A Comparison of Contrast Enhancement Techniques in Poor Illuminated Gray Level and Color Images

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ABSTRACT

Morphological transformations (Opening by reconstruction, Erosion-Dilation method) and Block Analysis is used to detect the background of gray level and color images. These techniques are first implemented in gray scale and are then extended to color images by individually enhancing the color components. For aiding better results, the compressed domain (DCT) technique is used exclusively for color image enhancement. The major advantage of the DCT method is that it can be used for any type of illumination. In all the above methods, the enhancement of the background detected image is done using Weber's law (modified Weber's law for compressed domain). In this paper, a critical analysis of the various advantages and drawbacks in each method are performed and ways for overcoming the drawbacks are also suggested. Here, the results of each technique are illustrated for various backgrounds, majority of them in poor lighting condition. The tool used in this study is MATLAB. Finally the performance metrics like Entropy, Color Enhancement Factor (CEF) , JPEG Quality Metric (JPQM) , Wang Bovik Quality metric (WBQM) and Structural Similarity Index (SSIM) are calculated and compared for the results of each technique.

Keywords

Image acquisition, Optimization problem, DCT, Weber's law

1. INTRODUCTION

In image acquisition, background detection is necessary in many applications to get clear and useful information from an image which may have been picturized in different conditions like poor lighting or bright lighting, moving or still etc.

A method to detect the background is proposed; the methodology consists in solving an optimization problem that maximizes the average local contrast of an image. We have proposed a number of techniques to detect the background of poor lighted images. The first one among these is the Opening by Reconstruction method [1] where the basic mathematical morphology and Weber's law is used in tandem to enhance the poor lighted image. Opening by reconstruction has following properties: a) it passes through regional minima, and b) it merges components of the image without considerably modifying other structures. The second method proposed is the block analysis [1] where the entire image is split into a number of blocks and each block is enhanced individually. The next proposed method is the erosion-dilation method [1] which is similar to block analysis but uses morphological operations

(erosion and dilation) for the entire image rather than splitting into blocks. All these methods were initially applied for the gray level images and later were extended to colour images by splitting the colour image into its respective R,G and B components, individually enhancing them and concatenating them to yield the enhanced image.

All the above mentioned techniques operate on the image in the spatial domain. The final method is the DCT where the frequency domain is used [12]. Here we scale the DC coefficients of the image after DCT has been taken. The DC coefficient is adjusted as it contains the maximum information. Here, we move from RGB domain to YCbCr domain for processing and in YCbCr, to adjust (scale) the DC coefficient, i.e. Y(0,0). The image is converted from RGB to YCbCr domain because if the image is enhanced without converting, there is a good chance that it may yield an undesired output image. The enhancement of images is done using the log operator [1]. This is taken because it avoids abrupt changes in lighting. For example, if 2 adjacent pixel values are 10 and 100, their difference in normal scale is 90. But in the logarithmic scale, this difference reduces to just 1, thus providing a perfect platform for image enhancement

There are also techniques based on data statistical analysis, such as global and local histogram equalization. In the histogram equalization process, gray level intensities are distributed over the entire area to obtain a uniformly spread histogram thus keeping all the distributed values nearly the same. The enhancement level is not significant and provides good results only for certain images but fails to provide good results for most of the images, especially those taken under poor lighting. In other words, it doesn't provide good performance for detail preservation. There are a lot of algorithms proposed for enhancement of images taken under poor lighting but obviously some methods prove better than others.

1.1 Weber's law

All the enhancement techniques that we have used are based on the simple Weber's law. This law has a logarithmic relation. Weber's law states that the relationship between the physical magnitudes of stimuli and the perceived intensity of the stimuli is logarithmic. This technique is applied to image processing to enhance the image effectively. Weber's law is defined as:

$$C = k \log L + b \quad (L>0) \tag{1}$$

where 'C' is the contrast, 'k' and 'b' are constants, 'b' being the background parameter and 'k' being the scaling factor for enhancement.

Weber's law can be best understood from the following example. Consider a photo taken in a dark room. The obtained photo actually consists of 2 different things. One is what we visually perceive in that image and the other is what is actually present in that image. Weber's law simply states that the relation between these two is logarithmic. The importance of the logarithmic operator is discussed earlier in this paper.

