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Research Paper

COMPARISON OF QUALITY INDICES OF DEBLOCKED IMAGES

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To improve the visual images which are degraded by blocking artifacts from compression. It is efficient method to use deblocking algorithms instead of using perceptually questionable PSNR. We proposed a block-sensitive index method named as PSNR-B, it produces objective judgements that accord with observations. The PSNR-B modifies PSNR by including a blocking effect factor. We also use the perceptually significant SSIM index, which produces results largely in agreement with PSNR-B. Simulation results show that the PSNR-B results in better performance for quality assessment of deblocked images than PSNR and a well-known blockiness-specific index.

Keywords: Image quality assessment, Quantization, Deblocking, Distortion, Blocking effect, PSNR, Blocking artifacts, Structural similarity, Deblocking filter, Distortion change

INTRODUCTION

Deblocking is a local operation which improves the appearance of the image in some regions, while degrading the quality elsewhere. We Analyse the efficiency of deblocking algorithms for improving visual signals degraded by blocking artifacts from compression. Blocking artifacts are the grey level discontinuties at block boundaries, Which are generally oriented horizontally and vertically. These arise from poor representation of the block luminance levels near the block boundaries.

Instead of using perceptually questionable PSNR, we propose PSNR-B.The PSNR-B modifies PSNR by including a blocking effect factor. The disadvantage of PSNR is it does not capture subjective quality well when blocking artifacts are present.

SSIM (Structural Similarity) Index metric is slightly complex than PSNR, but correlates highly with human subjectively. Most blocking artifact reduction methods assume that the distorted image contains noticeable amount of blocking. The degree of blocking depends upon several parameters, the most important

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of which is the quantization step for lossy compression. The recent advent of powerful modern Image Quality Assessment (IQA) algorithms that compare well with human subjectively makes this plausible. Here we investigate quality assessment of deblocked images, and in particular we study the effects of the quantization step of the measured quality of deblocked images. A deblocking filter can improve image quality in some aspects, but can reduce image quality in other regards.

We perform simulations on the quality assessment of deblocked images. We first perform simulations using the conventional Peak Signal-to-Noise Ratio (PSNR) quality metric and a state of the art quality index, the structural similarity (SSIM) index. We also propose a new deblocking quality index that is sensitive to blocking artifacts in deblocked images. We name this Peak Signal-to-Noise Ratio including blocking effects (PSNR-B).

The simulation results show that the proposed PSNR-B correlates well with subjective quality and with the SSIM index, and performs much better than the PSNR. We study a variety of image and video deblocking algorithms, including lowpass filtering, Projection Onto Convex Sets (POCS), and the H.264 in-loop filter.

QUALITY ASSESSMENT METHODS

We consider the class of Quality Assessment (QA) methods that are Full-Reference (FR) QA, which compares the test (distorted) image with a reference (original) image. In this project, the distorted images will ostensibly suffer from blocking artifacts or from the residual artifacts.

Mean Square Error

In statistics, the Mean Squared Error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the Root Mean Square Error or Root Mean Square Deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard error.

$$MSE = \frac{1}{MN}\sum_{Y=1}^{M}\sum_{X=1}^{N}\left[I(X,Y) - I'(X,Y)\right]^2$$

Peak Signal to Noise Ratio

The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

It is most easily defined via the Mean Squared Error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE(x,y) = \frac{1}{N}\sum_{i=1}^{N} e_i^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \qquad ...(1)$$

The PSNR is defined as:

$$PSNR(x,y) = 10\log_{10}\frac{255^2}{MSE(x,y)}, \qquad ...(2)$$

Let x and y represent the vectors of reference and test image signals, respectively. Let e be the vector of error signal between x and y. If the number of pixels in an image is N.

STRUCTURAL SIMILARITY INDEX METRIC

The structural similarity (SSIM) metric aims to measure quality by capturing the similarity of images. A product of three aspects of similarity are measured: luminance, contrast, and structure. The luminance comparison function $L(x, y)$ for reference image x and test image y is defined as

$$l(x,y) = \frac{2«_x«_y + C_1}{«_x^2 + «_y^2 + C_1} \qquad ...(3)$$

where $«_x$ and $«_y$ are the mean values of x and y respectively and C_1 is a stabilizing constant.

