International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 1 Issue 4, June - 2012

COMPARISON OF IMAGE QUALITY METRICS

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Abstract: **Generally quality metrics are used to measure the quality of improvement in the images after they are processed and compared with the original and other different alternatives methods. Measurement of image quality is very crucial to many image processing applications. Compression is one of the applications where it is required to monitor the quality of decompressed / decoded image. JPEG compression is the lossy compression which is most prevalent technique for image codecs. But it suffers from blocking artifacts Here in this paper Various objective evaluation algorithms for measuring image quality like MSE, PSNR, SSIM and PSNR-B are simulated and compared w.r.t. JPEG compression application. Different deblocking filters are used to reduce blocking artifacts and deblocked images are compared through various quality metrics. As the degree of blocking depends on the quantization step, the quality metrics are also simulated and compared by varying the quantization step size. We discussed a new concept called 'Modified PSNR-B' which is under review process that gives even better results compared to the existing PSNR-B which includes the blocking effect factor (BEF).**

Keywords--- **Blocking artifacts, Deblocked images, Image quality, MSE, PSNR, SSIM, PSNR-B and Quantization**

1. 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. So, measurement of image quality is very important to numerous image processing applications. 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]. 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.

1.1 Need of Quality Measure:

Basically, quality assessment algorithms are needed for mainly three types of applications:

(a) For optimization purpose, where one maximize quality at a given cost.
(b) For comparative analysis between different alternatives.
(c) For quality monitoring in real time applications.

2. Existing Quality Metrics

2.1 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

$$MSE(X,Y) = \frac{1}{N}\sum_{i=1}^{N} e_i^2 \quad = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)2 \qquad (2.1.1)$$

$$PSNR(X,Y) = 10log_{10}\frac{255^2}{MSE(X,Y)} \qquad (2.1.2)$$

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

$$l(X,Y) = \frac{2\mu_X\mu_Y + C1}{\mu_X^2 + \mu_y^2 + C1} \qquad (2.1.3)$$

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

$$c(X,Y) = \frac{2\sigma_x\sigma_y + C2}{\sigma_x^2 + \sigma_y^2 + C2} \qquad (2.1.4)$$

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

$$s(X,Y) = \frac{\sigma_{xy} + C3}{\sigma_x\sigma_y + C3} \qquad (2.1.5)$$

ISSN: 2278-0181
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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

$$SSIM(X,Y) = [l(X,Y)]^{\alpha}.[(c(X,Y)]^{\beta}.[(s(X,Y)]^{\gamma} \quad (2.1.6)$$

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

$$SSIM(X,Y) = \frac{(2\mu_X\mu_Y + C1)(2\sigma_{xy} + C2)}{(\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2)} \quad (2.1.7)$$

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].

$$SSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j - y_j) \quad (2.1.8)$$

Where x_j and y_j are image patches covered by the j^{th} window and the number of local windows over the image are represented by M.

3. New Approach of PSNR including blocking effect factor:

3.1) PSNR-B: PSNR-B is a new quality metric 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}

Fig1: 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.$\nu_B^C = \nu - \nu_B$.

$$N_{H_B} = N_V\left(\frac{N_H}{B}\right) - 1 \quad (3.1.1)$$

$$N_{H_B^C} = N_V(N_H - 1) - N_{H_B} \quad (3.1.2)$$

$$N_{V_B} = N_H\left(\frac{N_V}{B}\right) - 1 \quad (3.1.3)$$

$$N_{V_B^C} = N_H(N_V - 1) - N_{V_B} \quad (3.1.4)$$

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

$\mathcal{H}_B = \{(y_{25}, y_{33}), (y_{26}, y_{34}), \ldots\ldots (y_{32}, y_{40})\}$
$\mathcal{H}_B^C = \{(y_1, y_9), (y_9, y_{17}), (y_{17}, y_{25}), \ldots\ldots (y_{56}, y_{64})\}$
$\nu_B = \{(y_4, y_5), (y_{12}, y_{13}), \ldots\ldots (y_{60}, y_{61})\}$
$\nu_B^C = (y_1,y_2),(y_2,y_3),(y_3,y_4),(y_5,y_6),\ldots\ldots(y_{63},y_{64})\}$ (3.1.5)

