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Efficient Blocking Artifacts Removal on Color image using DCT Domain

Chikku Jose, Ajal.A.J

Abstract-Image enhancement techniques involve processingan image to make it look better to human viewers. Now,increasingly images are being represented in the compresseddomain format for efficient storage and transmission. Henceit has become imperative to investigate compressed domaintechniques to eliminate the computational overheads occur inspatial domain techniques. Processing in the DCT domain hasattracted significant attention of researchers due to its adoptionin the JPEG and MPEG compression standards. The imagesneed to be enhanced in terms of brightness along with colorsrestored with minimal computational overhead. This techniquetreats chromatic components in addition to the processingof the luminance component also removes blocking artifactsefficiently for improving the visual quality of the images to agreat extent.

Index Terms—Anisotropic diffusion, Blocking artifact, color enhancement, discrete cosine transform (DCT), DC and AC Coefficients, Y-Cb-Cr color space.

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1 INTRODUCTION

Color images provide more and richer information forvisual perception than that of the gray images. So colorimage enhancement plays an important role in Digital Image Processing. Image quality is very easily affected by lighting, weather, or equipment that has been used to capture the image. These conditions lead to image may suffer from loss of information. The purpose of image enhancement is to get finer details of an image and highlight the useful information and make it look better to human viewers. There are various reasons, why a raw image data requires processing before display [1]. An example of such an image is shown in Figure 1(a). It can be seen that in some places the scene appears to be too dark while in some other places it is too bright. In such images it is necessary to improve the local contrast. The result of such a processing with improved display is shown in Figure 1(b).

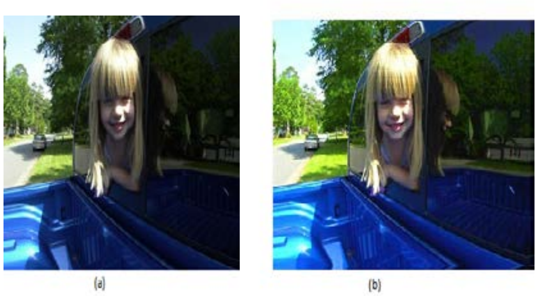

Figure 1. (a) Original image (b) Enhanced image.

According to the survey of available techniques foundfor image enhancement, the existing techniques can beclassified into two categories: spatial-domain techniques andcompressed-domain techniques. The spatial-domain methodsoperate directly on image pixels. The pixel values aremanipulated to achieve desired enhancement. These methodsinclude contrast stretching, histogram equalization, adaptivehistogram equalization, multi scale retinex theory, etc. Contrast stretching technique is used to stretch the dynamicrange of an image-where dynamic range is the range between the minimum intensity value and the maximum intensity value of an image. In this some of the detail may beloss due to saturation and clipping as well as due to poor visibility in under-exposure regions of the image. Histogram Equalization (HE) is a technique that made contrast adjustment using image's histogram. Histogram of an image tells us how the values of individual pixel in an image are distributed. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near uniform probability density function. The disadvantage of HE is that since it is a global enhancement technique, it will not preserve the brightness and color of original image. Even if adaptive histogram equalization overcomes this problem it has a tendency to over amplify noise in certain regions. Multi scale retinex theory [2] proposed by Jobson et al. achieves dynamic range compression and color constancy. However, their technique is computationally intensive as it requires filtering with multi scale Gaussian kernels and postprocessing stages for adjusting colors.

All above mentioned enhancement techniques are spatialdomain based. Mostly images are represented in compressed format to save memory space and bandwidth. So it is better if enhancement of the image can be achieved in compressed domain rather than transforming to spatial domain and applying the enhancement technique and transformingback to compressed domain, thereby increasing the computational overhead. The compressed-domain methods operate directly on the transform coefficients of the images that are compressed, for example, by fourier, wavelet, or discrete cosine transforms. The advantages of compressed domain processing techniques are: 1) low complexity of computations and 2) ease of viewing and manipulating thefrequency composition of the image. However, it is reported that the compressed domain method often introduce block artifacts, i.e., superfluous edges near block boundaries. As JPEG compression standard is more popular which uses DCT transform, processing in the DCT domain has attractedsignificant attention of researchers. Since the energy of theimage is concentrated

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on a few coefficients in the DCT domain, the number of nonzero coefficients can be reduced significantly after quantization.

