International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 4, April - 2013

A NEW QUALITY APPROACH FOR ANALYZING THE QUALITY OF DEBLOCKED IMAGES

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***Abstract* : JPEG compression is the lossy compression which is most prevalent technique for image codecs. But it suffers from blocking artifacts which are very serious at low bit rates, where network bandwidths are limited. In this paper deblocking filters are used to reduce blocking artifacts. The efficiency of deblocking algorithms were studied. Similarly a comparison of the perceptual quality of deblocked images based on various quality assessment metric is done. A proposed PSNR including blocking effect factor (PSNR-B) was used instead of perceptually questionable PSNR. Another quality assessment metric SSIM was used which produces results largely in accordance with PSNR –B. We show the simulation results, which prove PSNR-B produces objective judgments and results in better performance than well known blockiness specific index and PSNR.**

***Keywords*---Deblocked images, blocking artifacts, distortion, quality assessment, quantization**

I. Introduction

Digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction, any of which may result in a degradation of visual quality. Many practical and commercial systems use digital image compression when it is required to transmit or store the image over network bandwidth limited resources. JPEG compression is the most popular image compression standard among all the members of lossy compression standards family. JPEG image coding is based on block based discrete cosine transform. BDCT coding has been successfully used in image and video compression applications due to its energy compacting property and relative ease of implementation. Blocking effects are common in block-based image and video compression systems. Blocking artifacts are more serious at low bit rates, where network bandwidths are limited. Significant research has been done on blocking artifact reduction [7]–[13]. After segmenting an image in to blocks of size N×N, the blocks are independently DCT transformed, quantized, coded and transmitted. One of the most noticeable degradation of the block transform coding is the “blocking artifact”. These artifacts appear as a regular pattern of visible block boundaries. In order to achieve high compression rates using BTC (Block Transform Coding) with visually acceptable results, a procedure known as deblocking is done in order to eliminate blocking artifacts. A deblocking filter can improve image quality in some aspects, but can reduce image quality in other regards.

In this paper a research has done on quality assessment of deblocked images by estimating various quality metrics and the effect of quantization step of the measured quality of deblocked image is studied. Simulations are done using quality metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and PSNR-B. PSNR-B is a new quality metric which includes PSNR and a blocking effect factor. By going through simulation results, it is shown that PSNR-B correlates well with the SSIM index and subjective quality and its performance is much better than the PSNR.

Section II reviews the deblocking algorithms we consider. In section III we propose a method in order to analyze the deblocking filters. Section IV presents the estimation of quality metrics. Section V introduces the relationship between quantization step size and image quality. Section VI presents simulation results and discussions. Concluding remarks are presented in section VII.

II.EXISTING METHODS

(a)Deblocking:

To remove blocking effect, several deblocking techniques have been proposed in the literature as post process mechanisms after JPEG compression. If deblocking is viewed as

an estimation problem, the simplest solution is probably just to low pass the blocky JPEG compressed image. The advantage of low pass filtering technique is that no additional information is needed and as a result, the bit rate is not increased. However, it results in blurred images.More sophisticated methods involve iterative methods such as projection on convex sets [3, 4] and constrained least squares [4, 5].
images and report their quality without human involvement. Such methods could eliminate the need for expensive subjective studies. Objective image quality metrics can be classified according to the availability of an original (distortion-free) image, with which the distorted image is to be compared. Most existing approaches are known as Full reference, no reference, reduced reference. The work in this thesis is based on the design of full-reference image quality measure. Different quality metrics such as MSE, PSNR, SSIM have been proposed in the literature for image quality measurement.

In this paper we use deblocking algorithms including low pass filtering and projection on to convex sets. The efficiency of these algorithms and performance of new quality approach can be analyzed by introducing a proposed method in the following sections.

III.PROPOSED METHOD

Deblocking operation is performed in order to reduce blocking artifacts. Deblocking operation can be achieved by using various deblocking algorithms, employing deblocking filters. The effects of deblocking filters can be analyzed by introducing a change in distortion concept. The deblocking operation results in the enhancement of image quality in some areas, while degrading in other areas.