2. MATHEMATICAL MORPHOLOGY

Mathematical morphology is a tool for extracting image components that are useful for representation and description. The content of mathematical morphology is completely based on set theory. By using set operations, there are many useful operators defined in mathematical morphology. They are dilation, erosion, opening and closing. Morphological operations apply structuring elements to an input image, creating an output image of the same size. Structuring element determines exactly how the object will be dilated or eroded. Irrespective of the size of the structuring element, the origin is located at its center. Morphological opening $\gamma_{\mu B}(f)(x)$ and closing $\varphi_{\mu B}(f)(x)$ are illustrated as follows.

$$\gamma_{\mu B}(f)(x) = \delta_{\mu \breve{B}}(\varepsilon_{\mu B}(f))(x) \tag{2}$$

$$\varphi_{\mu B}(f)(x) = \varepsilon_{\mu \breve{B}}(\delta_{\mu B}(f))(x) \tag{3}$$

where μ is a homothetic parameter, size μ means a square of (2μ+1) × (2μ+1) pixels. B is the structuring element of size 3 × 3 (here μ = 1), while $\tilde{B}$ is the transposed set ($\tilde{B}$={ $-x$: $x \in$ B})

Block Analysis:

For Gray level images:

Let f be the original image which is subdivided into number of blocks with each block is the sub-image of the original image. For each and every block n, the minimum intensity m_i and maximum intensity M_i values are calculated.

m_i and M_i values are used to find the background criteria τ_i in the following way:

$$\tau_i = \frac{m_i + M_i}{2} \qquad \forall i = 1,2 \ldots\ldots n \tag{4}$$

τ_i is used as a threshold between clear(f > τ_i) and dark (f ≤ τ_i) intensity levels. Based on the value of τ_i , the background parameter is decided for each analysed block. Correspondingly the contrast enhancement is expressed as follows:

$$\Gamma_{\tau_i}(f) = \begin{cases} k_i \log(f+1) + M_i\,, & f \le \tau_i \\ \mathrm{k_i} \log(f+1) + m_i\,, & otherwise \end{cases} \tag{5}$$

It is clear that the background parameter entirely is dependent up on the background criteria τ_i value. For f ≤ τ_i, the background parameter takes the maximum intensity value M_i within the analysed block, and the minimum intensity value m_i otherwise. In order to avoid indetermination condition, unit was added to the logarithmic function.

$$\text{Where } k_i = \frac{255 - m_i^*}{\log(256)} \quad \forall i = 1,2,\ldots.,n \tag{6}$$

$$\text{With } m_i^* = \begin{cases} m_i\,, & f \le \tau_i \\ M_i\,, & f \ge \tau_i \end{cases} \tag{7}$$

The more is the number of blocks, the better will be quality of the enhanced image. In the enhanced images, it can be seen that the objects that are not clearly visible in the original image are revealed.

As the size of the structuring element increases it is hard to preserve the image as blurring and contouring effects are severe. The results are best obtained by keeping the size of the structuring element as 1 (μ=1).

Sample input (left half of the image) and output image (right half) for block analysis is shown below:

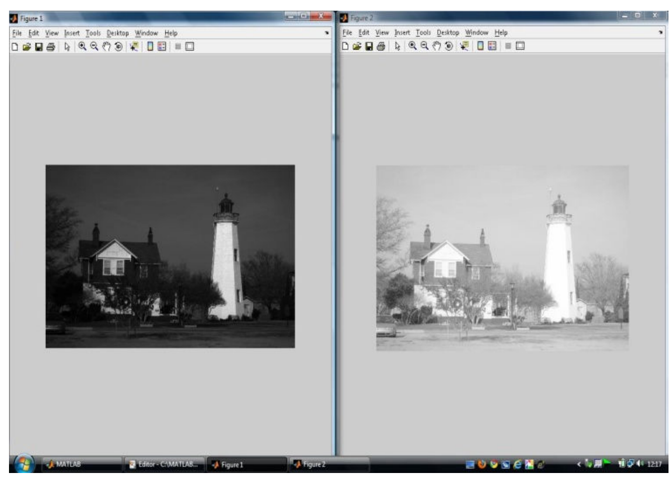


Figure 1(μ=2)

Erosion-Dilation method:

For Gray level images:

This method is similar to block analysis in many ways; apart from the fact that the manipulation is done on the image as a whole rather than partitioning it into blocks.

