New Metric for Quality Analysis of Deblocked Images

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Abstract— **The advanced quality assessment of Deblocked images is done in this new metric way. Also we study the efficiency of de-blocking algorithms for improving visual signals degraded by blocking artifacts from JPEG compression. Rather than using the existing PSNR metric, we instead propose a new block-sensitive index metric, named as PSNR-B, this metric produces objective judgments that accord with observations. The PSNR-B metric modifies PSNR by including a blocking effect factor (BEF). Also we study about Structural Similarity Metric (SSIM). The Simulation results shows the new metric PSNR-B results in better performance for quality assessment of Deblocked images than PSNR metric.**

Index Terms— **BEF (Blocking Effect Factor), de- blocked images, distortion, quality image assessment, quantization, and POCS deblocking filter.**

I. INTRODUCTION

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 used in so many number of image file formats. JPEG is one the most common image format used by Digital cameras and other photographic image capture devices. The term JPEG is an acronym for the Joint Photographic Expert Group. The drawback of JPEG technique is when we compressing the image or data by using JPEG compression blocking artifacts are present. Blocking artifacts are more serious at low bit rates, where network bandwidths are limited. Significant research has been done on the blocking artifact reduction techniques. Most blocking artifact reduction methods assume that the distorted image contains noticeable amount of blocking. 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.

We perform simulations on the quality analysis of Deblocked images. We first perform simulations using the peak signal-to-noise ratio (PSNR). The PSNR does not capture subjective quality well when blocking artifacts are present. We also propose a new de blocking quality index that is sensitive to blocking artifacts in Deblocked images. We name this Peak Signal-to-Noise ratio including blocking effects (PSNR-B). Results show that the proposed PSNR-B metric measures much better than the PSNR metric.

In this we are using many image de-blocking algorithms, such as low pass filtering, POCS. The image quality improvements afforded by these algorithms is measured using the PSNR, SSIM and PSNR-B metrics.

II. EXAMPLES OF BLOCKING ARTIFACTS

In JPEG compression in the compressed images the form of noise around contrasting edges (especially curves and corners) or 'blocky' images. These are due to the quantization step of the JPEG algorithm. They are especially noticeable around sharp corners between contrasting colors. 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. In these standard blocking artifacts are present at decoding end.Here below some blocking artifacts are given. Fig A is the original image and in Fig B the Blocking artifacts are presented, where as image is compressed one.

Fig(A): Original Image   Fig(B): Compressed Image

III. WHY WE ARE GOING FOR QUALITY ASSESSMENT METRICS…

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

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

IV. EXISTING QUALITY ANALISIS METRICS

So many techniques and metrics are measured objectively and automatically evaluated by a computer program. Those are classified as FR (full-reference) methods and NR (no-reference) methods. The FR metrics image quality assessment methods, the quality of a test image are evaluated by comparing it with a reference image that is assumed to have perfect quality. In the NR metrics try to assess the quality of an image without any reference to the original one.

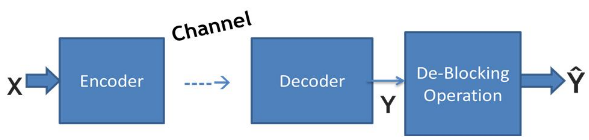


Fig.1: Block Diagram of the Deblocking Operation.

Here we are considering X = input image, Y = Decoded Images, Ŷ = Deblocked images.

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. PEAK SIGNAL TO NOISE RATIO [PSNR] METRIC

The Peak signal-to-noise ratio [PSNR] and the mean-squared error (MSE) are the simplest and most used Quality Assessment metrics.

As before we considered as X is the reference image and Y is the test image. The error signal between X and Y is assumed as

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

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

Though PSNR is an attractive Quality Assessment metric, however, the PSNR does not correlate well with perceived visual quality.

B. STRUCTURAL SIMILARITY METRIC [SSIM]

The SSIM metric is measures the quality by capturing the similarity of images. A product of three aspects of similarity is measured: luminance, contrast, and structure. The luminance comparison functions $l(x,y)$ for reference image X and Y test image is define as

$$l(x,y) = \frac{2\mu_x\mu_y + C1}{\mu_x^2+\mu_y^2+C1} \quad (3)$$

Where μ_x and μ_y re the mean values of X and Y, respectively, And C1 is a stabilizing constant.

