CHAPTER 5

QUALITY ASSESSMENT

5.1 INTRODUCTION

Digital image and video processing systems are generally involved with signals that are meant to convey reproductions of visual information for ‘human consumption’. Tradeoffs between system resources and the visual quality are typically involved in designing such systems, and accurate quality measurement algorithms are needed in order to make these tradeoffs efficiently. The obvious way of measuring quality is to solicit the opinion of human observers. However, such subjective evaluations are not only cumbersome and expensive, but they also cannot be incorporated into automatic systems that adjust themselves in real-time based on the feedback of output quality. The goal of Quality Assessment (QA) research is to discover automatic ways of accurately measuring visual quality.

Sheikh and Bovik (2006) proposed an image information measure that quantifies the information that is present in the reference image and how much of this reference information can be extracted from the distorted image. Combining these two quantities like loss of image information to the distortion process and the relationship between image information and visual quality is explored. It is a visual information fidelity measure for image QA.
Wang et al (2004) proposed that Objective methods for assessing perceptual image quality traditionally attempted to quantify the visibility of errors (differences) between a distorted image and a reference image using a variety of known properties of the human visual system. Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, they have introduced an alternative complementary framework for quality assessment based on the degradation of structural information.

Wang et al (2004) have also proposed another method wherein Image and video coding are presented as an optimization problem. A successful image and video coding algorithm delivers a good tradeoff between visual quality and other coding performance measures, such as compression, complexity, scalability, robustness, and security. They follow two recent trends in image and video coding research. One is to incorporate Human Visual System (HVS) models to improve the current state-of-the-art of image and video coding algorithms by better exploiting the properties of the intended receiver. The other is to design rate scalable image and video codecs, which allow the extraction of coded visual information at continuously varying bit rates from a single compressed bit stream.

Specifically, they have proposed a Foveation Scalable Video Coding (FSVC) algorithm which supplies good quality-compression performance as well as effective rate scalability. The key idea is to organize the encoded bit stream to provide the best decoded video at an arbitrary bit rate in terms of foveated visual quality measurement. A foveation-based HVS model plays an important role in the algorithm. The algorithm is adaptable to different applications, such as knowledge-based video coding and video communications over time-varying, multiuser and interactive networks.
The degree of blocking depends upon several parameters, the most important of which is the quantization step for lossy compression. Research has been done on comparing the perceptual quality of deblocked images. Here the quality assessment of deblocked images is investigated, and in particular the effects of the quantization step of the measured quality of deblocked images are studied. A deblocking filter can improve image quality in some aspects, but can reduce image quality in other regards. The recent advent of the powerful Image Quality Assessment (IQA) algorithm that compares well with human makes this plausible.

Various simulations are performed on the quality assessment of deblocked images. First, simulations using the conventional Peak Signal-To-Noise Ratio (PSNR) quality metric are performed and then with the state of the art quality index, the Structural SIMilarity (SSIM) index. The PSNR does not capture subjective quality well when blocking artifacts are present. The SSIM metric is slightly more complex than the PSNR, but correlates highly with human subjectively (Changhoon Yim & Alan Conrad Bovik 2011).

A new deblocking quality index that is sensitive to blocking artifacts in deblocked images is proposed. It is named as 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 of range 0.99, and performs much better than the PSNR of range above 55. Rather than relying on PSNR, which correlates poorly with subjective judgement, PSNR-B which is designed specifically to assess blocky and deblocked images in conjunction with the SSIM index is utilized.

To judge the performance of the proposed method, the Mean Absolute Error (MAE), the Peak-Signal-To Noise Ratio (PSNR) and the Normalized Color Difference (NCD) are used as objective measures of
similarity and dissimilarity between a filtered frame and the original one, each containing rows and columns of pixels.

The MAE is given by,

$$\text{MAE}(I_o(t), I_f(t)) = \frac{\sum_{c=R,G,B} \sum_{x=1}^{m} \sum_{y=1}^{n} |I_c^o(x,y,t) - I_c^f(x,y,t)|}{3nm}$$  \hspace{1cm} (5.1)$$

The lower the MAE is, the more similar (less dissimilar) are the images. The PSNR value is defined as,

$$\text{PSNR}(I_o(t), I_f(t)) = 10 \log_{10} \frac{S^2}{\text{MSE}(I_o(t), I_f(t))}$$  \hspace{1cm} (5.2)$$

where $S$ denotes the maximum possible value of a pixel component (here $S=255$). The higher the PSNR value is, the more similar (less dissimilar) are the images.