The contrast comparison function C(x, y) is defined similarly as:

$$C(x,y) = \frac{2±_x±_y + C_2}{±_x^2 + ±_y^2 + C_2} \qquad ...(4)$$

where $±_x$ and $±_y$ are the standard deviation of x and y, respectively, and C_2 is a stabilizing constant.

The structure comparison functions $S(x, y)$ is defined as

$$S(x,y) = \frac{±_{xy} + C_3}{±_x±_y + C_3} \qquad ...(5)$$

where $±_{xy}$ is the correlation between x and y and C_3 is also a constant that provides stability.

The *SSIM* index is obtained by combining the three comparison functions

$$SSIM(x,y) = [l(x,y)]^{‾} \cdot [C(x,y)] \cdot [S(x,y)]^{¥} \qquad ...(6)$$

the parameters are set as ~ = = ¥ = 1 and $C_3 = C_2/2$

$$SSIM(x,y) = \frac{(2«_x«_y + C_1)(2±_{xy} + C_2)}{(«_x^2 + «_y^2 + C_1)(±_x^2 + ±_y^2 + C_2)} \qquad ...(7)$$

Local *SSIM* statistics are estimated using a symmetric Gaussian weighting function. The mean *SSIM* index pools the spatial *SSIM* values to evaluate the overall image quality.

$$SSIM(x,y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \quad ...(8)$$

where *M* is the number of local windows over the image, and x_j and y_j are image patches covered by the j^{th} window.

IMAGE QUALITY AND QUANTIZATION STEP SIZE

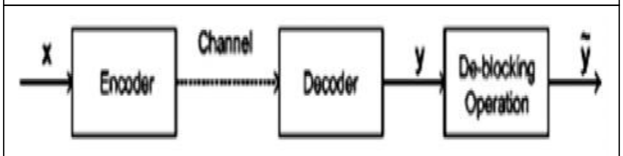
The amount of compression and the quality can be controlled by the quantization step. As the quantization step is increased, the compression ratio becomes larger, and the quality generally worsens. Quantization is a key element of lossy compression, but information is lost. There is a trade off between compression ratio and reconstructed image/ video quality.

In block transform coding, the input image is divided into L x L blocks, and each block is transformed independently into transform coefficients. An input image block is transformed into a DCT coefficient block.

$$B = TbT^t \quad ...(9)$$

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

Figure 1: Block Diagram for Reference, Decoded, and Deblocked Images



$$\tilde{B} = Q(B) = Q(TbT^t) \quad ...(10)$$

The quantization operator in (10) is nonlinear, and is a many-to-one mapping.

In the decoder, only quantized transform coefficients $\tilde{B}$ are available.

The output of the decoder is

$$\tilde{b} = T^t\tilde{B}T = T^tQ(TbT^t)T \quad ...(11)$$

Let Δ represent the quantization step. It is well known that the PSNR is a monotonically decreasing function of 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, and in particular the structure term *S*(*x*, *y*) will become smaller. Hence, the *SSIM* index would be a monotonically decreasing function of the quantization step size.

MEAN DISTORTION CHANGE

Let *x*, *y*, *y*^ are the original image,decoded image,and deblocked image respectively. If '*f*' represents the deblocking operation then *y*^ = *f*(*y*).

Let *M*(*x*, *y*) be the quality metric between *x* and *y*. Then the goal of the deblocking operation *f* is to maximize *M*(*x*,*f*(*y*)).