The contrast comparison function $c(x,y)$ is defined similarly as

$$c(x,y) = \frac{2\sigma_x\sigma_y + C2}{\sigma_x^2+\sigma_y^2+C2} \quad (4)$$

Where σ_x and σ_y are the standard deviation of X and Y respectively, and $C2$ is a stabilizing constant.
The structure comparison function $s(x,y)$ is defined as

$$s(x,y) = \frac{\sigma_x\sigma_y + C3}{\sigma_x\sigma_y + C3} \quad (5)$$

Where σ_{xy} is the correlation between x and y and $c3$ is also a constant that provides stability.
The SSIM index is obtained by combining the three comparison Functions.

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma}. \quad (6)$$

In parameters are set as α=β=γ=1 and $c_3 = \frac{c_2}{2}$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C1)(2\sigma_x\sigma_y + C2)}{(\mu_x^2+\mu_y^2+C1)(\sigma_x^2+\sigma_y^2+C2)}. \quad (7)$$

Local SSIM statistics are estimated using a symmetric Gaussian weighting function. The mean SSIM index pools the spatial SIM 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 x_j are image patches covered by the jth window.

V. INTRODUCTION TO THE DEBLOCKING FILTERS

Let x is the reference/original image and y is the decoded/test image that has been distorted by quantization errors. Let $\tilde{y}$ represent the deblocked image and f represent the deblocking operation: $\tilde{y} = f(y)$. Fig.1 shows a block diagram depicting the flow of reference, decoded, and

Deblocked images.

Let $M(x, y)$ be the quality metric between x and. The goal of the de-blocking operation f is to maximize, $M(x, f(y))$ given image y.

Let $d(x_i, y_i)$ be the distortion between the ith pixels of x and y, expressed as squared Euclidean distance

$d(x_i, y_i) = \|x_i - y_i\|^2$ (9)

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

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

The amount of distortion decrease for the ith pixel $\propto_i$ in the DDR A is

$\propto_i = d(x_i, y_i) - d(x_i, \tilde{y}_i)$. (10)

The distortion may also increase at other pixels by application of the deblocking filter. We similarly define the distortion increase region (DIR) β.

$i \in \beta$, if $d(x_i, y_i) < d(x_i, \tilde{y}_i)$.

The amount of distortion increase for the i th pixel β_i in the DIR β is

$\beta_i = d(x_i, \tilde{y}_i) - d(x_i, y_i)$. (11)

We define the mean distortion decrease (MDD)

$$\bar{\alpha} = \frac{1}{N}\sum_{i\in\beta}(d(x_i, y_i) - d(x_i, \tilde{y}_i)) \quad (12)$$

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

$$\bar{\beta} = \frac{1}{N}\sum_{i\in\beta}\big(d(x_i, \tilde{y}_i) - d(x_i, y_i)\big). \quad (13)$$

A reasonable approach for designing a deblocking filter would be to seek to maximize the MDD $\bar{\alpha}$ and minimize the MDI$\bar{\beta}$. This is generally a very difficult task and of course, may not result in optimized improvement in perceptual quality.

Lastly, let $\bar{\alpha}$ be the mean distortion change (MDC), defined as the difference between MDD and MDI

$$\bar{\gamma} = \bar{\alpha} - \bar{\beta}. \quad (14)$$

If $\bar{\gamma} < 0$, then the deblocking operation is likely un successful since the mean distortion increase is larger than the mean distortion decrease. We would expect a successful deblocking operation to yield $\bar{\gamma} > 0$. Nevertheless, these conditions are not equated with levels of perceptual improvement or loss.

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 low pass filtering operation is performed in the spatial domain, while a projection operation is performed in the DCT domain.

VI. PROPOSED METRIC [PSNR-B] PSNR INCLUDING BLOCKING EFFECTS

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. 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.

Let N_H and N_V be the horizontal and vertical dimensions of the $N_H\ X\ N_V$ image I. Let H be the set of horizontal neighboring pixel pairs in I. Let $H_B \subset H$ be the set of horizontal neighboring pixel pairs that lie across a block boundary. Let H_B^C be the set of horizontal neighboring pixel pairs, not lying across a block boundary, i.e.$H_B^C = H - H_B$ similarly, Let V be the set of vertical neighboring pixel pairs, and V_B be the set of vertical neighboring pixel pairs lying across block boundaries. Let V_B^C be the set of vertical neighboring pixel pairs not lying across block boundaries, i.e., $V_B^C = V - V_B$.

