In the CIELAB color space model, discrete wavelet transform is applied up to two levels to obtain approximation and detail coefficient bands. Based on these sub-bands, gamma correction is applied adaptively to brighten the features of dark and dull images. Experimental results and evaluation parameters exhibit the efficiency of the proposed method. The proposed algorithm can be used efficiently for image acquisition to obtain enhanced images. The proposed algorithm is suitable for real-time applications and can be easily adapted to devices that support limited memory with predefined operations.

Keywords: Image enhancement, Contrast, Gamma correction, Discrete wavelet transform.

1. Introduction

Digital archive of historical images lays a foundation of preserving and restoring and digitizing images of cultural importance [1] [2]. Murals and sculptures have been an integral part of our culture for thousands of years. They are prone to get deteriorated due to several inevitable reasons like exposure to climate changes or frequent touching by spectators leading to chipping or loss of paint, formation of cracks and colour distortions in murals [3]. Illumination and lighting also play an important role while taking pictures of these artifacts of historical importance. The poorly lit surroundings will result in dark and low contrast digital images while over exposed lighting conditions may give high contrast and bright images. Hence, restoring these ancient artifacts digitally is a challenging task. Virtual restoration of degraded historical images requires multiple image processing operations to obtain enhanced images preserving the structure, texture and colors [4]–[7].

The digital image processing techniques [8] are manipulations on a digital image using computers. These tasks are image acquisition, image compression, geometrical transformations, image inpainting, image restoration, image enhancement and many more. These manipulations help to retrieve valuable information present in the image. Spatial domain image enhancement methods [9] manipulate the pixel values of an image, whereas frequency domain methods manipulate the values of the coefficients of an image, as shown in Eq. (1), where, $f(x,y)$ is input image, $g(x,y)$ is output image and T is transformation function. These techniques are widely used in many applications like medical visualization, law enforcement, human-computer interfaces, artistic effects, image restoration and many more.

$$g(x,y) = T[f(x,y)] \tag{1}$$

Contrast [10] is an essential element in qualitative assessment of an image. It is the difference in luminance of two surfaces which makes different objects distinguishable from each other as well as the background. Contrast stretching [11] develops the contrast of an image by distributing the pixel intensities to extent to a desirable range of values. Many

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algorithms are developed for accomplishing contrast enhancement and used in solving image processing problems. When contrast is highly concentrated within a specific range, it results in very dark image for low contrast regions and very bright image for high contrast regions in an image. The information may be lost in both cases. The objective is to improve the contrast of overall image so as to minimize the information loss and obtain maximum information of input image.

2. Related Work

Histogram equalization [12] finds its place in a variety of image processing applications of contrast enhancement. This method is prevalent due to its simple function and effectiveness. In [13], Yeong-Taeg Kim proposed an algorithm to decompose an image and obtain two sub-images on the basis of its mean and then applying histogram equalizations independently over these two separate sub-images, hence resulting in equalized sub-images which are bound to each other around the input mean. In [14], the author introduced an algorithm to maintain the average brightness of the image but fails for images with high density and narrow range. Coltuc et al. [15] used the image enhancement method on watermarking images which gives maximum image information with good visual quality though it may not offer any obvious choice for the desired histogram. The method proposed in [16] preserves the brightness and gives more probabilities to gray levels which are infrequent in medical images, but it drops some statistical information and recursive nature consumes more time. Zihan et al. [17] introduced an unsharp-masking technique that enhances the contrast and spatially sharpens the texture in images. It preserves the hue of colors in image and adaptively controls the contrast magnification ratio.

In [18], Huang et.al. proposed an adaptive method to enhance the contrast of an image using gamma correction with weighting distribution which combined the traditional gamma correction method and histogram equalization together. The AGCWD method fails in the absence of bright pixels as the peak intensity in the resultant image is bound by maximum intensity of input image, although it preserves the overall brightness of the image. The Dynamic Contrast Ratio Gamma Correction (DCRGC) method [19] concurrently apply TGC and THE (Traditional Histogram Equalization) and directly sets a parameter as a ratio, though it cannot be generated automatically. Automatic Weighting Mean-separated Histogram Equalization (AWMHE) method [20] equalize sub-histogram to accurately preserve the brightness by optimizing the threshold values through recursive function. In Conventional Piecewise Linear Transformation, some parameters are set manually making it ineffective and inefficient for real time images. Further, Tsai et al. [21] proposed a method to alleviate these limitations by introducing a parameter free method for color images called an Automatic Piecewise Linear Transformation (APLT) function. Later, in [22] Tsai et al. proposed an algorithm for enhancement of an image based on decision-tree, which is used to take decisions whether the input image is dark or bright. Initially a decision is made about the type of degraded image, then piecewise linear transformation is done to improve this image. This method shows excellent performance for skin detection and visual perception, though some local features of the face image may get weak, as stated in a study conducted by Li et al. [23] in which Histogram Equalization (HE) is used in order to increase the performances of the Illumination Compensation based on Multiple Regression Model (ICR) and Affine Transform (AT) algorithms. In [24], Salah-eldin et al. suggested a method in which Histogram Equalization experiences the Gamma correction and Retinal filter's compression function (GAMMA-HM-COMP) combined together to solve illumination effect on face images.