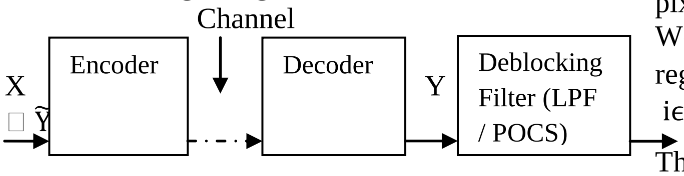

Fig1: Block diagram showing JPEG compression

X – Original Image Y – Compressed/ Decoded Image Ỹ- Deblocked Image

Objective measurement and Subjective measurement are basically two approaches that have been proposed in the literature for image Quality measurement [20]. Subjective evaluation is usually too inconvenient, time-consuming and expensive. Objective measurements are automatic algorithms for quality assessment that could analyze

Let X be the reference image and Y be the test image (decoded image) distorted by quantization errors and Ỹ be the deblocked image as shown in figure1. Let f represent the deblocking operation and is given by Ỹ=f(Y). Let the quality metric between X and Y be M(X,Y). For the given image Y, the main aim of deblocking operation f is to maximize M(X, f(Y)). Let α_i represent the amount of decease in distortion in the decrease in distortion region (DDR) and is given by

$$\alpha_i = d(x_i, y_i) - d(x_i, \tilde{y}_i) \quad (1)$$

Where $d(x_i, y_i)$ the distortion between ith pixels of X and Y and is expressed as squared Euclidian distance

$$d(x_i, y_i) = \|x_i - y_i\|^2 \quad (2)$$

Where $d(x_i, \tilde{y}_i)$the distortion between ith pixels of X and Y□ and is expressed as squared Euclidian distance

Next, we define the distortion decrease region (DDR) to be composed of those pixels where the distortion is decreased by the deblocking operation

$$i \in A, \text{ if } d(x_i,\tilde{y}_i) < d(x_i,y_i) \quad (3)$$

The amount of distortion decrease for the ith pixel α_i in the DDR $\mathcal{A}$ is

$$\alpha_i = d(x_i, y_i) - d(x_i, \tilde{y}_i) \quad (4)$$

We define the mean distortion decrease (MDD)

$$\overline{\alpha} = \frac{1}{N} \sum_{i \in A} (d(x_i, y_i) - d(x_i, \tilde{y}_i)) \quad (5)$$

The distortion may also increase at other pixels by application of the deblocking filter. We similarly define the distortion increase region (DIR)$\mathcal{B}$

$$i \in B, \text{ if } d(x_i, y_i) < d(x_i,\tilde{y}_i) \quad (6)$$

The amount of distortion increase for the ith pixel β_i in the DIRB is

$$\beta_i = d(x_i,\tilde{y}_i) - d(x_i,y_i) \quad (7)$$

Where N is the number of pixels in the image. Similarly the mean distortion increase (MDI) is

$$\overline{\beta} = \frac{1}{N} \sum_{i \in B} (d(x_i, \tilde{y}_i) - d(x_i, y_i)) \quad (8)$$

The difference between MDD and MDI can be represented as Mean distortion change (MDC) and is given by

$$\bar{\gamma} = \bar{\alpha} - \bar{\beta} \quad (9)$$

From this it can be stated that the deblocking operation is likely successful if $\bar{\gamma} > 0$.This is because the mean distortion decrease is larger than the mean distortion increase. Nevertheless, the level of perceptual improvement or loss does not meet these conditions. Based on these conditions, the effect of deblocking filters can be analyzed.

1) Low pass filter: A simple L×L lowpass deblocking filter can be represented as

$$g\big(N(x_i)\big) = \sum_{k=1}^{L^2} h_k \, . \, x_{i,k} \quad (10)$$

Where $N(x_i)$ represent Neighborhood of pixel x_i
'g' represents deblocking operation function
'h_k'represents Kernel for the L×L filter
$x_{i,k}$ represents the kth pixel in the L×L neighbourhood
of pixel

While lowpass filter is used as deblocking filter to reduce blocking artifacts, the distortion will decrease for some pixels defined by (DDR-A)and the distortion will likely increase for some pixels defined by (DIR-B)and it is possible that $\gamma < 0$ could result. The image will be degraded due to blurring as critical high frequency is lost.

2) POCS: Deblocking algorithms based upon projection into convex sets (POCS) have demonstrated good performance for reducing blocking artifacts and have proved popular [9]-[13]. In POCS Projection operation is done in the DCT domain and lowpass filtering operation is done in the spatial domain. Forward DCT and inverse DCT operations are required because the lowpass filtering and the projection operations are performed in various domains. Convergence require Multiple iterations and the lowpass filtering, DCT, Projection, IDCT operations require one iteration. POCS filtered images converge to an image that does not exhibit blocking artifacts under certain conditions [9], [12], [13]. But computational complexity is more as it requires more iterations.