Firstly minimum $I_{min}(x)$ and maximum intensity $I_{max}(x)$ contained in a structuring element (B) of elemental size 3 × 3 is calculated.

The above obtained values are used to find the background criteria τ_i as described below

$$\tau(x) = \frac{I_{min}(x)+I_{max}(x)}{2} \tag{8}$$

Where $I_{min}(x)$ and $I_{max}(x)$ corresponds to morphological erosion and dilation respectively, therefore

$$\tau(x) = \frac{\varepsilon_\mu(f)(x)+\delta_\mu(f)(x)}{2} \tag{9}$$

In this way the contrast operator can be described as

$$\Gamma_{\tau(x)}(f) = \begin{cases} k_{\tau(x)} \log(f+1) + \delta_\mu\,(f)(x), & f \leq \tau(x) \\ \mathrm{k}_{\tau(\mathrm{x})}\log(f+1) + \varepsilon_\mu\,(f)(x), & otherwise \end{cases} \tag{10}$$

and

$$k_{\tau(x)} = \frac{255-\tau(x)}{\log(256)} \tag{11}$$

By employing Erosion-Dilation method we obtain a better local analysis of the image for detecting the background criteria $\tau(x)$ than the previously used method of Blocks. This is because the structuring element µB permits the analysis of neighbouring pixels at each point in the image. By increasing the size of the structuring element more pixels will be taken into account for finding the background criteria. It can be easily visualized that several characteristics that are not visible at first sight appear in the enhanced images.

The trouble with this method is that morphological erosion or dilation when used with large size of µ to reveal the background, undesired values maybe generated.

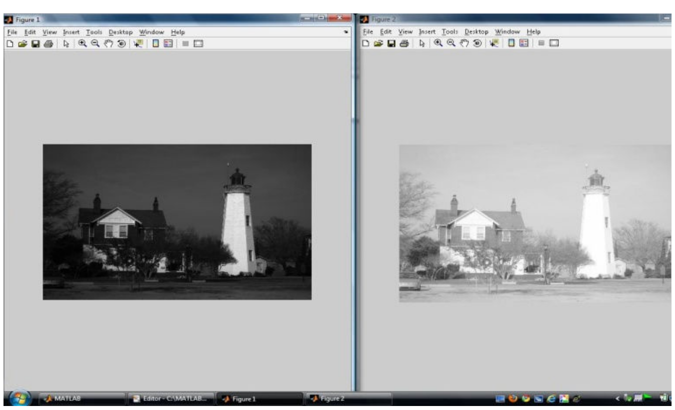


Figure-2 (µ=2)

Opening by reconstruction:

For Gray level images:

In general it is desirable to filter an image without generating any new components. The transformation function which enables to eliminate unnecessary parts without affecting other regions of the image is defined in mathematical morphology which is termed as transformation by reconstruction.

We go for opening by reconstruction because it restores the original shape of the objects in the image that remain after erosion as it touches the regional minima and merges the regional maxima (as shown in Fig opr). This particular characteristic allows the modification of the altitude of regional maxima when the size of the structuring element increases thereby aiding in detection of the background criteria as follows:

$$\tau(x) = \tilde{\gamma}_{\mu B}(f)(x) \tag{12}$$

where opening by reconstruction is expressed as

$$\tilde{\gamma}_{\mu B}(f)(x) = \lim_{n\to\infty} \delta_f^n \left(\varepsilon_{\mu B}(f)\right)(x) \tag{13}$$

It can be observed from the above equation that opening by reconstruction first erodes the input image and uses it as a marker. Here marker image is defined because this is the image which contains the starting or seed locations. For example, here the eroded image can be used as the marker. Then dilation of the eroded image i.e. marker is performed iteratively until stability is achieved.