In [25], authors proposed frequency domain based image enhancement algorithm, where they have included measure of variance for each coefficient to oobtain the enhanced images which are compressed with JPEG. Also, this algorithm is more suitable for those images, where direction contrast is required to improve the enhancement. In [26], Gomez et al. proposed an approach which focused on low pass band of DWT to extract the illumination from the images by using a homomorphic filtering function to obtain the illumination model making an effective approach for video sequences. The wavelet methods had not only enhanced the contrast, yet improve the edges and other details to further enable the face recognition process. Zhang et.al. proposed a different color correction process [27] for underwater images to improve the quality on the basis of sub-interval linear transformation. L channel is decomposed using Gaussian low-pass filter and optimal equalization threshold strategy enhances the contrast of image.

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3. Background

3.1 Discrete Wavelet Transform

The conversion of a signal from spatial domain or time domain to the frequency domain using mathematical operators is called transforms [28]. Any image in the spatial domain can be represented in a frequency domain with two major components. High-frequency components relate to edges present in the image and low-frequency components correspond to smooth regions. A discrete wavelet transform (DWT) [29], [30] is used for high-dimensional data analyses, such as image processing and analysis. DWT decomposes an input signal into a series of coefficients. DWT coefficients contain temporal information of the analyzed signal. One level-DWT [30] and inverse discrete wavelet transform are represented by Eq. (2) and Eq. (3):

$$D(a,b) = \sum_a \sum_b S(a)\Phi_{ab}(n) \tag{2}$$

$$S = \sum_a \sum_b D(a,b)\,\Phi_{ab}(n) \tag{3}$$

where, $D(a,b)$ defines the coefficient of DWT. Shift parameters and scale transform are denoted by a and b, respectively. $\Phi_{ab}(n)$ represents the base time wavelet of the function. A bottom-up approach is used to reconstruct the original signal S by applying Inverse-DWT.

3.2 Gamma Correction

A digital image (color or grayscale) created from a digital device is bound to have gamma added to it. This created bright ones too bright, but dim tones got lost in the dark, and tonal images are really hard to show. Gamma correction [18], [31], [32] monitors the contrast of an image. Varying the amount of gamma correction changes the red to green to blue ratio hence changing the brightness. The power-law transformation of the gamma correction (TGC) is represented by Eq. (4).

$$T(l) = l_{max}(l/l_{max})^{\gamma} \tag{4}$$

Where, l_{max} represents maximum intensity and intensity l of each pixel which is transformed as $T(l)$. Images which are not properly corrected can look either bleached or washed out or too dark which leads to loss of image details.

3. Proposed method

In the first phase of the proposed algorithm, degraded digital image $I_{m\times n}$ is taken as an input and it is converted into CIELAB or (L*a*b) color space model. Discrete wavelet transform is applied to L channel to get sub-band coefficients. These coefficients are represented by LL, LH, HL and HH, where LL band is called the approximation band and is taken for the next level. DWT uses low pass and high pass filters in horizontal and vertical directions to generate these sub-bands. In the second phase, adaptive gamma correction is applied on the basis of coefficient values. The minimum and maximum values in the sub-band play an important role in adapting the mechanisms of gamma correction. In order to generate the output image as per the spatial domain, Inverse DWT is applied in the reverse order. It is observed that coefficient values require 16-bit format to store the fractional value. The detailed procedure of the first and second phases is explained in *Algorithm I* and *Algorithm II* and pictorially demonstrated in Fig. 1.