IV. Estimation of Quality Metrics:

To Measure the quality degradation of an available distorted image with reference to the original image, a class of quality assessment metrics called full reference (FR) are considered. Full reference metrics perform distortion measures having full access to the original image. The quality assessment metrics are estimated as follows

a)PSNR : Peak Signal-to-Noise Ratio (PSNR) and mean Square error are most widely used full reference (FR) QA metrics [2], [13].As before X is the reference image and Y is the test image. The error signal between X and Y is assumed as 'e'. Then

$$MSE(X,Y) = \frac{1}{N}\sum_{i=1}^{N} e_i^2 \quad = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)2 \quad (11)$$

$$PSNR(X,Y) = 10log_{10}\frac{255^2}{MSE(X,Y)} \quad (12)$$

Where N represent Number of pixels in an image. However, The PSNR does not correlate well with perceived visual Quality[14],[15]-[18].

b) SSIM: The Structural similarity (SSIM) metric aims to measure quality by capturing the similarity of images [2]. Three aspects of similarity: Luminance, contrast and structure is determined and their product is measured. Luminance comparison function *l*(X,Y) for reference image X and test image Y is defined as below

$$l(X,Y) = \frac{2\mu_X\mu_Y + C1}{\mu_x^2 + \mu_y^2 + C1} \quad (13)$$

Where μ_x and μ_y are the mean values of X and Y respectively and C1 is the stabilization constant.
Similarly the contrast comparison function *c*(X, Y) is defined
as

$$c(X,Y) = \frac{2\sigma_x\sigma_y + C2}{\sigma_x^2 + \sigma_y^2 + C2} \quad (14)$$

Where the standard deviation of X and Y are represented as σ_x and σ_y and C2 is the stabilization constant.
The structure comparison function *s*(X, Y) is defined as

$$s(X,Y) = \frac{\sigma_{xy} + C3}{\sigma_x\sigma_y + C3} \quad (15)$$

Where σ_{xy} represents correlation between X and Y and C_3 is a constant that provides stability.
By combining the three comparison functions, The SSIM index is obtained as below

$$SSIM(X,Y) = [l(X,Y)]^{\alpha}.[(c(X,Y)]^{\beta}.[(s(X,Y)]^{\gamma} \quad (16)$$

and the parameters are set as $\alpha = \beta = \gamma = 1$ and C3=C2/2 From the above parameters the SSIM index can be defined as

$$SSIM(X,Y) = \frac{(2\mu_X\mu_Y+C1)(2\sigma_{xy}+C2)}{(\mu_x^2+\mu_y^2+C1)(\sigma_x^2+\sigma_y^2+C2)} \quad (17)$$

Symmetric Gaussian weighting functions are used to estimate local SSIM statics. The mean SSIM index pools the spatial SSIM values to evaluate overall image quality [2].

$$SSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j - y_j) \quad (18)$$

Where x_j and y_j are image patches covered by the jth window and the number of local windows over the image are represented by M.

c) PSNR-B: A new quality metric called PSNR-B which includes ordinary PSNR by blocking effect factor is considered. PSNR-B correlates well with subjective quality when compared to PSNR. Consider an image that contains integer number of blocks such that the horizontal and vertical dimensions of the image are divisible by block dimension and the blocking artifacts occur along the horizontal and vertical dimensions.

Y_1	Y_9	Y_{17}	Y_{25}	Y_{33}	Y_{41}	Y_{49}	Y_{57}
Y_2	Y_{10}	Y_{18}	Y_{26}	Y_{34}	Y_{42}	Y_{50}	Y_{58}
Y_3	Y_{11}	Y_{19}	Y_{27}	Y_{35}	Y_{43}	Y_{51}	Y_{59}
Y_4	Y_{12}	Y_{20}	Y_{28}	Y_{36}	Y_{44}	Y_{52}	Y_{60}
Y_5	Y_{13}	Y_{21}	Y_{29}	Y_{37}	Y_{45}	Y_{53}	Y_{61}
Y_6	Y_{14}	Y_{22}	Y_{30}	Y_{38}	Y_{46}	Y_{54}	Y_{62}
Y_7	Y_{15}	Y_{23}	Y_{31}	Y_{39}	Y_{47}	Y_{55}	Y_{63}
Y_8	Y_{16}	Y_{24}	Y_{32}	Y_{40}	Y_{48}	Y_{56}	Y_{64}