2 Mathematical Priliminaries

2.1 Y-Cb-Cr Color Space

In color image enhancement techniques the R-G-B colorcoordinates are transformed into a different space such as Y-Cb-Cr, where chromatic components are more uncorrelated from the achromatic component. Y is the luma component and Cb and Cr are the blue difference and red difference chroma components. The following equations are used to convert R-G-B to Y-Cb-Cr:

$$Y = 0.502G + 0.098B + 0.256R$$

$$Cb = -0.290G + 0.438B - 0.148R + 128$$

(1)

$$Cr = -0.366G - 0.071B + 0.438R + 128$$

2.2 Discrete Cosine Transform

Color images mostly uses JPEG compression format for saving bandwidth and memory space which uses populardiscrete cosine transform (DCT). The 2-D DCT is a linear, separable transform which represents a block of sample values as the weighting factors of sampled cosine functionsat various frequencies. The DCT has following advantages.It is one of the fastest transform among other transforms. It significantly reduces the number of computations and it has strong energy compaction property.

The Type II DCT is more commonly used in image compression algorithms. Equation (2) represents two dimensionalDCT where C(k,l)represents transformed DCT coefficients for the input image x(m,n) assuming a square image of size (NXN).

$$C(l,k) = \frac{2}{N}\alpha(l)\alpha(k)\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} x(m,n)\cos\left(\frac{(2n+1)\pi l}{2N}\right)\cos\left(\frac{(2n+1)\pi k}{2N}\right)$$

For $0 \le k,l \le N-1$ (2)

Where $\alpha(p)$ is given by

$$\alpha(p) = \sqrt{\frac{1}{2}} \quad \text{for } p = 0$$
$$= 1 \quad \text{otherwise} \qquad (3)$$

In DCT-Based Image Compression Scheme, An image isfirst divided into a set or”tiles” of blocks where a blockis an array of 8X8 pixels. Each block is then transformedinto the spatial frequency domain via a forward DCT. Theelement in the upper left corner of

- *Chikku Jose is currently working as an Assismasters Professor at Government Engineering College Kozhikode,Kerala, India, E-mail: chikkujose1989@gmail.com*
- *Ajal.A.J is currently working as an Assismasters Professor at Government Engineering College Idukki,Kerala, India, Mob: 0- 8907305642 E-mail: professorajal@gmail.com*

an 8 X 8 DCT encoded block is the DC coefficient, whereas the sixty-three otherelements are the AC coefficients [3].