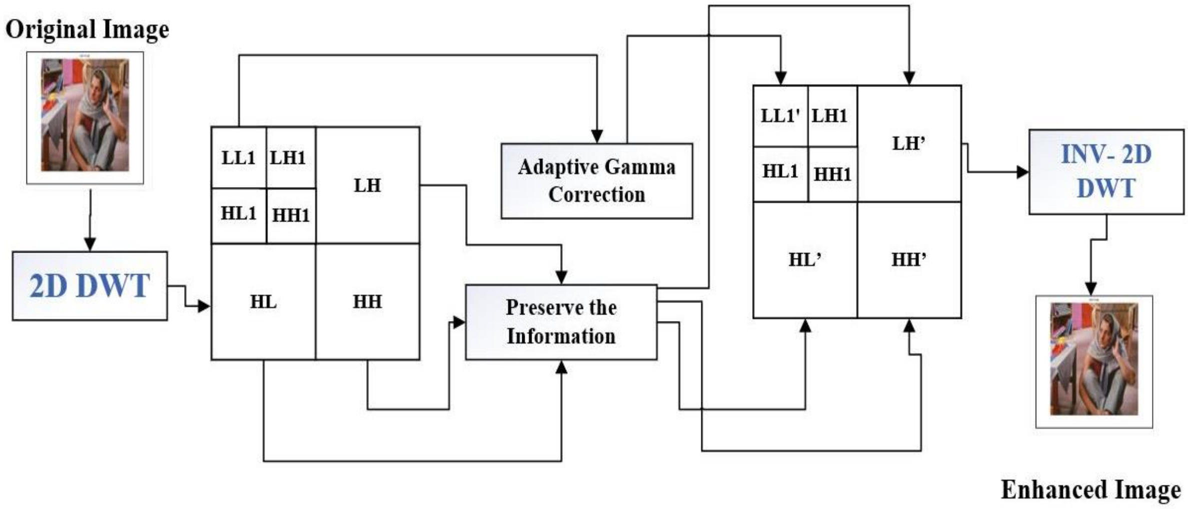

Fig. 1: An overview of the proposed method.

3.1 Sub-bands coefficients generations using DWT

Transform domains are applied to images to analyze the sensitive information within the image. 2D-DWT is applied to the historical images in the proposed algorithm to obtain the approximation and detailed coefficients. The detailed procedure to generate the coefficients is explained in Algorithm I.

$\boldsymbol{Pseudo\ code:\ Algorithm\ I}$

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1. Input: Input image $\boldsymbol{I_{m\times n}}$
2. Output: Sub-band coefficients
3. Start
4. Read input RGB image $\boldsymbol{I_{m\times n}}$.
5. Convert $\boldsymbol{I_{m\times n}}$ to CIELAB color space model $\boldsymbol{L*a*b}$
6. $\boldsymbol{level \leftarrow 1}$
7. $\boldsymbol{Input}= \boldsymbol{L_{m\times n}}$
8. $\boldsymbol{i=0}$
9. $\boldsymbol{While\ (level\ <\ 3)}$
10. Apply DWT to the Input using Eq. (1)
11. Generated sub-bands are stored in $\boldsymbol{LL}[\boldsymbol{i}], \boldsymbol{LH}[\boldsymbol{i}], \boldsymbol{HL}[\boldsymbol{i}], \boldsymbol{HH}[\boldsymbol{i}]$ bands
12. Input $\leftarrow \boldsymbol{LL}[\boldsymbol{i}]$
13. $\boldsymbol{level = level + 1}$
14. $\boldsymbol{i++}$
15. $\boldsymbol{While - end}$
16. The generated $\boldsymbol{LL}[\boldsymbol{1}]$ sub-band is used as input for next phase, which is discussed in Algorithm II.
17. end

3.2 Adaptive Gamma correction algorithm

The digital images are captured by camera sensors and the result is completely based on temperature, focal length, aperture, light and size of the camera sensor. Mural images are captured in the low light area, which produces the noisy and low contrast images. Therefore, an algorithm must be designed such that it can enhance image quality without

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compromising with other details of the image. In the proposed work, we have designed an algorithm to preserve all the details of an image along with the enhancement of contrast. Thus, the proposed algorithm is completely different from the traditional way of gamma correction. The detailed procedure is illustrated in Algorithm II.