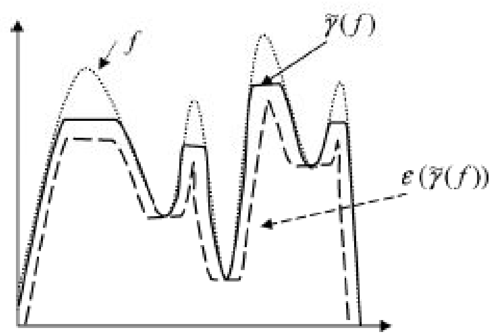


Figure 3

Background parameter $b(x)$ is calculated by eroding the above obtained background criterion $\tau(x)$ which is described below:

$$b(x) = \varepsilon_1[\tilde{\gamma}_\mu(f)](x) \tag{14}$$

As it is already mentioned that morphological erosion will generate unnecessary information when the size of the structuring element is increased, in this study, the image background was calculated by choosing the size of the structuring element as unity.

Contrast enhancement is obtained by applying Weber's law as expressed below:

$$\xi_{\tilde{\gamma}_\mu}(f) = k(x)\log(f+1) + \varepsilon_1[\tilde{\gamma}_\mu(f)] \qquad (15)$$

$$k(x) = \frac{maxint - \varepsilon_1[\tilde{\gamma}_\mu(f)]}{log(maxint+1)} \qquad (16)$$

Where, maxint refers to maximum gray level intensity which is equal to 255. If the intensity of the background increases, the image becomes lighter because of the additive effect of the whiteness (i.e. maximum intensity) of the background. It is to be remembered that it is the objective of opening by reconstruction to preserve the shape of the image components that remain after erosion.

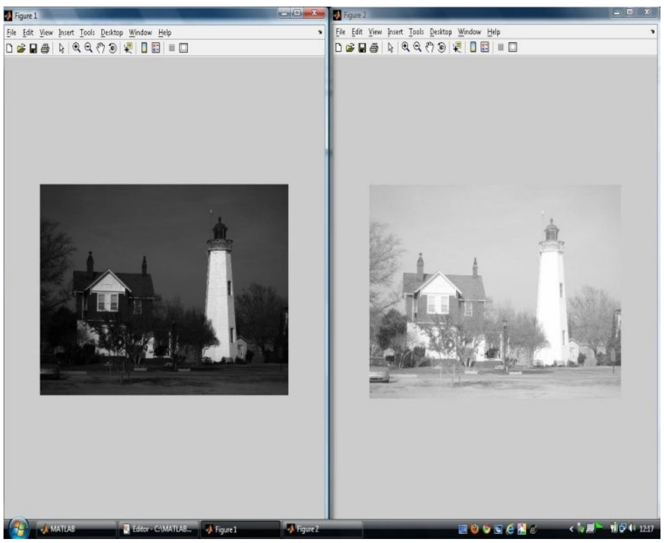


Figure-4 (μ=2)

Colour image enhancement:

Once the contrast enhancement is implemented in gray scale it is possible to extend them for colour images. It is to be noted that the objective of image enhancement lies not only in enhancing the quality of the image but also in revealing the objects which are not visible in the original image. Firstly spatial domain techniques are considered, and then transform domain. All the above implemented methods in gray scale can be also extended to colour images by following a standard procedure.

Firstly partition the original image into R, G and B components.

Consider a separate component at first (say R), perform the algorithm for the corresponding method i.e. if block analysis is to be implemented for colour images, follow the previously mentioned algorithm for block analysis for the R component. Then repeat the same procedure for G and B component. To obtain the enhanced version of the colour image as a whole, the R, G and B components are concatenated. This will produce the desired enhanced version of the original image. This procedure can also be successfully applied for Erosion-Dilation method and opening by reconstruction.

Sample input and output for each method is illustrated below.