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}

Fig.,2. Example for illustration of pixel blocks

Let N_{H_B} $N_{H_B^C}$ N_{V_B} and $N_{V_B^C}$ be the number of pixel pairs in H_B, H_B^C, V_B and V_B^C respectively. If B is the block size, Then

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

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

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

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

Fig. 2 is a simple example for representation 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

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

Then we define the mean boundary pixel squared difference (D_B) and the mean non boundary pixel squared difference (D_B^C) for image y to be

$$D_B(y) = \frac{\sum_{(y_i, y_j) \in H_B} (y_i - y_j)^2 + \sum_{(y_i, y_j) \in V_B} (y_i - y_j)^2}{N_{H_B} + N_{V_B}}. \quad (15)$$

$$D_B^c(y) = \frac{\sum_{(y_i, y_j) \in H_B^C} (y_i - y_j)^2 + \sum_{(y_i, y_j) \in V_B^C} (y_i - y_j)^2}{N_{H_B^C} + N_{V_B^C}}. \quad (16)$$

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 emphasizes the BEF as a function of block size.

$$BEF(y) = \eta.[D_B(y) - D_B^c(y)] \quad (17)$$

Where

$$\eta = \begin{cases} \frac{\log_2 B}{\log_2(\min(N_H, N_V))} & D_B(y) > D_B^c(y) \\ 0 & \end{cases} \quad (18)$$

The assumption here is that the visibility of blocking effects increases with block size.
Of course, there can be multiple block sizes in a particular decoded mage/video. For example, there can be 16 X 16 macro blocks and 4 X 4 transform blocks, both contributing to blocking effects, as in H.264 video coding. Let $D_{B_k}, D_{B_k}^C$, BEF_k,and η_k modify (19)(22) for block size B_k.

$$BEF_k(y) = \eta_k . [D_{B_k}(y) - D_{B_k}^C(y) \quad (19)$$

The BEF over all block sizes is defined as

$$BEF_{TOT}(y) = \sum_{k=0}^{K} BEF_k(y) \quad (20)$$

The mean-squared error including blocking effects (MSE-B) for reference image X and Y test image is then defined as the MSE(X,Y) in (1) and $BEF_{TOT}(y)$ in (20).

$$MSE - B(x, y) = MSE(x, y) + BEF_{TOT}(y) \quad (21)$$

Finally, we propose the PSNR-B as

$$PSNR - B(x, y) = 10 \log_{10} \frac{255^2}{MSE - B(x,y)}. \quad (22)$$

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. 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.The PSNR-B is attractive since it is specific for assessing image quality, specifically the severity of blocking artifacts.

VII. SIMULATION RESULTS

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 define 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.

A. Analysis of PSNR Metric

Fig. 3&5 shows that the comparison with respect to **PSNR**. When the quantization step size was large ($\Delta \geq 120$), the 3 X 3 filter, 7 X 7 filter, and **POCS** method resulted in higher PSNR than the no-filter case on the Tiger and Flower images. On the more complex Barbara image, all the methods resulted in similar **PSNR** values, while the **POCS** gave a slightly higher **PSNR** at $\Delta = 160$.
When the quantization step was small($\Delta \leq 40$), deblocking methods produced lower **PSNR** compared to the no-filter case. The **POCS** did not produce improvement. When the quantization step is small, the MDI was larger than the MDD.

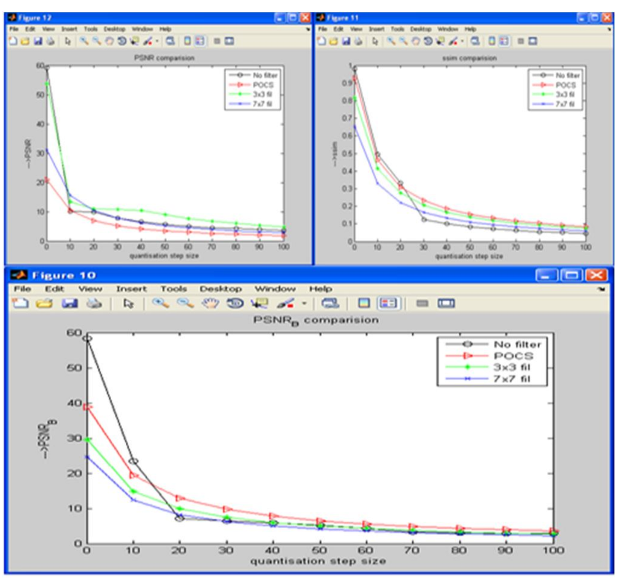
B. Analysis of SSIM Metric

Fig. 3&5 shows that the result of comparing images using the well known and perceptually Significant **SSIM** index [1]. When the quantization step was large ($\Delta \geq 120$), all the filtering methods resulted in larger **SSIM** values on the Tiger and Flower images. On the Flower image, only **POCS** produced a larger SSIM value than the no-filter case. When the quantization step size was small ($\Delta < 40$), the 3 X 3 and 7 X 7 low pass filters resulted in lower SSIM values than the no-filter case, while the POCS method had little effect on the SSIM.