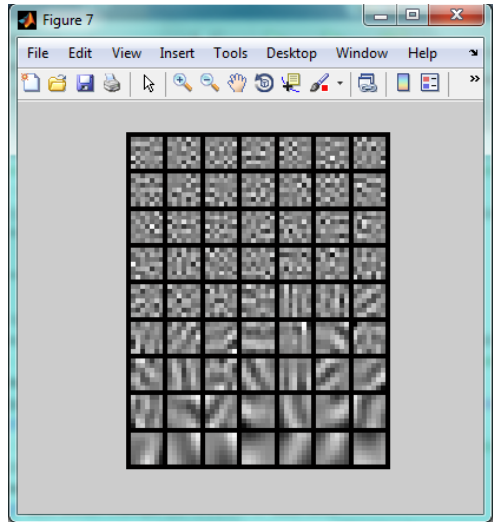

Figure 2. DCT coefficients of an image block

Figure 2 shows anarray of 64 DCT bases. These basis functions are arranged in order of increasing spatial frequencies from the upper left corner to the lower right corner. Each coefficient represents the contribution from the DCT basis function located at the k th column and l th row in Figure 2. After DCT, the64 DCT coefficients in the 8x8 block are quantized, i.e., each coefficient is divided by a corresponding quantization parameter (quantization step) and then rounded to the nearest integer. The default values of the quantization parameters are usually determined by the compression standard. Finally, the quantized DCT coefficients are aligned in a zigzag scan order and entropy coded. The entropy coding scheme that is often used is the run-length coding where a long string of zeros is effectively compressed. The encoding process with a block DCT followed by quantization results in a very few nonzero coefficients remaining in each 8x8 block. The zigzag scan and run-length entropy coding takes advantage of this property. Any compressed domain algorithm for image enhancement also benefits from this property when improving the computation speed and complexity. To reconstruct the original image in the decoding process, the compressed image is first entropy decoded, dequantized by point-to-point multiplication with the quantization parameters, and inverse transformed through the inverse DCT (IDCT).

Each block of an image is reconstructed from the weightedsum of the DCT coefficients that correspond to the specificspatial frequency contributions. Thus, the distribution of the DCT coefficients provides a natural way to define a spectralcontent measure of the image in the DCT domain. The normalized transform coefficients are defined as

$$\hat{c}(k,l) = \frac{C(k,l)}{N} \qquad (4)$$

Let µand σ denote the mean and standard deviation of anN x N image. The mean and standard deviation of the image are given by

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$$\mu = \hat{c}(0,0) \tag{5}$$

$$\sigma = \sqrt{\sum_{k=0}^{N-1}\sum_{l=0}^{N-1} \hat{c}(k,l)^2 - \mu^2.} \tag{6}$$

Contrast (ζ) of an image is usually modelled with the Weber law where ζ= (ΔL/L), where ΔL is the difference in luminance between a stimulus and its surround, whereas L is the luminance of the surround . As μ provides a measure for surrounding luminance and σis strongly correlated with ΔL, contrast (ζ) of an image can be redefined as follows:

$$\zeta = \frac{\sigma}{\mu} \tag{7}$$

2.3 Anisotropic Diffusion

Anisotropic Diffusion (AD) is a non-linear partial differentialequation-based diffusion process. Overcoming the undesirable effects of linear smoothing filtering, such asblurring or dislocating the semantically meaningful edgesof the image, AD has become a very useful tool in imagesmoothing, edge detection, image segmentation and imageenhancement. AD filtering can successfully smooth noisewhile respecting the region boundaries and small structures within the image, as long as some of its crucial parameters are determined or estimated correctly. The conductance function, the gradient threshold parameter and the stopping parameter form a set of parameters which define the behavior and the extent of the diffusion. The basic equation of anisotropic diffusion can be represented as

$$\frac{dI(x,y,t)}{dt} = div[g(\|\nabla I(x,y,t)\|)\nabla I(x,y,t)] \tag{8}$$

wheretis the time parameter, *I(x,y, t)*is the original image, ∇ I(x, y,t) is the gradient of the version of the image attime t and g(·) is called conductance function.This functionis chosen to satisfy limx->0 g(x) = 1, so that the diffusion is maximal within uniform regions, and limx->1 g(x) = 0, so that the diffusionis stopped across edges.The anisotropic diffusion equation can be discretized as

$$I_{t+1}(s) = I_t(s) + \frac{\lambda}{|\eta_s|}\sum_{p\epsilon\eta_s} g_k(|\nabla I_{s,p}|)\nabla I_{s,p} \tag{9}$$

whereI is a discretely sampled image, s denotes the pixelposition in the discrete 2-D grid, t denotes the iteration step, g is the conductance function and k is the gradientthreshold parameter. Constant λ(0,1) determines the rate of diffusion and ηsrepresents the spatial 4 -pixel neighborhoodof pixel s : ηs= {N, S ,E,W}. whereN, S, E and W are the North, South, East and West neighbors of pixel s respectively. Consequently, |ηs|is equal to 4 (except for the image borders). The symbol which in the continuous form is used for the gradient operator, now represents a scalar defined as the difference between neighbouring pixels in each direction. The four directional derivatives are givenby

$$\nabla I_{s,p} = I_t(p) - I_t(s), p\epsilon\eta_s = \{N,S,E,W\}.$$

$$\begin{aligned} \nabla_N I_{i,j} &= I_{i-1,j} - I_{i,j} \\ \nabla_S I_{i,j} &= I_{i+1,j} - I_{i,j} \\ \nabla_E I_{i,j} &= I_{i,j+1} - I_{i,j} \\ \nabla_W I_{i,j} &= I_{i,j-1} - I_{i,j} \end{aligned} \tag{10}$$