Figure-5 (Block Analysis)

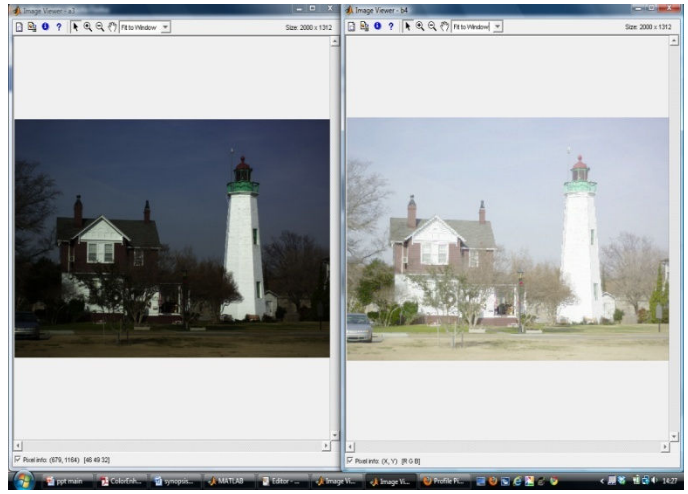


Figure-6 (Erosion-Dilation method)

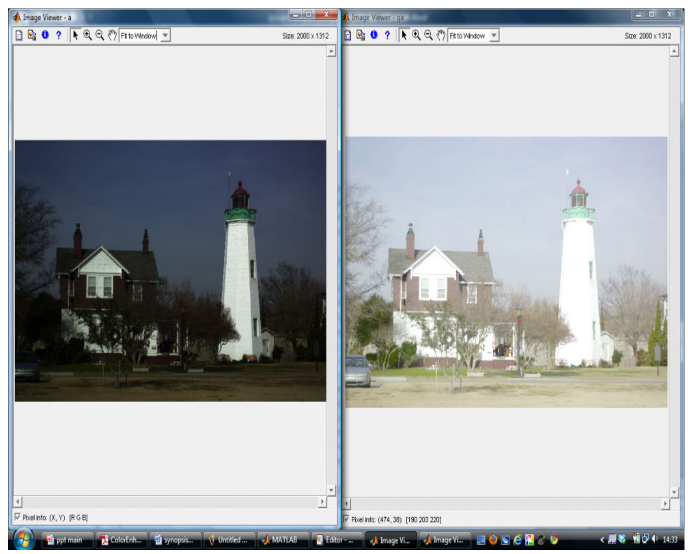
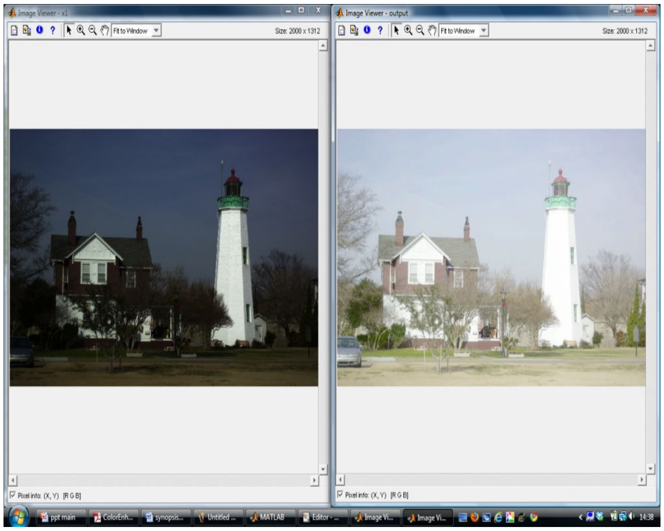


Figure-7 (Opening by reconstruction)



The methods of Block Analysis, Erosion Dilation and Opening by Reconstruction face a common problem of over enhancement in the resultant image. To be precise, no proper way is found to be exercised in these methods to control the enhancement in images. Another thing is that the results are best obtained only for high resolution images. To overcome these problems we go for transform domain i.e. frequency domain techniques.

Image enhancement by scaling the DC coefficients in the compressed (DCT) domain:

In this paper, a new technique for color enhancement in the compressed domain is proposed. This technique is simple but more effective than existing techniques in spatial domain. The proposed technique is computationally more efficient than the spatial domain based method, is found to provide better enhancement compared to other compressed domain based approaches.