Let *d*(*xi*, *yi*) be the distortion between i^{th} pixels of *x* and *y*, expressed as squared euclidean distance

$$d(x_i, y_i) = \|x_i - y_i\|^2 \quad ...(12)$$

The Distortion Decrease Region (DDR) '*A*' to be composed of those pixels where the distortion is decreased by the deblocking operation

$i \in A$, if $d\left(x_i, \tilde{y}_i\right) < d\left(x_i, y_i\right)$

The amount of distortion decrease for the i^{th} pixel in the DDRA is

$$\sim_i = d\left(x_i, y_i\right) - d\left(x_i, \tilde{y}_i\right) \quad ...(13)$$

The distortion may also increase at other pixels by application of the deblocking filter. We similarly define the Distortion Increase Region (DIR) B

$i \in B$, if $d\left(x_i, y_i\right) < d\left(x_i, \tilde{y}_i\right)$

The amount of distortion increase for the i^{th} pixel $_i$ in the DIRB is

$$_i = d\left(x_i, \tilde{y}_i\right) - d\left(x_i, y_i\right) \quad ...(14)$$

We define the Mean Distortion Decrease (MDD)

$$\bar{\sim} = \frac{1}{N} \sum_{i \in A} \left(d\left(x_i, y_i\right) - d\left(x_i, \tilde{y}_i\right) \right) \quad ...(15)$$

where N is the number of pixels in the image.

Similarly, the Mean Distortion Increase (MDI) is

$$\bar{} = \frac{1}{N} \sum_{i \in B} \left(d\left(x_i, \tilde{y}_i\right) - d\left(x_i, y_i\right) \right) \quad ...(16)$$

A reasonable approach for designing a deblocking filter would be to seek to maximize the MDD $\bar{\sim}$ and minimize the MDI $\bar{}$. This is generally a very difficult task and of course, may not result in optimized improvement in perceptual quality. Lastly, let be the Mean Distortion Change (MDC), defined as the difference between MDD and MDI

$$¥ = \bar{\sim} - \bar{} \quad ...(17)$$

If $¥ < 0$, then the deblocking operation is likely unsuccessful since the mean distortion increase is larger than the mean distortion decrease. We would expect a successful deblocking operation to yield $¥ > 0$.

DEBLOCKING FILTER

Deblocking can be considered as an image restoration problem. Let represent the deblocking operation function and $N(x_i)$ represent a neighborhood of pixel x_i. A lowpass filter is a simple deblocking filter. An L x L lowpass filter can be represented as:

$$g\left(N\left(x_i\right)\right) = \sum_{k=1}^{L^2} h_k \cdot x_{i,k} \quad ...(18)$$

where h_k is the kernel for the L x L filter and is the th pixel in the neighborhood of pixel x_i. While lowpass filtering does reduce blocking artifacts, critical high frequency information is also lost and the image is blurred. While the distortion will certainly decrease for some pixels that define the DDR, the distortion will likely increase for a significant number of pixels in DIR. Indeed, it is quite possible that $¥ < 0$ could result. Moreover, blur is perceptually annoying. A variety of nonlinear methods have been proposed to reduce the blocking artifacts, while minimizing the loss of original information. For example, deblocking algorithms based upon Projection Onto Convex Sets (POCS) have demonstrated good performance for reducing blocking artifacts and have proved popular.

In POCS, a lowpass filtering operation is performed in the spatial domain, while a projection operation is performed in the DCT domain. Typically, the projection operation is a clipping operation on the filtered coefficients, confining these to fall within a certain range defined by the quantization step size. Since the lowpass filtering and the projection operations are performed in different domains, forward DCT and Inverse DCT (IDCT) operations are required.

The lowpass filtering, DCT, projection, IDCT operations compose one iteration, and multiple iterations are required to achieve convergence. It is argued that under certain conditions, POCS filtered images converge to an image that does not exhibit blocking artifacts.

As another example, the H.264 in-loop deblocking filter is a key component in the H.264 video coding standard. It is claimed that the in-loop filtering significantly improves both subjective and objective video quality. The key idea of the H.264 in-loop filter is to adaptively select the filtering operation and the neighborhood using the relative pixel location with respect to the block boundary and the local gray level gradient information. Generally, the MDI value is reduced while the MDD value is similar to lowpass filtering. The H.264 in-loop filter uses separate 1-D operations and integer multiplications to reduce complexity. However, it still requires a large amount of computation. In fact, the H.264 in-loop filter requires about one-third of the computational complexity of the decoder.