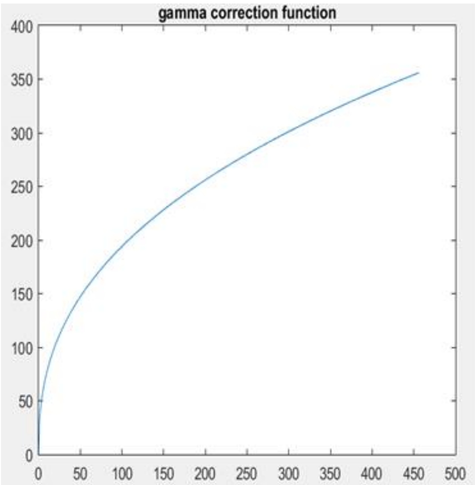
Pseudocode: Algorithm II

Start
Read subband $\boldsymbol{LL}[\mathbf{1}]$.
Calculate $\boldsymbol{min}$ and $\boldsymbol{max}$ in $\boldsymbol{LL1}$
c=1;
$\boldsymbol{r} = \boldsymbol{min}\colon \boldsymbol{max}$
%Adaptative Gamma function start
$\boldsymbol{s} = \boldsymbol{c} \times \boldsymbol{r}.\hat{}\boldsymbol{gamma}$
s1=s;
s=(s/max(s)) ×double(max);
$\boldsymbol{threshold} = (\boldsymbol{max} + \boldsymbol{c1})/\mathbf{2}$
$\boldsymbol{for}$ I ←1 to m
$\boldsymbol{for}$ j ←1to n
$\boldsymbol{If}$ LL1(I,j) <threshold
$\boldsymbol{LL1}' = \boldsymbol{s}(\boldsymbol{LL1})$
$\boldsymbol{else}$
$\boldsymbol{LL1}' = (\boldsymbol{LL1})$
$\boldsymbol{If - end}$
$\boldsymbol{for - End}$
$\boldsymbol{for - end}$
%Adaptative Gamma function end
Inverse-2D DWT is used to reconstruct the $\boldsymbol{LL1}'$
It is passed further to reconstruct the image $\boldsymbol{Rec\_I}$ as shown below:
a. $\boldsymbol{Rec\_I} = \boldsymbol{IDWT}(\boldsymbol{IDWT}(\boldsymbol{LL}_1', \boldsymbol{LH}_1, \boldsymbol{HL}_1, \boldsymbol{HH}_1)\boldsymbol{LH}^0, \boldsymbol{HL}^0\boldsymbol{HH}^0)$
Convert $\boldsymbol{Rec\_I}$ to the color space model.
end

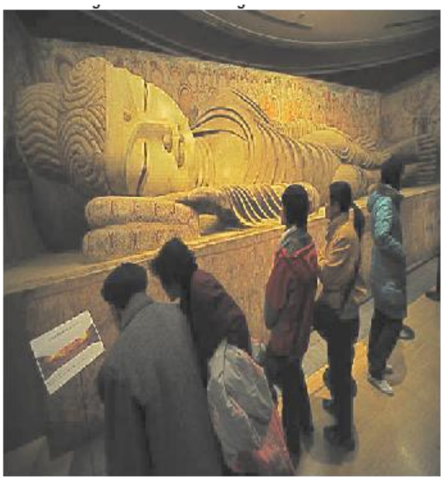
4. Experimental Results

This section involves an analysis of the proposed algorithm for efficiency and performance. The proposed method for enhancement of historical images is applied on 64-bit machine architecture with Matlab R2015a software. The test images are selected from several historical images of the online database of Dunhuangand Mogao caves. The input image goes through Algorithm I to generate DWT coefficients and further algorithm II results in the enhancement of low-contrast input image. Fig. 2 displays intermediate results obtained after the proposed method is applied over the test image.

(a) (b)



(c)



(d)

Fig. 2: Step-by-step results of the proposed method. (a)Low-contrast image; (b)DWT image after 2-level decomposition in CIE L*a*b color space (c)Gamma correction function for L channel (d)Enhanced image.