A majority of techniques advanced so far have focused on the enhancement of gray-level images in the spatial domain. These methods include adaptive histogram equalization, Opening by reconstruction, Block analysis and Erosion-Dilation method etc. These methods have also been adapted for color image enhancement. In this compressed domain technique, we transform from the R-G-B to the Y-Cb-Cr space. This allows the representation of the color in terms of Luminance and Chrominance components which provides a better platform for enhancing the images. There are also a few works reported in the R-G-B space. However, their technique is computationally intensive as it requires filtering with multiscale Gaussian kernels and post-processing stages for adjusting colors. There are also other advantages of using compressed domain representation. For example, due to the spectral separation, it is possible to enhance features by treating different frequency components differently. To this end, different algorithms have been proposed for both color and gray level images in the block DCT domain. Here, we adjust the DC coefficient of the 'Y' component of the image. This is done because the DC coefficient (Y(0,0)) contains majority of the information. This technique also works faster than the techniques used in the spatial domain as computing DCT coefficients is a faster process than working in the spatial domain.

Algorithm for calculating scaling factor for DCT technique:

Input: Y component of the image.

Input Parameters: Imax, k, blk(Block size).

Output: $\tilde{Y}$, DC adjusted Y component

1. Decompose the given image component into block of images of the given block size.

2. Compute maximum intensity 'Imax' for each blocks 'I' and determine the scaling factor 'k' for each block as described below:

z= dct(I);

y= z/N

original DC= y(0,0)

x= y(0,0)/Imax

mapped DC = $\tau(x)$ * Imax , where Twicing function, $\tau(x)=x*(2-x)$

Now, k=mapped DC/original DC.

3. Scale the coefficients:

original DC=k*original DC.

4. Compute the IDCT for each block and merge it back to form single block of the image.

End

After this scaling factor is calculated, it is multiplied with the DC component of each block and hence results in the enhanced image.

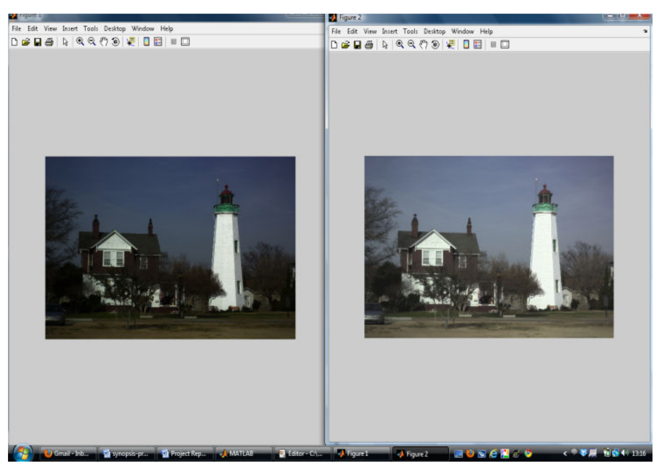


Figure-7 (DCT Technique)

Performance Metrics:

A metric is a system or standard of measurement.

The opening by reconstruction method, Block analysis and dilation- erosion method is compared by measuring the parameters SSIM values and Normalized Entropy.

Structural Similarity Index (SSIM):

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric, in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proved to be inconsistent with human eye perception.
The SSIM metric is calculated on various windows of an image. All distorted images have roughly the same mean squared error (MSE) values with respect to the original image, but very different quality in experiment. SSIM gives a much better indication of image quality.

The measure between two windows of size NXN x and y is:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (17)$$

With μ x the average of x, μ y the average of y , σ_x^2 the variance of x, σ_y^2 the variance of y .covxy the covariance of x and y, c1=(K1 l)2 and c 2=(k2 l)2 two variables to stabilize the division with weak denominator; L the dynamic range of the pixel-values, k 1=0.01 and k2=0.03 by default..