Diffusion coefficients in each direction are

$$\begin{aligned} c_{N_{i,j}} &= g(|\nabla_N I_{i,j}|) \\ c_{S_{i,j}} &= g(|\nabla_S I_{i,j}|) \\ c_{E_{i,j}} &= g(|\nabla_E I_{i,j}|) \\ c_{W_{i,j}} &= g(|\nabla_W I_{i,j}|) \end{aligned} \tag{11}$$

Where

$$g(\nabla I) = e^{(-(\|\nabla I\|/K)^2)} \tag{12}$$

3 PROPOSED TECHNIQUE

In DCT domain techniques an image is first divided into a set or " tiles" of blocks where a block is an array of 8x8 pixels. Each block is then transformed into the spatial frequency domain via a forward DCT. This technique enhancing color images in the block DCT domain by scaling the transform coefficients. The unique feature of this algorithm is that it also treats chromatic components in addition to the processing of the luminance component for improving the visual quality of the images to a great extent. The simplicity of this algorithm lies in the fact that the computation requires only scaling of the DCT coefficients mostly by a factor which remains constant in a block. In contrast, previous algorithms [4] dealt with non uniform scaling of DCT coefficients in a block. For example, thescale factors are computed for every coefficient (both the DC and AC coefficients) by taking their roots. In the technique [5] proposed by S. Lee the amount of scaling of the relative contrast between the successive bands of AC coefficients varies from one block to the other. It also varies betweenthe low-frequency bands and the high frequency bands. Onthe other hand, this algorithm not only uses the same scalefactor for both the DC and AC coefficients, but also scalesthe chromatic components as well with the same factor with the exception of their DC coefficients.

This algorithm performs the color image enhancementoperation in four steps. First, it adjusts the backgroundillumination. The next step preserves the local contrast ofthe image then pre-

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serves the colors of the image and the last one removes blocking artifacts. Moreover, in a block DCT space, the algorithm attempts to exploit the advantage of having localized information from the DCT coefficients. The algorithm is designed in such a way that each block (of size 8 X 8) for all the components could be handled independently. This makes it more suitable for parallel implementation

3.1 Adjustment of Local Background Illumination

In adjusting the local background illumination, the DC coefficient of a block is used. The DC value gives the mean of the brightness distribution of the block. This adjustment may be performed by mapping the brightness values to a value in the desired range. This function should be monotonic in the given range. Let us denote the maximum brightness valueof the image as Imax. Let the DCT coefficients of a 8 X8 block of the luminance component (Y)be denoted by {Y (k,l)/7,0 ≤ k,l≤7. Then Y (0,0) is the DC coefficient and the rest are the AC coefficients. The normalized DC and AC coefficients by ^y(k, l) = (Y (k,l)/7,0 ≤k, l ≤ 7 . In adjusting the local brightness, this DC coefficient is mapped to ~ ^y(0,0) by using a monotonically increasing functiony = {f(x),0 ≤x, y ≤1}in the interval [0,1] as follows:

$$\tilde{\hat{y}}(0,0) = I_{max} \cdot f\left(\frac{\hat{y}(0,0)}{I_{max}}\right) \quad (13)$$

In this scheme we selected a mapping functionwhich is given by

f(x)= log(kx+1)/log(k+1) (14)

In the technique proposed by mithra and mugherjee, monotonicallyincreasing function they chose is the twicing functionT(x), is simple to implement since it has no parameterand is given by

T(x)= x(2-x) (15)

Though the dark regions get brightened by this process,the images lack the sharpness or details of the original one.So the next step is for preserving the local contrast of theoriginal image.