Fig2: Example for illustration of pixel blocks

Let N_H and N_v be the horizontal and vertical dimensions of the $N_H X N_v$ image I. Let $\mathcal{H}$ be the set of horizontal neighboring pixel pairs in I. Let $\mathcal{H}_B \subset \mathcal{H}$ be the set of horizontal neighboring pixel pairs that lie across a block boundary. Let $\mathcal{H}_B^C$ be the set of horizontal neighboring pixel pairs, not lying across a block boundary, i.e. $\mathcal{H}_B^C = \mathcal{H} - \mathcal{H}_B$, . Similarly, let ν be the set of vertical neighboring pixel pairs, and ν_B be the set of vertical neighboring pixel pairs lying across block boundaries. Let ν_B^C be the set of vertical neighboring pixel pairs not lying across block boundaries i.e. $\nu_B^C = \nu - \nu_B$.

$$N_{H_B} = N_V\left(\frac{N_H}{B}\right) - 1$$
$$N_{H_B^C} = N_V(N_H - 1) - N_{H_B}$$
$$N_{V_B} = N_H\left(\frac{N_V}{B}\right) - 1$$
$$N_{V_B^C} = N_H(N_V - 1) - N_{V_B}.$$

Where $N_{H_B}, N_{H_B^C}, N_{V_B}, N_{V_B^C}$ be the number of pixel pairs in $\mathcal{H}_B, \mathcal{H}_B^C, \nu_B$ and ν_B^C respectively and B is the block size.
Fig. 2 shows a simple example for illustration of pixel blocks with $N_H = 8, N_V = 8$, and B=4 . The thick lines represent the block boundaries. In this example $N_{H_B} = 8$, $N_{H_B^C} = 48$, $N_{V_B} = 8$, and $N_{V_B^C} = 48$. The sets of pixel pairs in this example are

$\mathcal{H}_B =$ {(y_{25}, y_{33}), (y_{26},y_{34}),……..(y_{32},y_{40})}

$\mathcal{H}_B^C =$ {y_1, y_9),(y_9,y_{17}), (y_{17},y_{25}),……..(y_{56},y_{64})}
ν_B ={(y_4,y_5),(y_{12},y_{13}),……..(y_{60},y_{61})}
ν_B^C=(y_1,y_2),(y_2,y_3),(y_3,y_4),(y_5,y_6),…….(y_{63},y_{64})
}

Then we define the mean boundary pixel squared difference(D_B) and the mean nonboundary pixel squared difference (D_{B_C})for image y to be

$$D_B(\mathbf{y}) = \frac{\sum_{(y_i,y_j)\in\mathcal{H}_B}(y_i - y_j)^2 + \sum_{(y_i,y_j)\in\mathcal{V}_B}(y_i - y_j)^2}{N_{H_B} + N_{V_B}} \quad (19)$$

$$D_B^C(\mathbf{y}) = \frac{\sum_{(y_i,y_j)\in\mathcal{H}_B^C}(y_i - y_j)^2 + \sum_{(y_i,y_j)\in\mathcal{V}_B^C}(y_i - y_j)^2}{N_{H_B^C} + N_{V_B^C}} ,(20)$$

Blocking artifacts will become more visible as the quantization step size increases; mean boundary pixel squared difference will increase relative to mean non boundary pixel square difference. The blocking effect factor is given by

$$\mathrm{BEF}(\mathbf{y}) = \eta \cdot [D_B(\mathbf{y}) - D_B^C(\mathbf{y})]$$

Where

$$\eta = \begin{cases} \frac{\log_2 B}{\log_2(\min(N_H, N_V))}, & \text{if } D_B(\mathbf{y}) > D_B^C(\mathbf{y}) \\ 0, & \text{otherwise} \end{cases} \quad (21)$$

A decoded image may contain multiple block sizes like 16×16 macro block sizes and 4×4 transform blocks, both contributing to blocking effects. Then the blocking effect factor for k[th] block is given by

$$\mathrm{BEF}_k(\mathbf{y}) = \eta_k \cdot [D_{B_k}(\mathbf{y}) - D_{B_k}^C(\mathbf{y})] \quad (22)$$

For overall block sizes BEF is given by

$$\mathrm{BEF}_{\mathrm{Tot}}(\mathbf{y}) = \sum_{k=1}^{K} \mathrm{BEF}_k(\mathbf{y}) \quad (23)$$