PSNR-B is defined as,

$$\text{PSNR-B}(I_o(t), I_f(t)) = 10 \log_{10} \frac{S^2}{\text{MSE-B}(I_o(t), I_f(t))}$$  \hspace{1cm} (5.3)$$

Here, $\text{MSE-B}(I_o(t), I_f(t))$ represents the mean-squared error including blocking effects.
5.2 RESULT VALIDATION BY USING QUALITY METRICS

5.2.1 PSNR - Performance Analysis

The simplest and most widely used FR QA metrics are the Peak Signal-to-Noise Ratio (PSNR) and the Mean-Squared Error (MSE). The phrase peak signal-to-noise ratio, often abbreviated as 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) as in equation (3.8) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other.
From equation (3.9), \( \text{MAX}_i \) is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with \( B \) bits per sample, \( \text{MAX}_i \) is \( 2^B - 1 \). For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space, e.g., YCbCr or HSL.

When the quantization step was small, all the de-blocking 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. In other words, the amount of information that was distorted was larger than the amount of information recovered by de-blocking filters. When the quantization step size fell in the middle range of about 80, the 3×3 filter gave a slightly higher PSNR.

5.2.2 SSIM - Performance Analysis

The Structural SIMilarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric, in other words, the measuring of 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 (Sumohana et al 2008).
When the quantization step size was small, low pass filters resulted in lower SSIM values than the no-filter case, while the POCS method had little effect on the SSIM value. The system diagram of structural similarity measurement system is shown in Figure 5.1.

**Figure 5.1 Structural similarity index measurement system**

Suppose $x = \{x_i | i = 1, 2---N\}$ and $y = \{y_i | i = 1, 2---N\}$ are two finite-length image signals, which have been aligned with each other, SSIM is defined as the product of three local quantities: luminance comparison (function of mean), contrast comparison (function of variance), and structure comparison (function of correlation coefficient and variance).
\[
SSIM(x, y) = [I(x, y)]^\alpha [c(x, y)]^\beta [s(x, y)]^\gamma
\]  \hspace{1cm} (5.5)

where

\[
l(x, y) = 2 \frac{\mu_x \mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}
\]  \hspace{1cm} (5.6)
\[
c(x, y) = 2 \sigma_x \sigma_y + c_2 / \sigma_x^2 + \sigma_y^2 + c_2
\]  \hspace{1cm} (5.7)
\[
s(x, y) = \sigma_{xy} + c_3 / \sigma_x \sigma_y + c_3
\]  \hspace{1cm} (5.8)

where, \( \mu_x \) and \( \mu_y \) are the means of \( x \) and \( y \) respectively. \( \sigma_x \) and \( \sigma_y \) are the standard deviations of the images \( X \) and \( Y \) respectively.

\( \sigma_{x,y} \) is the covariance of \( X \) and \( Y \).

\( C_1, C_2 \) and \( C_3 \) are small constants such that

\[
C_1 = L^2 K_1^2
\]  \hspace{1cm} (5.9)
\[
C_2 = (K_2 L^2) \hspace{0.5cm} \text{and} \hspace{0.5cm} C_3 = C_2 / 2
\]  \hspace{1cm} (5.10)

where, \( K_1, K_2 \) & \( L \) are constants. SSIM can have a maximum value of 1.

To compare any two images the MSE and its derivative PSNR are the convectional metrics. The difference between the original and distorted pixels is given by MSE and the inverse logarithmic representation of this difference is given by PSNR. Even though PSNR and MSE do not correlate with subjective quality, PSNR is easy to compute and well understood. The SSIM metric is similar to the human perception of the video sequence. While most other proposed methods use error sensitivity method, this method uses structural distortion as an estimate of perceived visual distortion.

5.2.3 PSNR-B Performance Analysis

A new deblocking quality index that is sensitive to blocking artifacts in deblocked images is proposed. It is named as peak signal-to-noise ratio including blocking effects (PSNR-B). The proposed PSNR-B correlates well with subjective quality and with the SSIM index, and performs much
better than the PSNR and a variety of image and video deblocking algorithms including low pass filtering, Projection onto Convex Sets (POCS) and the H.264 in-loop filter.

The image improvements afforded by these algorithms is measured using the PSNR PSNR-B, and SSIM. Rather than relying on PSNR, which correlates poorly with subjective judgment utilize PSNR-B which is designed specifically to assess blocky and deblocked images (but has no proven perceptual significance) in conjunction with the SSIM index which is perceptually significant but has not been demonstrated on deblocked images. Hence, an attempt has been made to address the issue. The following is the proposed deblocking methodology that is associated with it.