6.1Preservation of Local Contrast

Let us define the enhancement factor for a block duringadjustment of its luminance as

$$k = \frac{\tilde{Y}(0,0)}{Y(0,0)} \quad (16)$$

whereỸ(0,0) is the mapped DC coefficient and Y (0,0)is the original DC coefficient. Since the DCT is a lineartransform, multiplying all the coefficients of Y by k resultsin the multiplication of the pixel values in the block bythe same factor. This also preserves the contrast of theblock. However, there is a risk of overflow of some of thepixel values beyond the maximum allowable representation(say Bmax). This can be controlled by taking into accountof the standard deviation σand mean μof the brightnessdistribution of the block. Let us assume that the brightnessvalues of this distribution lie within μ±λσ, where λ>0is a constant. After this step the colors look less saturated in the enhanced images and there is a scope for further improvement on the display of colors. This task is performedin the next stage.

6.2Preservation of Colors

The previous techniques only change the luminance component (Y)and keep the chrominance components (CbandCr, respectively) unaltered. Though in the Y- Cb-Cr colorspace the chrominance components are decorrelated betterthan that in the R-G-B color space, the increasing valuesin the Y component usually tend to desaturate the colors.So the chromatic components should be also processedfor preserving the colors. Let U and V denote the DCTcoefficients of the Cband Cr components, respectively.Preservation of colors means that in the R-G-B color spacethe color vector of a pixel in the processed image hasthe same direction as that in the original. Since there isnonlinearity in the transformation of the R -G -B colorspace to Y Cb Cr color space, in the block DCT spacethis requires separate treatment for the DC coefficient andthe AC coefficients. The colors of the processed image withỸ ,Ũand Vare preserved by the following operations:

$$\tilde{U}(i,j) = \begin{cases} N(k(\frac{U(i,j)}{N} - 128) + 128), i = j = 0 \\ kU(i,j), otherwise \end{cases}$$

$$\tilde{V}(i,j) = \begin{cases} N(k(\frac{V(i,j)}{N} - 128) + 128), i = j = 0 \\ kV(i,j), otherwise \end{cases} \quad (17)$$

6.3 Removing BlockingArtifacts

In this algorithm, local background illumination can beadjusted by scaling the DC coefficient of a block with aconstant. However, since the constant scaling factors foreach block are determined independently, that algorithmproduces noticeable blocking artifacts. Blocking artifacts aremore visible in the regions where brightness values varyting of your paper, some figures may have to be moved from significantly, especially near the edges of sharp transitionsof luminance values. For suppressing these artifacts in[1] theauthors identified the blocks having significant variations byexamining their standard deviations. If the σ is beyond a threshold (denoted σ thresh), they decompose a 8x8 blockinto four 4 x 4 sub-blocks. Then the same enhancementalgorithm is applied to each sub-block. Finally, the fourenhanced sub-blocks are combined again to a 8x8 block.But we find from simulation that even if all the blocks inthe image are subdivided by lowering σ thresh, the blockingartifacts are still remaining in the processed image. Thus, thisapproach of block subdivision is not effective.Other approaches for removing the blocking artifact arealso proposed. For example, the techniques in [6]&[7] and make use of the information from neighboring blocks for reducing or removing these artifacts. However, this comes at the cost of more computation and more buffer requirements and also significantly reduces the enhancement performance. In the modified approach, we use nonlinear anisotropicdiffusion [8], [9]& [10]for removing the blocking artifacts.

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Anisotropic diffusion process can smooth an image whilekeeping the image edge sharp. The DC coefficient of eachblock of Y component of image is updated using theequation(10).

Algorithm: The overall algorithm is summarized below. As each block is independently processed, in thedescription processing with a single block is narrated.Input:Y;U; V : DCTs of three components of a block.

Input parameters: f(x) (the mapping function), Imax,Bmax, k, σ thresh, N (Block size).

Output: Ỹ,Ũand ~ V

1) Compute mean value μ (DC coefficient) and standarddeviation σfor each block.