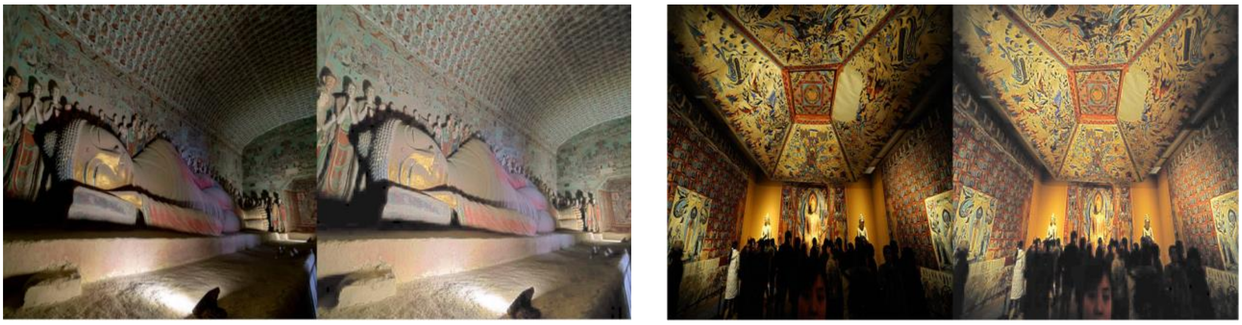
The results of our proposed algorithm are found impressive and capable to restore deteriorated digital historical images and improve them to obtain the image details more clearly. This method helps to enhance the contrast of an image in to get detailed information of an image more accurately with reduced computational cost. It is important to establish empirical measures to prove the efficacy of the proposed algorithm. The metric under observation are Mean square error (MSE), Peak signal to noise ratio (PSNR), Structural similarity index measure (SSIM) and mean for the measure of brightness of the image. Fig 3 shows few examples of images taken from the database.

1(a) 1(b)

2(a) 2(b)

3(a) 3(b)

4(a) 4(b)



5(a) 5(b) 6(a) 6(b)

Fig. 3: Several test images. (a) Low-contrast image, (b) Enhanced image obtained by proposed method.

4.1 PSNR, MSE and SSIM

PSNR (Peak Signal to noise ratio) usually checks the distortion level of a signal and its quality after retrieval at the receiver's end. In image enhancement, PSNR is calculated between the low contrast original image and its enhanced restored image. Researchers suggest that the higher values of PSNR indicate that a proposed method enhances the contrast of image and provides more image details. MSE values must be low in order to support efficient image enhancement. MSE and PSNR are inversely proportional to each other, i.e., low MSE indicates higher values of PSNR as shown in Table 1. The following equation calculates PSNR (in dB):

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [\,(I(i,j) - \mathrm{I}'(\mathrm{i},\mathrm{j}))^2] \quad (5)$$

$$PSNR = 10 \log_{10}(\frac{255^2}{MSE}) \quad (6)$$

Where $I(i,j)$ and $I'(i,j)$ represents the low-contrast image and enhanced image, respectively.

Structural Similarity Index (SSIM) is used to measure similarity between two digital images, degraded image and restored image; in case of image enhancement. Its values generally lie between 0 to 1, for a perfect match, this value is 1 and 0 when two images are entirely different. The values of MSE, PSNR and SSIM of test images are illustrated in Figure 4. The value of SSIM shows that the restored image is similar in structure to that of the original image and has additional information of data content of the image.

Table 1: Experimental values of MSE, PSNR and SSIM

Image name	MSE	PSNR	SSIM
1	0.0309	63.22	0.5894
2	0.0334	62.891	0.5835
3	0.0405	62.055	0.7551
4	0.0419	61.907	0.678
5	0.0500	61.137	0.6967
6	0.0390	62.199	0.6250

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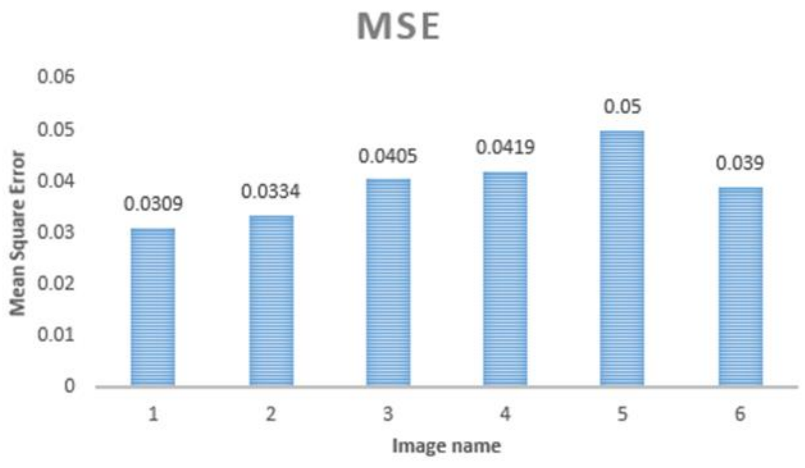