C. PSNR-B Analysis

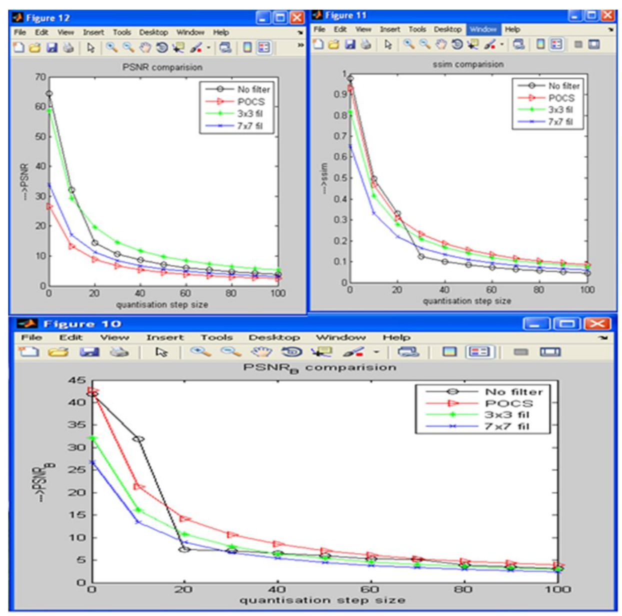
Fig. 3&5 shows the comparison of deblocking algorithms using the distortion-specific PSNR-B index. For moderate to large range of quantization step sizes$\Delta > 40$, POCS produced improved PSNR-B values relative to the no-filter case over all the images. For large quantization steps ($\Delta > 100$), the simple low pass filtering methods also improved the PSNR-B values on the Tiger and Flower images. Since the local spatial variations are relatively larger in Flower image, the BEF was relatively large even at small quantization steps in no-filter case. Hence, the POCS resulted in improved PSNR-B values compared to the no-filter case even at small quantization steps in Flower image. Compared to PSNR, 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.

Fig. 3: Reconstructed images of Tiger image with quantization step 80. **No filter** (PSNR = 29:38dB, PSNR-B = 26:52dB, SSIM = 0:7700). **POCS de-blocking filter** (PSNR = 29:31dB, PSNR-B = 29:31dB, SSIM = 0:7926).



Fig, 4: Simulation Results of Tiger Image All metrics.

Fig. 5: Reconstructed images of Flower image with quantization step 80. **No filter** (PSNR = 29:88 dB, PSNR-B = 27:48 dB, SSIM = 0:7680). **POCS de-blocking filter** (PSNR = 29:91 dB, PSNR-B = 29:91 dB, SSIM = 0:8053).



Fig, 6: Simulation Results of Flower Image for All metrics.

D. Comparison of Quality Indices

Fig. 3 shows Tiger reconstructed from compression using quantization step 80. When no filter was applied as in Fig.3 (a), annoying blocking artifacts are clearly visible. When the POCS de-blocking filter was applied [Fig. 3(b)], the blocking effects were greatly reduced, resulting in better subjective quality. The PSNR index produced slightly lower values than on the no filtered image. Conversely, the PSNR-B and SSIM quality indices produced larger values on the POCS filtered image.

Fig.5 shows Peppers reconstructed from compression, also using quantization step 80. When no filter is applied as in Fig. 5(a), blocking artifacts are clearly visible, especially on the peppers. When the POCS deblocking filter was applied as in Fig. 5(b), the blocking effects were mostly removed, resulting in better subjective quality. The PSNR-B and SSIM quality indices produced larger values on the POCS filtered image, in agreement with observation.

VIII. CONCLUDING REMARKS

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. We proposed the block-sensitive image quality index PSNR-B for quality assessment of Deblocked images. The simulation results show that PSNR-B results in better performance than PSNR for image quality assessment of these impaired images. By comparison, the blockiness-specific index GBIM effectively assesses blockiness, but has limitations for image quality assessment. PSNR-B shows similar trends with the perceptually proven index SSIM. It is attractive since it is specifically 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. For future work, we look forward to new problems to solve in this direction of inquiry.

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