2) Modify DC coefficient of each block of Y componentusing non-linear anisotropic diffusion equation (9)

3) Compute the enhancement factor (k) as follows:

a) Find mapped DC coefficient using the equation (13) where mapping function is given by equation (14).

b) k= mapped DC coefficient / original DC coeffent

c) k= min(k; (Bmax=μ±kσ)),

d) k= max(k,1)

4) Scale the coefficients:

a) Ỹ= kY, and

b) Apply equations (17) on U and V forpreserving the colors.

4. PERFORMANCE METRICS

4.1. Wang- Bovic-Quality-Metric (WBQM)

For perceptual quality evaluation purposes, we have usedthe metric proposed by Wang and Bovic in [11] and callthis metric as Wang- Bovic-Quality-Metric (WBQM). Letx = {xi = 1,2,…,N}andy = {yi= 1,2,…,N}be theoriginal and the test image signals, respectively. The WBQMbetween these two is defined as

$$WBQM(x,y) = \frac{4\sigma_{xy}^2 \bar{x}\bar{y}}{(\sigma_x^2+\sigma_y^2)(\bar{x}^2+\bar{y}^2)} \quad (18)$$

σ_{xy}^2 is the covariance between xand y,σ_x and σ_y arethe standard deviations of x and y respectively, and $\bar{x}$aswell as $\bar{y}$are their respective means. This quality metricmodels any distortion as a combination of three differentfactors: loss of correlation, luminance distortion, and contrastdistortion. The WBQM values should lie in the interval[-1 1]. Processed images with WBQM values closer to 1 aremore similar in quality according to our visual perception.

The best value 1 is achieved if and only if yi= xi for all i= 1,2,…,N. The lowest value of occurs whenyi= 2$\bar{x}$_xi for all i= 1,2,…,N. We have measuredWBQM measures independently for each component in theY-Cb -Cr space and called them as Y-WBQM, Cb-WBQMand Cr-WBQM, respectively

4.2 JPEG quality metric (JPQM)

JPEG quality metric (JPQM) is a no reference metric[12] for judging the image quality reconstructed from the block DCT space to take into account visible blocking and blurringartifacts; was proposed by wang et al. Peak Signal to Noise-Ratio (PSNR), which requires the reference images is a poorindicator of subjective quality. We consider blurring andblocking as the most significant artifacts generated duringthe JPEG compression process. JPQM is computational andmemory efficient but is no reference quality assessment-model for JPEG images. The method is computationallyefficient since no complicated transforms are computed andthe algorithm can be implemented without storing the entireimage (or even a row of pixels) in memory, which makesembedded implementations easier. The score typically has avalue between 1 and 10. It may be noted that for an imagewith good visual quality, the JPQM value should be closeto 10. Score 1 is given to worst quality image.

4.3 Colorfulness Metric (CM)

we have used a no-reference metric called colorfulnessmetric (CM) as suggested by Susstrunk and Winkler[13]to observe the quality in terms of color enhancement.Thedefinition for this metric in the R -G -B color space isas given below. Let the red, green and blue components ofan Image I be denoted by R,G,and B , respectively. Let4α= R- Gand β= ((R+G/2))-B.Then the colorfulnessof the image is defined as

$$CM = \sqrt{\sigma_\alpha^{\ 2} + \sigma_\beta^{\ 2}} + 0.3\sqrt{\mu_\alpha^{\ 2} + \mu_\beta^{\ 2}} \quad (19)$$

whereσ_α and σ_β are standard deviations of αand βrespectively.Similarly,μ_α and μ_β are their means. Inour comparison, however, we have used the ratio of CMsbetween the enhanced image and its original for observingthe color enhancement factor CEF.