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

$$D_B(Y) = \frac{\sum_{(y_i,y_j)\in\mathcal{H}_B}(y_i - y_j)2 + \sum_{(y_i,y_j)\in\nu_B}(y_i - y_j)2}{N_{H_B} + N_{V_B}} \quad (3.1.6)$$

$$D_B^C(Y) = \frac{\sum_{(y_i,y_j)\in\mathcal{H}_B^C}(y_i - y_j)2 + \sum_{(y_i,y_j)\in\nu_B^C}(y_i - y_j)2}{N_{H_B^C} + N_{V_B^C}} \quad (3.1.7)$$

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

$$BEF(Y) = \eta[D_B(Y) - D_B^C(Y)] \quad (3.1.8)$$

Where

$$\eta = \begin{cases} \frac{log_2^B}{log_2^{(\min(N_H,N_V))}} & , \quad if\ D_B(Y) > D_B^C(Y) \\ 0 \quad , & otherwise \end{cases} \quad (3.1.9)$$

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

$$BEF_k(Y) = \eta_k[D_{B_k}(Y) - D_{B_k}^C(Y)] \quad (3.1.10)$$

For overall block sizes BEF is given by

$$BEF_{Tot}(Y) = \sum_{k=1}^{K} BEF_k\,(y) \quad (3.1.11)$$

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

$$MSE - B(x,y) = MSE(x,y) + BEF_{Tot}(y) \quad (3.1.12)$$

Finally the proposed PSNR-B is given as,

ISSN: 2278-0181
Vol. 1 Issue 4, June - 2012

$$PSNR - B(x,y) = 10log_{10}\frac{255^2}{MSE-B(x,y)} \quad (3.1.13)$$

The MSE term in (2.1.1) measures the distortion between the reference image and the test image, while the BEF term in (3.1.8) 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. 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 PSNR-B is attractive since it is specific for assessing image quality, specifically the severity of blocking artifacts.

A new approach of PSNR-B is introduced which gives better results compared to well known blockiness specific index. In this method, a set of diagonal neighboring pixel pairs which are not lying across block boundaries are considered. Simulation results shows that the modified PSNR-B gives better results compared to well known blockiness specific indices.

4. Quantization step size and Deblocking:

Compression and Deblocking operations are performed on original images. JPEG Compression is used to compress the image in which quantization step size is a key factor 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

$$B = TbT^t \quad (4.1)$$

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

$$\tilde{B} = Q(B) = Q(TbT^t) \quad (4.2)$$

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

$$\tilde{b} = T^t\tilde{B}T = T^tQ(TbT^t)T \quad (4.3)$$

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.To remove blocking artifacts, 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].In this paper deblocking algorithms including low pass filtering, median filtering and projection on to convex sets have used. The efficiency of these algorithms will be studied after performing simulations on compressed and deblocked images. After performing simulations on compressed and deblocked images, various objective quality metrics are applied for assessing the image quality. Among all the quality metrics, PSNR-B produced better results compared to other well known blockiness specific indices.

5. Simulation Results:

Simulations are performed using Matlab software which possesses 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 approach of PSNR-B and well known objective evaluation algorithms for measuring image quality such as MSE, PSNR, Structural Similarity Index Metric (SSIM) have used.