In practice, one usually requires a single overall quality measure of the entire image. The mean SSIM(MSSIM) index is used to evaluate the overall image quality.

$$\mathrm{MSSIM} = \frac{1}{M}\sum_{j=1}^{M} \mathrm{SSIM}(x_j, y_j) \qquad (18)$$

Table 1 (MSSIM values (gray scale images))

Input image	Dilation erosion Method	Opening by reconstruction	Blocks
Image 1	0.4600	0.4872	0.4497
Image2	0.2048	0.2228	0.2024
Image 3	0.4834	0.5093	0.4732
Image4	0.5840	0.5836	0.5815
Image5	0.5043	0.5349	0.4867

Normalized Entropy:

Shannon entropy is a measure of the information contained in the image and is defined as,

$$H = -\sum_{x=0}^{N_{GL}-1} p(x)\log_2(p(x)) \qquad (19)$$

Where, p(x) is the probability of Gray level x occurring in the image.

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. In order to compare the processing effect on a population of images with widely divergent H values, normalized entropy, HN was adopted .This is defined as the ratio of the entropy of the treated image to that of the original image.

E = entropy (I) returns E, a scalar value representing the entropy of intensity image I

Table 2 (Normalized Entropy (gray scale images))

Input image	Dilation erosion Method	Opening by reconstruction
Image 1	0.9333	0.92762
Image2	0.9723	0.97706
Image 3	0.9295	0.92580
Image4	0.99410	0.9929
Image5	0.8987	0.9036

Wang–Bovic-Quality-Metric (WBQM):

Let x and y be two distributions . let x={x_i|i=1,2 ,. . .N}, y={y_i|i=1,2 ,. . .N} be the original and the test image signals, respectively. The WBQM between these two distributions is defined as

$$\mathrm{WBQM}(x,y) = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)(\bar{x}^2 + \bar{y}^2)} \qquad (20)$$

Where σ_{xy} is covariance between x and y respectively and $\bar{x}$ and $\bar{y}$ are their respective means. It may be noted that this measure takes into account of the correlation between the two distributions and also their proximity in terms of brightness and contrast. The WBQM values should lie in the interval [-1 1]. Processed images with WBQM values closer to 1 are more similar in quality according to our visual perception. We have measured WBQM measure for component Y. This metric performs better than widely used distortion metric mean square error. The "universal quality index" (UQI) corresponds to the special case when $c_1 = 0$ and $c_1 = 0$ in ssim(x,y) which produces unstable results when either $\bar{x}^2 + \bar{y}^2$ =0 or $\sigma_x^2 + \sigma_y^2$ =0 .

Table 3 (Y-WBQM (Colour images))

Input image	Dilation erosion Method	Opening by reconstruction	Blocks	DCT
Image 1	0.3426	0.3822	0.1342	0.8250
Image2	0.2155	0.2392	0.2130	0.7145
Image 3	0.3595	0.4074	0.3137	0.8007
Image4	0.5556	0.5808	0.5745	0.7429
Image5	0.3627	0.4579	0.2129	0.8172

JPQM:
JPEG quality metric (JPQM) is a no reference metric for judging the image quality reconstructed from the block DCT space to take into account visible blocking and blurring artifacts; was proposed by wang et al. Peak Signal to Noise Ratio (PSNR), which requires the reference images is a poor indicator of subjective quality .We consider blurring and blocking as the most significant artifacts generated during the JPEG compression process. NR quality assessment algorithms must have the capability to effectively predict perceived JPEG image quality. JPQM is computational and memory efficient but is no reference quality assessment model for JPEG images. The method is computationally efficient since no complicated transforms are computed and the algorithm can be implemented without storing the entire image (or even a row of pixels) in memory, which makes embedded implementations easier.
The score typically has a value between 1 and 10. It may be noted that for an image with good visual quality, the JPQM value should be close to 10.score 1 is given to worst quality image.

Table 4 (JPQM (Colour images))

Input image	Dilation erosion Method	Opening by reconstruction	Blocks	DCT
Image 1	11.2937	11.0015	9.2997	8.8472
Image2	5.5805	5.1637	4.4481	3.8234
Image 3	9.2407	9.0028	7.4515	4.7800
Image4	3.8406	4.8766	3.0936	2.8485
Image5	10.8749	11.0015	8.8725	7.5655

CEF (Colour Enhancement Factor):

we have used a no-reference metric called colorfulness metric (CM) as suggested by Susstrunk andWinkler. Let the red, green and blue components of an Image I be denoted by R,G,B respectively.Let α=R-G and β=((R+G/2)-B)
Then the colorfulness of the image is defined as

$$CM(I)=\sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2} \qquad (21)$$

where σ_α and σ_β are standard deviations of α and β respectively.