The mean square error including blocking effects for reference image X and test image Y is defined as follows,

$$\text{MSE-}B(\mathbf{x},\mathbf{y}) = \mathrm{MSE}(\mathbf{x},\mathbf{y}) + \mathrm{BEF}_{\mathrm{Tot}}(\mathbf{y}) \quad (24)$$

Finally the proposed PSNR-b is given as,

$$\text{PSNR-}B(\mathbf{x},\mathbf{y}) = 10\log_{10}\frac{255^2}{\text{MSE-}B(\mathbf{x},\mathbf{y})} \quad (25)$$

The MSE term in (24) measures the distortion between the reference image and the test image , while the BEF term in (24) specifically measures the amount of blocking artifacts just using the test image . These no-reference quality indices claim to be efficient for measuring the amount of blockiness, but may not be efficient for measuring image quality relative to full-reference quality assessment. On the other hand, the MSE is not specific to blocking effects, which can substantially affect subjective quality. We argue that the combination of MSE and BEF is an effective measurement for quality assessment considering both the distortions from the original image and the blocking effects in the test image. The associated quality index PSNR-B is obtained from the MSE-B by a logarithmic function, as is the PSNR from the MSE. The PSNR-B is attractive since it is specific for assessing image quality, specifically the severity of blocking artifacts.

V. Effect of Quantization Step Size.

Quantization is a key element of lossy compression, but information is lost. The amount of compression and the quality can be controlled by the quantization step. As quantization step increases, the quality of the image degrades due to the increase in compression ratio. The trade off exists between compression ratio and deblocked images. The input image is divided into L×L blocks in block transform coding in which each block is transformed independently in to transform coefficients. Therefore an input image block 'b' is transformed into a DCT coefficient block is given by

$$B = TbT^t \quad (26)$$

Where T is the transform matrix and T^t is the transpose matrix of T. The transform coefficients are then quantized using a scalar quantizer Q

$$\tilde{B} = Q(B) = Q(TbT^t) \quad (27)$$

The quantized coefficients are stored or transmitted to decoder. Therefore the output of the decoder is then given by

$$\tilde{b} = T^t\tilde{B}T = T^tQ(TbT^t)T \quad (28)$$

Quantization step is represented by Δ. The SSIM index captures the similarity of reference and test images. As the quantization step size becomes larger, the structural differences between reference and test image will generally increase. Hence, the SSIM index and PSNR are monotonically decreasing functions of the quantization step size Δ .

VI. Simulation Results:

Simulations are performed using Matlab software which possess excellent graphics and matrix handling capabilities . Matlab has a separate toolbox for image processing applications, which provided simpler solutions for many of the problems encountered in this research. In this paper image quality assessment is done by objective measurement in which evaluations are automatic and mathematical defined algorithms. A new image quality metric PSNR-B and well known objective evaluation algorithms for measuring image quality such as MSE, PSNR, Structural Similarity Index Metric(SSIM) have used.

Following operations are applied on the original images.

1. Compression
2. Deblocking using LPF, Median filter and POCS
3. Then the quality of compressed and deblocked images using LPF and POCS are measured and compared using image quality metrics.