Original image Compressed Image Deblocked images (a) LPF

(b) 3x3 filter (c) 7x7 filter (d) POCS filter

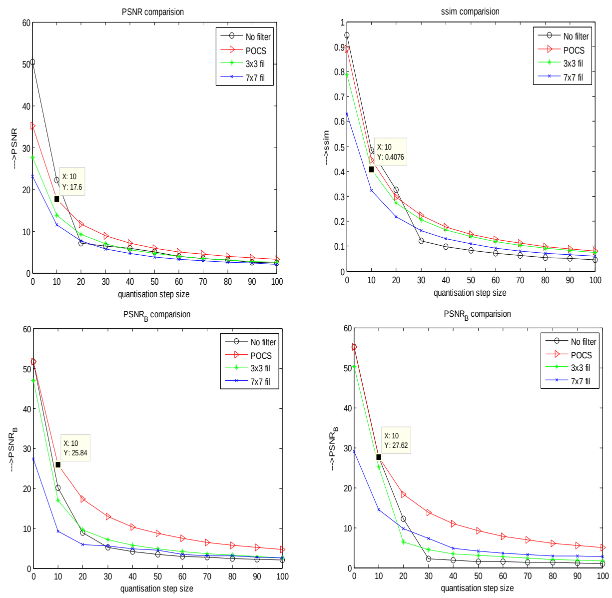
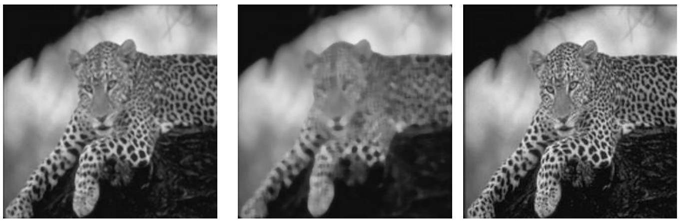


Figure 2: Comparison of quality metrics for cameraman image (a) PSNR (b) SSIM (c) PSNR-B(d)modified PSNR-B

Original image Compressed Image Deblocked images (a) LPF



(b) 3x3 filter (c) 7x7 filter (d) POCS filter

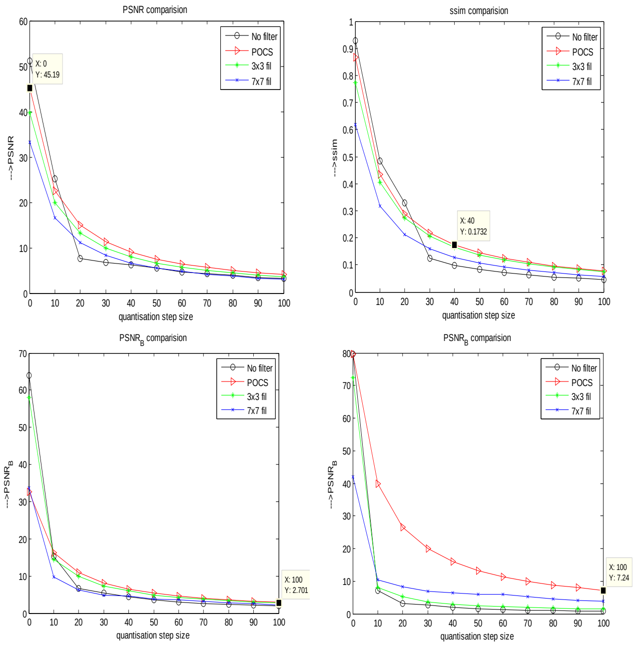
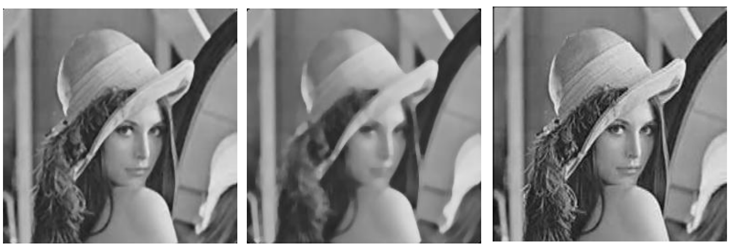


Figure 3: Comparison of quality metrics for leopard image (a) PSNR (b) SSIM (c) PSNR-B (d) modified PSNR-B