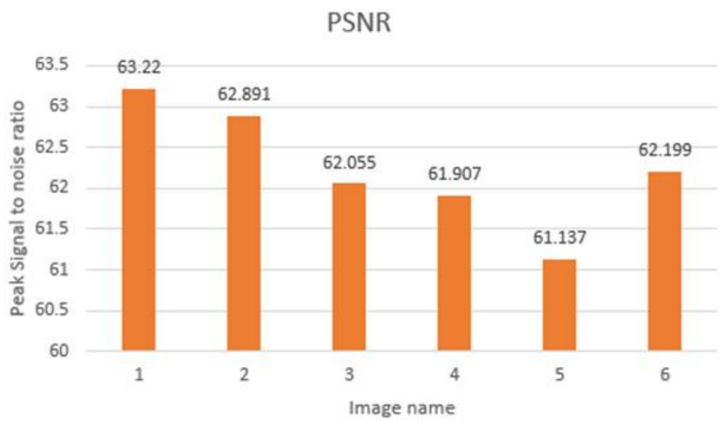

Fig. 4: Graph of Mean Squared Error, Peak Signal to Noise Ratio, Structured Similarity Index measure

.4.2 Mean value and entropy analysis

Mean value analysis is used to determine the uniform level of intensity values within an image. It represents the amount of brightness of a pixel. Mean value of an improved image is more as compared to mean of low-contrast image. The entropy of an image is a statistical measure of randomness of pixels. High value of Entropy implies the high amount of information depicted by an image. The proposed method results in enhanced image with higher value of entropy and mean as compared to degraded input image as shown in Table 2 and represented in Figure 5.

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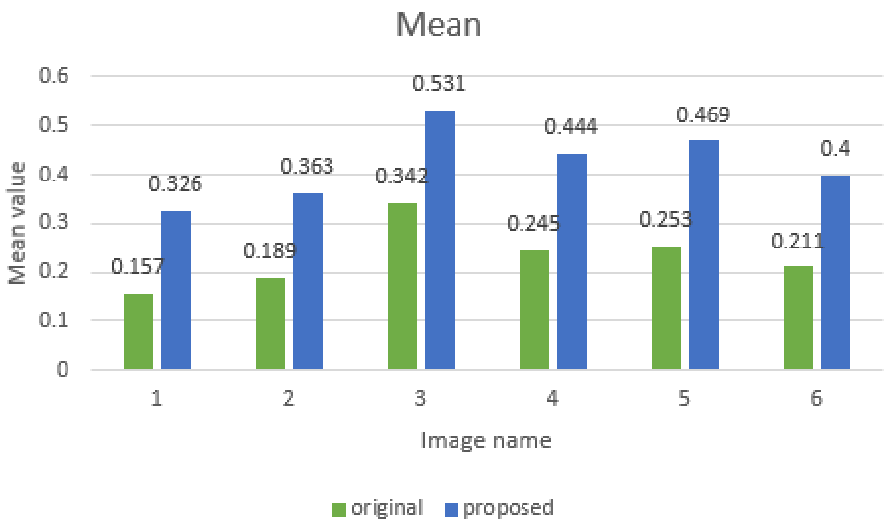

Fig 5: Graph of Entropy of image and mean values

Table 2: Comparison of Entropy and mean of original image and enhanced image

Image name	Entropy		Mean	
	Original	**Proposed**	**Original**	**proposed**
1	6.654	7.083	0.157	0.326
2	6.766	7.038	0.1899	0.363
3	7.723	7.960	0.342	0.531
4	7.381	7.616	0.245	0.444
5	7.310	7.462	0.253	0.469
6	7.024	7.466	0.211	0.400

5. Conclusion

The proposed algorithm is applied to several historical images. It is evident from visual analysis of output image that the low contrast input image with dark regions is enhanced to an extend that the output or the restored image displays all of the regions clearly. To evaluate the performance of the proposed method PSNR, MSE and SSIM are evaluated. Values of entropy and mean of enhanced image when compared to that of the degraded image clearly indicate that the proposed method results in bright image with maximum structural details. The future work can be extended to other color models using other transforms. Since the proposed algorithm is based on simple mathematical calculations, therefore, the method can be implemented in real-time applications such as IoT image acquisition. It is evident that proposed algorithm retains the structural properties of the images after improving the contrast of image due to adaptive feauture of gamma correction along with DWT. Adaptive gamma correction also prevents the resultant image to get washed out in high intensity regions.

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