PSNR-B

We propose a new block-sensitive image quality metric which we term peak signal-to-noise ratio including blocking effects (PSNR-B). As the quantization step size increases, blocking artifacts generally become more conspicuous. Blocking artifacts are gray level discontinuities at block boundaries, which are ordinarily oriented horizontally and vertically. They arise from poor representation of the block luminance levels near the block boundaries. The following definitions are relative to an assumed block-based compression tiling, e.g., 8 x 8 blocks as in JPEG compression.

Figure 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

$H_B = \{(y4, y5), (y12, y13), \ldots, (y60, y61)\}$

$H_B^C = \{(y1, y2), (y2, y3), (y3, y4), (y5, y6), \ldots, (y63, y64)\}$

$V_B = \{(y25, y33), (y26, y34), \ldots, (y32, y40)\}$

$V_B^C = \{(y1, y9), (y9, y17), (y17, y25), (y33, y41), \ldots, (y56, y64)\}$

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

Figure 2: Example for Illustration of Pixel Blocks

y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8
y_9	y_{10}	y_{11}	y_{12}	y_{13}	y_{14}	y_{15}	y_{16}
y_{17}	y_{18}	y_{19}	y_{20}	y_{21}	y_{22}	y_{23}	y_{24}
y_{25}	y_{26}	y_{27}	y_{28}	y_{29}	y_{30}	y_{31}	y_{32}
y_{33}	y_{34}	y_{35}	y_{36}	y_{37}	y_{38}	y_{39}	y_{40}
y_{41}	y_{42}	y_{43}	y_{44}	y_{45}	y_{46}	y_{47}	y_{48}
y_{49}	y_{50}	y_{51}	y_{52}	y_{53}	y_{54}	y_{55}	y_{56}
y_{57}	y_{58}	y_{59}	y_{60}	y_{61}	y_{62}	y_{63}	y_{64}

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

$$D_B^C(y) = \frac{\sum_{(y_i,y_j)\in H_B^C}(y_i - y_j)^2 + \sum_{(y_i,y_j)\in V_B^C}(y_i - y_j)^2}{N_{H_B^C} + N_{V_B^C}} \quad ...(20)$$

Generally, as the quantization step size increases (D_B will increase relative to D_{B_C}), and blocking artifacts will become more visible. Of course, this does not establish any level of correlation between (19), (20) and perceptual annoyance.

Also define the blocking effect factor

$$BEF(y) = ¦ \cdot \left[D_B(y) - D_B^C(y)\right] \quad ...(21)$$

where

$$¦ = \begin{cases} \dfrac{\log_2 B}{\log_2(\min(N_H, N_V))} & \text{if } D_B(y) > D_B^C(y) \\ 0 & \text{otherwise} \end{cases} \quad ...(22)$$

Of course, there can be multiple block sizes in a particular decoded image/video. For example, there can be 16 x 16 macroblocks and 4 x 4 transform blocks, both contributing to blocking effects.

Let D_{B_k}, $D_{B_k}^C$, BEF_k, and $¦_k$ modify (19)-(22) for block size. Then

$$BEF_k(y) = ¦_k \cdot \left[D_{B_k}(y) - D_{B_k}^C(y)\right] \quad ...(23)$$

The BEF over all block sizes is defined as

$$BEF_{Tot}(y) = \sum_{k=1}^{K} BEF_k(y) \quad ...(24)$$

The mean-squared error including blocking effects (MSE-B) for reference image *x* and test image *y* is then defined as the sum of the MSE(*x*, *y*) in (1) and $BEF_{tot}(y)$ in (24)

$$MSE - B(x,y) = MSE(x,y) + BEF_{Tot}(y) \quad ...(25)$$

Finally, we propose the PSNR-B as

$$PSNR - B(x,y) = 10\log_{10}\frac{255^2}{MSE - B(x,y)} \quad ...(26)$$

The MSE term in (25) measures the distortion between the reference image and the test image, while the BEF term in (25) specifically measures the amount of blocking artifacts just using the test image. The BEF itself can be used as a no-reference quality index, similar to the Generalized Block-edge Impairment Metric (GBIM) and the Mean Noticeable Blockiness Score (MNBS). 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.