Blocking artifacts are less visible in texture and edge areas. In order to extract them, the following steps are to be followed.

- Find blocks at the boundaries of homogenous areas.
- Apply similar process for horizontal and vertical Search.

A. SEMAPHORE EXTRACTION

- The semaphore is extracted by looking for block pairs that have relatively homogenous pixel values & Discontinuity at the boundary. The deblocking methodology is illustrated by using Figure 5.2.

B. STEPS IN DE-BLOCKING METHODOLOGY

- De-Blocking is applied only to blocks extracted by semaphore extraction step.
- The number of pixels to update is adaptive & the Magnitude of the abrupt change is denoted as (Δ). Also, check the number of connected blocks on both sides of boundary.

- Similar process is carried out for both horizontal and vertical de-blocking.

- Calculate number of homogenous blocks on each side of the block boundary. For each row, apply boxcar filter around block Boundary.

![De-blocking method](image)

*Figure 5.2 De-blocking method*

- An FIR with all coefficients equal to one (boxcar) Length Creates smooth transition between pixel values around block boundary needed to compare between de-blocking methods.

- The edge information is used from original image & Count Difference between columns 8n, 8n+1.

- Both the vertical and horizontal blocking artifact values are computed & thus the metric is derived from 2N 1-D DCT of a block pair.
C. QUANTIZATION STEP SIZE AND IMAGE QUALITY

The 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. The amount of compression and there quality can be controlled by the quantization step. As the quantization step is increased the compression ratio becomes larger, and the quality generally worsens. However, there has not been a study made of how perceptual quality suffers as a function of step size or the degree to which deblocking augments perceptual quality. The emergency of new and powerful IQA indices suggests this possibility.

In the block transform coding (as shown in Figure 5.3), the input image is divided into L×L blocks, and each block is transformed independently into transform coefficients.

![Figure 5.3 Block Transform coding](image)

An input image block b is transformed into a DCT coefficient block

\[ B = T b T^t \]  \hspace{1cm} (5.11)

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

\[ B' = Q(B) = Q(TbT^t) \]  \hspace{1cm} (5.12)

The quantization operators is non linear and is a many-to-one mapping from \( RL^2 \) to \( RL^2 \). In the decoder, only quantized transform coefficients B are available. The output of the decoder is...
Let $\Delta$ represent the quantization step. It is well known that the PSNR is a monotonically decreasing function of $\Delta$. The SSIM index captures the similarity of the reference and test images. As the quantization step size becomes larger, the structural difference 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 $\Delta$.

D. FILTERING ALGORITHM

The estimated $Q_s$ obtained by the estimation algorithm are used to control the adaptive deblocking filter. In the filter operations, two modes are used separately depending on the pixel conditions around a boundary: DC offset mode and default mode. The type of filter to be applied is determined by the pixel conditions. The parameters used are $V_{\text{Threshold}} = 2$ and $D_{\text{Threshold}} = 6$. In this default mode a signal adaptive smoothing scheme is applied at the pixels at the block boundaries, by replacing the boundary pixels by

$$V_4 = v_4 - d \text{ and } v5' = v_5 + d$$

(5.14)

where, $d$ depends on the neighboring pixels and $Q_s$. In every smooth region, filtering in default mode is not good enough. For these regions, a DC offset mode filter is applied instead. The boundary area around a block is shown in Figure 5.4.
Figure 5.4 Boundary area around block

Let $v_0$-$v_9$ be the 10 pixel values across a block boundary (horizontal or vertical), 5 pixels per block

$\Phi (v_i - v_{i-1}) = 1$ if $|v_i - v_{i-1}| < V_{\text{threshold}}$

if $\text{diff-count} = \sum_{i=1}^{8} i = 0 \Phi(v_i - v_{i-1})$

if (diff-count > D threshold) then
Apply DC offset mode filter
else
Apply default mode filter

$V_{\text{max}} = \max (v_1 \ldots v_8)$ \hspace{1cm} (5.15)

$V_{\text{min}} = \min (v_1 \ldots v_8)$ \hspace{1cm} (5.16)