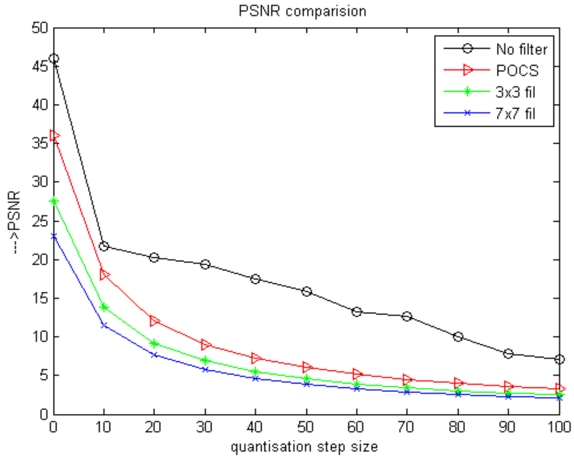

Figure 3 PSNR comparisons of cameraman image

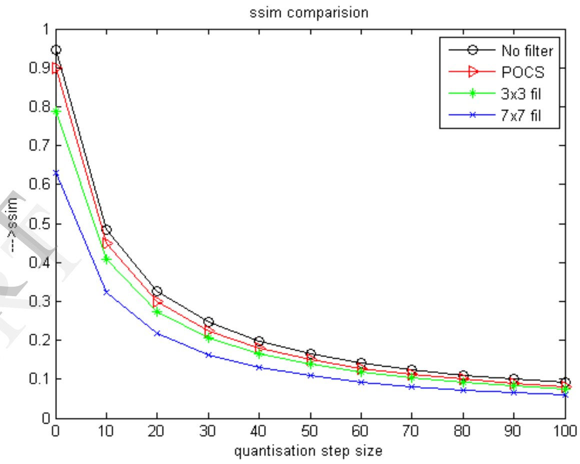

Figure 4 SSIM comparisons of cameraman image

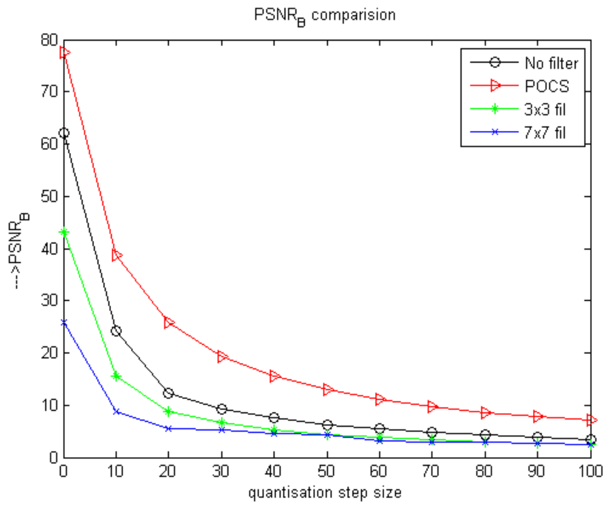

Figure 5 PSNR-B comparisons of cameraman image.

Table : Comparison of MSE, PSNR, SSIM, PSNR-B for Cameraman Image

Compressed Image(No filter)		
S.No	Quality Metric	Quality Value
1	MSE	0.1933
2	PSNR	27.6343
3	SSIM	0.0120
4	PSNR-B	51.2688
Deblocked Image (LPF)		
S.No	Quality Metric	Quality Value
1	MSE	0.1933
2	PSNR	27.6346
3	SSIM	0.0120
4	PSNR-B	51.3122
Deblocked Image (Median Filter)		
S.No	Quality Metric	Quality Value
1	MSE	
2	PSNR	
3	SSIM	
4	PSNR-B	
Deblocked Image (POCS)		
S.No	Quality Metric	Quality Value
1	MSE	0.1930
2	PSNR	27.6380
3	SSIM	0.0131
4	PSNR-B	51.7034

Consider a sample image cameraman as shown in the above figure. Simulations are performed on these image and quality metrics are estimated. Quantization step sizes of 10, 20, 30 , 40 , 50 ,100 are used in the simulations to analyse the effects of quantization step size

A.PSNR Analysis:

Figure 3 shows that when the quantization step size was large (Δ≥ 80), the 3×3 filter, 7×7filter and POCS methods resulted in higher PSNR than the no filter case on both the images. All the deblocking methods produced lower PSNR when the quantization step size was small (Δ≤ 30).

B.SSIM Analysis :

Figure 4 shows that when the quantization step was large (Δ≥ 80), on the two images, all the filtered methods resulted in larger SSIM values. The 3×3 and 7×7 lowpass filters resulted in lower SSIM values than the low filter case when the quantization step size was small (Δ≤ 30).

C.PSNR-B Analysis:

For large quantization steps, the PSNR-B values improved for the two images by employing lowpass filtering methods. The POCS resulted in improved PSNR-B values compared to the no filtered case, even at small quantization step size.

Conclusion

Image quality assessment plays an important role in various image processing applications. Experimental results indicate that MSE and PSNR are very simple, easy to implement and have low computational complexities. But these methods do not show good results. MSE and PSNR are acceptable for image similarity measure only when the images differ by simply increasing distortion of a certain type. But they fail to capture image quality when they are used to measure across distortion types. SSIM is widely used method for measurement of image quality. It works accurately can measure better across distortion types as compared to MSE and PSNR, but fails in case of highly blurred image. We have tested our algorithm on few natural images. Those sample images are shown in above figure. We have found that PSNR-B is the better quality metric for JPEG compression which shows better performance than the other well known quality metrics .This Analysis will brings out a new trend in the quality metrics of the image and proves to be efficient than the conventional metrics.

For future work, quality studies of PSNR-B and perceptually proven index SSIM in conjunction are of considerable value, not only for studying deblocking operations, but also for other image improvement applications, such as restoration, denoising, enhancement, and so on.

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