4.4Structural Similarity Index (SSIM)

The structural similarity (SSIM) index is a method formeasuring the similarity between two images. The SSIMindex is a full reference metric, in other words, the measuingof 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, butverydifferent quality in experiment. SSIM gives a muchbetter indication of image quality. The measure between two windows of size NXN x and y is:

$$SSIM(x,y) = \frac{(2\mu_{x\mu_y} + c1)(2\sigma_{xy} + c2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)} \quad (20)$$

With μx the average of x, μy the average of y ,σ_x^2 thevariance of x and σ_y^2 the variance of y, σxythe covariance ofx and y, c1 and c2 are two variables to stabilize the divisionwith weak denominator. In practice, one usually requires asingle overall quality measure of the entire image. The meanSSIM (MSSIM) index is used to evaluate the overall image quality.

$$MSSIM = \frac{1}{N}\sum_{i=1}^{N} SSIM(x_i, y_i) \quad (21)$$

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Results and Discussions

We have compared the performance of the proposedapproach (LOG-CES-AD) with that of the technique proposed by Mukherjee and Mitra (TW-CES-BLK).

Figure 3. Original image

Figure 4. Enhanced images by scaling only Y component

Figure 3 shows the original image. The enhancement results after adjusting the local background illumination and preserving local contrast is shown in figure 4. In the resulting images after the application of these operations, it can be seen that the colors look less saturated in the enhanced images and there is a scope for further improvement on the display of colors. This task is performed in the next and final stage of preservation of colors The

(a)

Next section shows another example of results of enhancement of image 2. Figure 6 is the original image and figure 7 shows enhanced images before blocking artifacts removal using both mapping functions. Figure 8 shows enhanced images with blocking artifacts removal by block decomposition as suggested in **[1]**and artifacts removal by nonlinear anisotropic diffusion. Figure 9 shows zoomed portion of image 2 in which (a) represents original

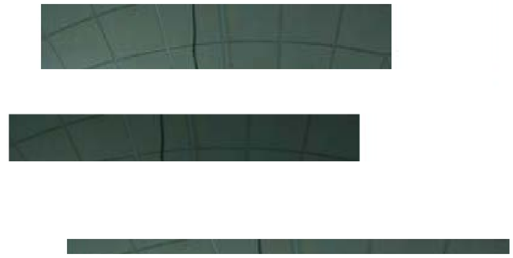

Figure 7. Enhanced images without blocking artifacts removal

Figure 7. Enhanced images without blocking artifacts removal

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Figure 9. Comparison of blocking artifacts removal

Technique	TW-CES-BLK	LOG-CES-AD
YWBQM	0.7533	0.9381
Cb-WBQM	0.7911	0.8160
Cr-WBQM	0.7422	0.7484
MSSIM	0.7999	0.9566
JPQM	8.0157	8.3959
CEF	1.1625	1.1844

Table 1
Performance combarison with image 1

Technique	TW-CES-BLK	LOG-CES-AD	
YWBQM	0.6741	0.8763	
Cb-WBQM	0.6796	0.7569	
Cr-WBQM	0.7396	0.7432	
MSSIM	0.8133	0.9538	
JPQM	8.2674	8.7047	
CEF	1.2947	1.4073	

Table 2
Performance combarison with image 2

The performance metrics comparison of proposed technique (LOG-CES-AD) and the technique suggested by mitra and mukherjee (TW-CES-BLK) are tabulated. The WBQM measures independently for each component in the Y-Cb-Cr space (Y-WBQM, Cb-WBQM, Cr-WBQM) for TW-CESBLK technique are significantly poorer than those obtained by proposed method (LOG-CES-AD).It has been found that the proposed technique (LOG-CES-AD) leads to an image that is almost similar to its original, and, hence, its JPQM measures are higher than other scheme (TW-CESBLK). Color enhancement factor (CEF) and mean structural similarity index also better for proposed method.

5 Conclusion

Compared to spatial domain image enhancement techniquesdct domain techniques are computationally more efficient. Since the majority of the DCT coefficients in the compressed domain are zero after quantization, DCT domaintechniques does not require significant memory occupancyand computational load for the image enhancement. Thetechnique described in this report treats chromatic componentsin addition to the processing of the luminancecomponent and removes the blocking artifacts efficientlyfor improving the visual quality of the images to a greatextent. The qualitative and quatitative analysis shows thatthe proposed technique gives better results than existingtechniques.

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