If $(|V_{\text{max}} - V_{\text{min}}| < 2Q_s)$ then

$V = \sum_{k=4}^{8} b_k - P_n + k_i \quad \text{for} \quad n < 8$ \hspace{1cm} (5.17)
else
no change

where \( b_k = \{1,1,2,24,2,2,1,1\} \) and

\[
P_{n+k} = \begin{cases} 
V_0 & \text{if } (V_1-V_0) < Q_s, \text{ when } n+k<1 \\
V_1 & \text{if } (V_1-V_0) > Q_s, \text{ when } n+k<1 \\
V_n & \text{when } 1<n+k<8 \\
V_0 & \text{if } (V_8-V_9) < Q_s, \text{ when } n+k>8 \\
V_0 & \text{if } (V_8-V_9) > Q_s, \text{ when } n+k>8 
\end{cases}
\]

(5.18)

\[
V_1 \text{ if } (V_1-V_0) > Q_s, \text{ when } n+k<1
\]

\[
V_n, \text{ when } 1<n+k<8
\]

\[
V_0 \text{ if } (V_8-V_9) < Q_s, \text{ when } n+k>8
\]

\[
V_0 \text{ if } (V_8-V_9) > Q_s, \text{ when } n+k>8
\]

Table 5.1  PSNR for original decoded sequence and after applying de-blocking Filter (Bitrates 2 and 3 mbit/s)

<table>
<thead>
<tr>
<th>FRAMES</th>
<th>PSNR w/o post process</th>
<th>PSNR with post process</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE2M 240</td>
<td>39.17 dB</td>
<td>32.29 dB</td>
</tr>
<tr>
<td>CREW 2M 300</td>
<td>33.79 dB</td>
<td>34.08 dB</td>
</tr>
<tr>
<td>SOCCER2M 300</td>
<td>31.71 dB</td>
<td>31.90 dB</td>
</tr>
<tr>
<td>ICE3M 240</td>
<td>40.39 dB</td>
<td>40.47 dB</td>
</tr>
<tr>
<td>CREW 3M 300</td>
<td>35.96 dB</td>
<td>36.24 dB</td>
</tr>
<tr>
<td>SOCCER3M 300</td>
<td>34.00 dB</td>
<td>34.22 dB</td>
</tr>
</tbody>
</table>

The difference in PSNR for the decoded sequence after applying deblocking filter with and w/o post process is graphically shown in Figure 5.5.
As for the hardware implementation, because the filter mask coefficients are powers of two, no multipliers are required. To increase the memory bandwidth, vertical filtering is applied to two boundaries of four blocks in parallel (16 rows of pixels), and this requires two identical filters working in parallel.

The deblocking filter using the estimated $Q_s$ values was tested on six test sequences. The sequences are progressive SDTV sequences (704 x 576 pixels) CREW, ICE and SOCCER coded at 2 and 3 Mbit/s. The sequence ICE has 240 frames and both CREW and SOCCER have 300 frames. For the inter P-frames and B-frames the average value from the last I-frame has been used. A GOP length of 12 frames between I-frames and two B-frames between P-frames was used. The new deblocking scheme robustly improved the Peak Signal- to-Noise Ratio (PSNR) on all images the three MPEG image types I, P, and B on all sequences.

The average improvement is 0.33 dB for I-frames and 0.21 dB over the whole sequence. The coded test sequences covered a PSNR range from
31.8 to 40.4dB. The results are comparable to those reported for the state-of-the-art deblocking filter where the post-processing reads and utilizes the actual Qs values, for all frames types, i.e. all of I-, P- and B-frames at the MB level. The PSNR improvement values are shown in Table 5.1.

E. DEBLOCKING FILTER AND DISTORTION CHANGE:

Deblocking is a local operation. The deblocking operation may improve the appearance of the image in some regions, while degrading the quality elsewhere. 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 low pass 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.

F. COMPARITIVE STUDY

The proposed new block-sensitive image quality metric is termed as 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 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.

For moderate to large range of quantization step sizes, POCS produced improved PSNR-B values relative to the no-filter case over all the images. For large quantization steps, the simple low pass filtering methods also improved the PSNR-B values. Hence, the POCS resulted in improved PSNR-B values compared to the no-filter case even at small quantization steps. 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 SSIM index.

5.2.4 Experimental Results

Figure 5.6 is considered to be the sample image. Figure 5.7 is the reference original image chosen to perform the simulations on the quality assessment of the deblocked images.