SIMULATION RESULTS

The Images are compressed using DCT block coding as JPEG. In JPEG, quantization is applied using a different quantization step size for each DCT coefficient, as defined by a quantization table. Here, we apply the same quantization step size for all DCT coefficients, to more directly investigate the effects of quantization step size on image quality. Quantization step sizes of 5, 10, 20, 40, 80, 120, and 160 were used in the simulations to investigate the effects of quantization step size. Deblocking was applied on the decoded images for comparison.

In the reconstructed Barbara image with quantization step 100. Blocking artifacts are visible in the no-filtered image and are mostly removed in the POCS filtered image.

The PSNR produced slightly large values on the no-filtered image,while the SSIM index

Figure 3a: The Original Image: Barbara

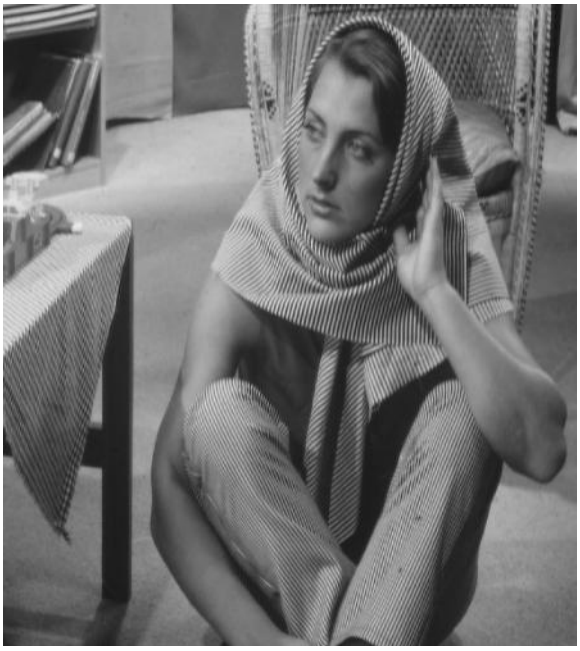


Figure 3b: Reconstructed Image of Barbara with No Filter (Quantization Step: 100)

Figure 3c: Reconstructed Image of Barbara with POCS Deblocking Filter (Quantization Step: 100)

Figure 4a: The Original Image: Lena

Figure 4b: Reconstructed Image of Lena with No Filter (Quantization Step: 100)

Figure 4c: Reconstructed Image of Lena with POCS Deblocking Filter (Quantization Step: 100)

was almost unchanged. PSNR-B produced slightly large values on the POCS filtered image.

In the reconstructed lena image with quantization step 100. When no filter was applied annoying Blocking artifacts are clearly visible. When the POCS deblocking filter was applied the blocking effects were greatly reduced, resulting in better subjective quality.

Again, PSNR produced slightly large values on the no-filtered image,while the SSIM index was almost unchanged. PSNR-B produced slightly large values on the POCS filtered image.

COMPARISON OF QUALITY INDICES

The below shown graphs prove that POCS produced improved PSNR-B values relative to the no-filter case of lena image.

Compared to PSNR, SSIM the PSNR-B improves more markedly on the deblocked images, especially for large quantization steps. The PSNR-B was largely in agreement with the SSIM index.

The PSNR-B metric captures subjective quality on images containing blocking artifacts as well as deblocking artifacts. The PSNR does not perform as well as might be expected. Both the PSNR-B and SSIM index indicate that the POCS approach improves the perceptual quality of block degraded images more than does simple low pass filtering.