Original image Compressed Image Deblocked images (a) LPF



(b) 3x3 filter (c) 7x7 filter (d) POCS filter

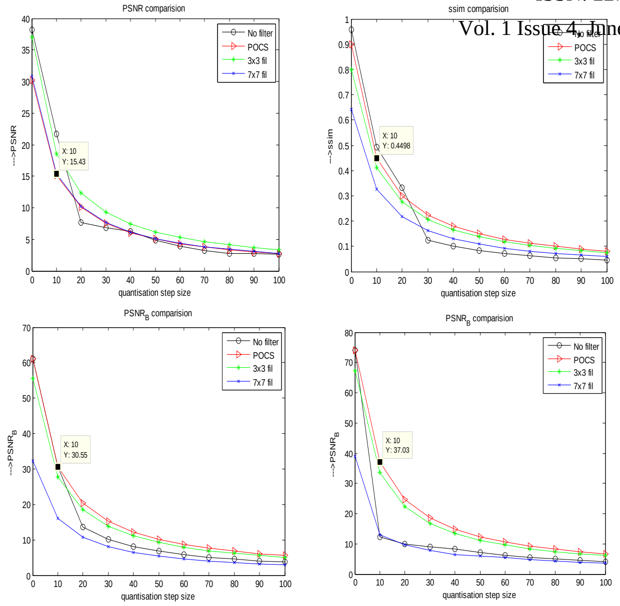


Figure 4: Comparison of quality metrics for Lena image (a) PSNR (b) SSIM (c) PSNR-B (d) modified PSNR-B

5.1 Comparison of quality metrics: 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, and 100 are used in the simulations to analyze the effects of quantization step size

A.PSNR Analysis:

Figure 3 shows that when the quantization step size was large ($\Delta \geq 20$), the 3×3 filter and POCS methods resulted in higher PSNR than the no filter and 7x7 filter case on the image. All the deblocking methods produced lower PSNR when the quantization step size was small ($\Delta \leq 20$).

B.SSIM Analysis:

Figure 4 shows that when the quantization step was large ($\Delta \geq 20$), on the image, all the filtered methods resulted in larger SSIM values. The 3×3 and 7×7 low pass filters resulted in lower SSIM values than the no filter case when the quantization step size was small ($\Delta \leq 30$).

C.PSNR-B Analysis:

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

D .New approach of PSNR-B Analysis: (modified PSNR-B)

For large quantization steps, the PSNR-B values improved for the cameraman image by employing low pass filtering methods. The POCS resulted in improved PSNR-B values compared to the no filtered case, even at small quantization step size. Modified PSNR-B produced better results compared to the existing well known quality indices.

Cameraman Image				
Filtering methods	**SSIM**	**PSNR**	**PSNR-B (H&V Pixel pairs)**	**Modified PSNR-B (Diagonal Pixel pairs)**
No filter	0.4551	20.01	20.21	27.61
POCS	**0.4454**	**17.6**	**25.84**	**27.62**
3x3 filter	0.4076	13.81	16.88	25.11
7x7 filter	0.3242	10.51	9.57	14.54
Leopard Image				
Filtering methods	**SSIM**	**PSNR**	**PSNR-B (H&V Pixel pairs)**	**Modified PSNR-B (Diagonal Pixel pairs)**
No filter	0.4846	25.22	14.47	15.48
POCS	**0.4319**	**22.6**	**22.84**	**39.82**
3x3 filter	0.4054	19.91	14.47	8.010
7x7 filter	0.3173	16.59	9.636	8.008
Lena Image				
Filtering methods	**SSIM**	**PSNR**	**PSNR-B (H&V Pixel pairs)**	**Modified PSNR-B (Diagonal Pixel pairs)**
No filter	0.4935	21.65	30.55	12.99
POCS	**0.4498**	**15.43**	**30.55**	**37.03**
3x3 filter	0.4117	18.52	27.77	33.67
7x7 filter	0.327	15.43	16.08	12.99

Table 5.1: Comparison of Quality metrics for Cameraman, Leopard and Lena images (at quantization step size=10)

6. 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. Standard and natural images were tested by these quality metrics. Those sample images are shown in above figure. We have found that new approach of 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, we look forward to new problems in this direction of inquiry. 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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