Similarly μ_α and μ_β are their means.

In our comparison, however, we have used the ratio of CMs between the enhanced image and its original for observing the color enhancement factor CEF.

Table 5 (CEF (Colour images))

Input image	Dilation erosion Method	Opening by reconstruction	Blocks	DCT
Image 1	0.4658	0.6303	0.3464	0.8463
Image2	0.3039	0.3730	0.3427	0.770
Image 3	0.6432	1.0060	1.0093	0.9542
Image4	0.2252	0.2039	0.2892	0.6720
Image5	0.613	0.9660	0.9794	0.8543

Images used for calculating the performance metrics:

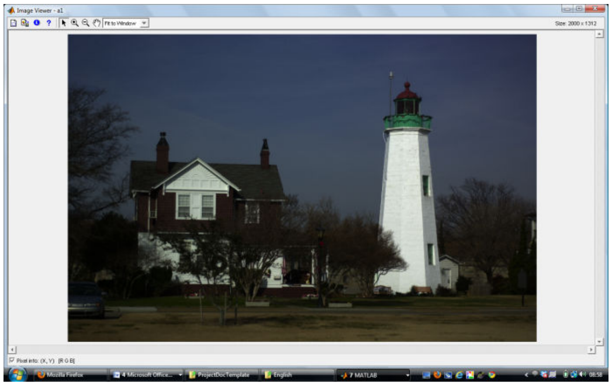


Image-1

Image-2

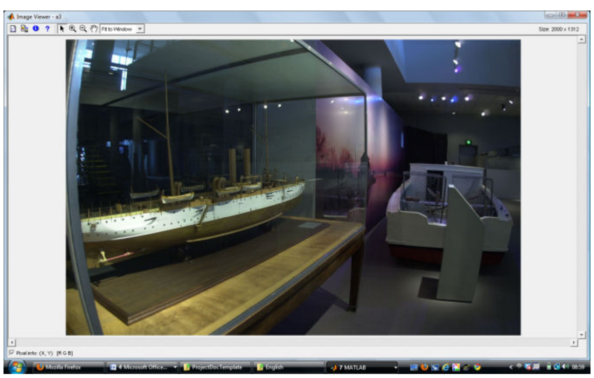


Image-3

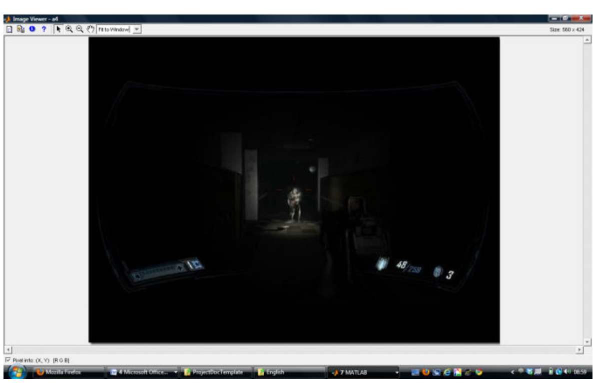


Image-4

Image-5

3. CONCLUSION

We have implemented various methods for image enhancement. After thorough analysis of each of the methods using the various performance metrics, results showed that the DCT method effectively enhances the image even if not taken under poor lighting conditions. So, the frequency domain enhancement proves to be an effective tool for proper and effective enhancement of images and hence can be used in various applications

Future Scope: Even though we have proved that the DCT technique is the most efficient technique for image enhancement, it can be further improved and made to provide better results by making changes in the algorithm for calculating the scaling factor for the DC coefficients for each block. In our project, we have taken into consideration only the luminance (Y) component of the image but one can also take into consideration the Chrominance components (Cb and Cr) of the image and enhance them. We can also take into consideration the adjustment of the AC coefficients of the image for more accuracy, but these are ignored generally as it contain very less information in the image.

Limitations: All the spatial domain techniques are limited to poor lighted images and high resolution images. They provide undesired results for other kind of images.

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