Figure 5a: PSNR Comparison of Lena Image

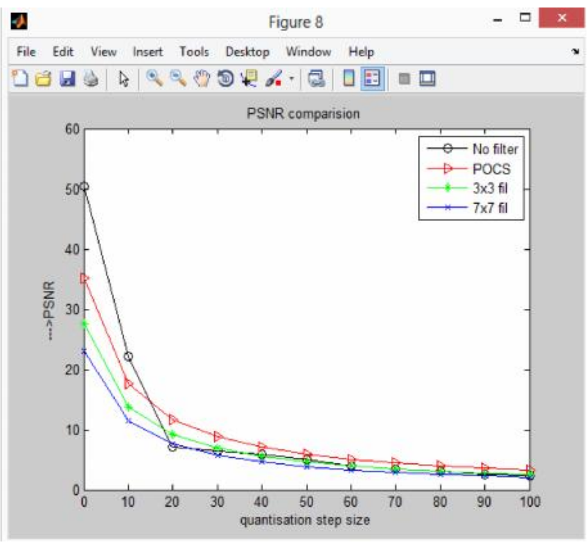


Figure 5b: SSIM Comparison of Lena Image

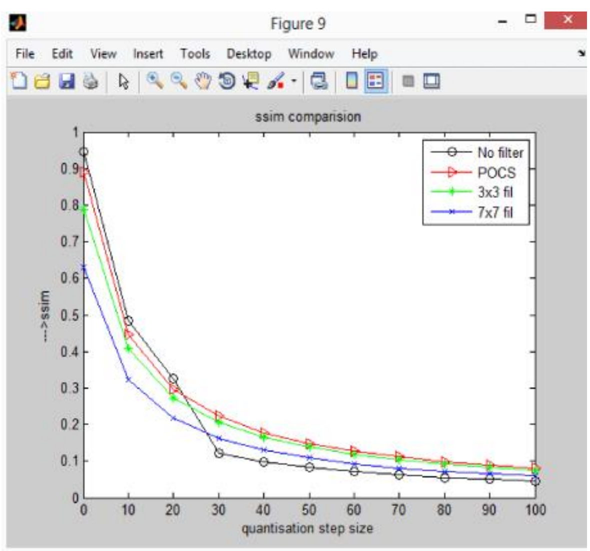
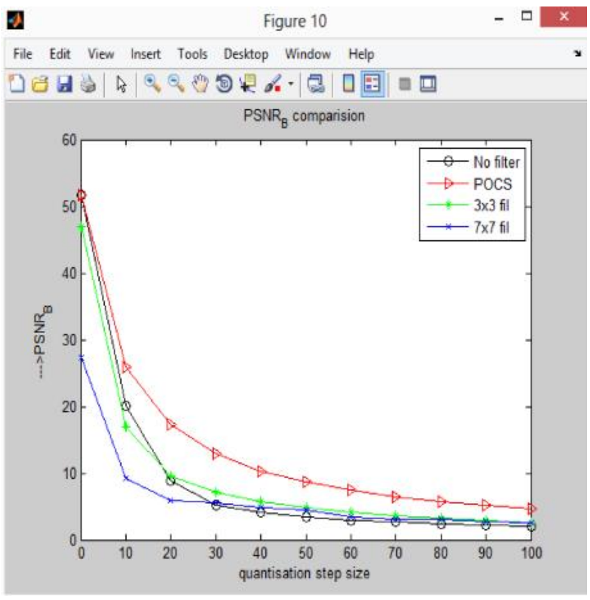


Figure 5c: PSNR-B Comparison of Lena Image



Type of Filter Used	PSNR	SSIM	PSNR-B
No Filter	8.52Db	0.085	3.820
POCS Deblocking Filter	8.80Db	0.130	6.900

CONCLUSION

In simulations, we compared relevant image quality indices for deblocked images. The simulation results show that PSNR-B results in better performance than PSNR for image quality assessment of these impaired images. We proposed the block-sensitive image quality index PSNR-B for quality assessment of deblocked images. It modifies the conventional PSNR by including an effective blocking effect factor. PSNR-B shows similar trends with the perceptually proven index SSIM.

It is attractive since it is specific for assessing image quality, specifically the severity of blocking artifacts. The PSNR-B takes values in a similar range as PSNR and is, therefore, intuitive for users of PSNR, while it results in better performance for quality assessment of deblocked images.

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