![Sample Image (Leopard)](image)

**Figure 5.6 Sample Image (Leopard)**
The image is first decomposed into blocks (4x 4 or 8 x8 pixels as usual); the DCT transform is applied on each block, in order to eliminate a part of the information contained in the image, that is, high frequencies which are not visible to human eyes. The DCT transform is applied. However in the transformed block, low-frequency coefficients are grouped in the upper-left corner, while high frequency ones are grouped in the lower-right corner. The low-pass filter on the transformed block will thus keep only the coefficients
nearest from the upper left corner as shown in Figure 5.8, supposing that they
do not contribute too much to the visual quality of the image.

![Image](image-url)

**Figure 5.9 Performance of Block Processed IDCT Image**

The Inverse Discrete Cosine transform reconstructs a sequence from its Discrete Cosine Transform (DCT) coefficients. The IDCT function is the inverse of the DCT function. The IDCT block computes the Inverse Discrete Cosine Transform (IDCT) of each channel in the M-by-N input matrix. For both sample-based and frame-based inputs, the block assumes that each input column is a frame containing M consecutive samples from an independent channel. The frame size, M, must be a power of two. To work with other frame sizes, use the Pad block to pad or truncate the frame size to a power of two lengths. The output is an M-by-N matrix whose 1st column contains the length-M IDCT of the corresponding input column shown in Figure 5.9.
When the POCS deblocking filter was applied to the input image, 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 as shown in fig 5.10. The blocking effects were mostly removed.
When the quantization step was small, all the de blocking methods produced lower PSNR compared to the no-filter case. The POCS did not produce improvement. When the quantization step (x-axis) is small, the MDI was larger than the MDD, i.e., the amount of information that was distorted was larger than the amount of information recovered by deblocking filters.

When the quantization step size fell in the middle range of about 80, the 3x3 filter gave a slightly higher PSNR. The image quality is better in SSIM when compared to 3x3 and 7x7 filters, as indicated by the blue line in the above graph (Figure 5.11).

![Figure 5.12 Performance of SSIM](image)

The Structural SSIMilarity (SSIM) metric aims to measure by capturing the similarity of images. A product of three aspects of similarity luminance, contrast, and structure are measured. When the quantization step size (x-axis) was small($\Delta<40$), the 3x3 and 7x7 lowpass filters resulted in lower SSIM values than the no-filter case, while the POCS method had little effect on the SSIM value.
When the quantization step was large ($\Delta \geq 120$), all the filtering methods resulted in larger SSIM values as shown in Figure 5.12.

The associated quality index PSNR-B obtained from the MSE-B by a logarithmic function (as is the PSNR from the MSE) was calculated and its typical values for various test images are tabulated in Table 5.2.

**Table 5.2  Comparison and Difference of SSIM, PSNR and PSNR-B for Various Test Images**

<table>
<thead>
<tr>
<th>IMAGES</th>
<th>SSIM</th>
<th>PSNR</th>
<th>PSNR_B</th>
<th>DIFFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leapord</td>
<td>0.94 dB</td>
<td>27.81942971 dB</td>
<td>40.98541662 dB</td>
<td>13.1659869 dB</td>
</tr>
<tr>
<td>Bangalore-Pune</td>
<td>0.9361 dB</td>
<td>34.61064576 dB</td>
<td>44.38102464 dB</td>
<td>9.770378882 dB</td>
</tr>
<tr>
<td>Highway</td>
<td>0.9361 dB</td>
<td>34.61064576 dB</td>
<td>44.38102464 dB</td>
<td>9.770378882 dB</td>
</tr>
<tr>
<td>Cameraman</td>
<td>0.6346 dB</td>
<td>18.52277956 dB</td>
<td>36.33709154 dB</td>
<td>17.81431198 dB</td>
</tr>
<tr>
<td>Us Airforce</td>
<td>0.94 dB</td>
<td>33.09895737 dB</td>
<td>43.62518044 dB</td>
<td>10.52622308 dB</td>
</tr>
<tr>
<td>Garden</td>
<td>0.9276 dB</td>
<td>28.3093547 dB</td>
<td>41.23037911 dB</td>
<td>12.92102441 dB</td>
</tr>
<tr>
<td>Fish</td>
<td>0.9705 dB</td>
<td>33.45037294 dB</td>
<td>43.80088823 dB</td>
<td>10.35051529 dB</td>
</tr>
<tr>
<td>Meenakshi Temple</td>
<td>0.9602 dB</td>
<td>37.23882577 dB</td>
<td>45.69511465 dB</td>
<td>8.45628877 dB</td>
</tr>
<tr>
<td>Nepal Children</td>
<td>0.9177 dB</td>
<td>27.75008017 dB</td>
<td>40.95074185 dB</td>
<td>13.20066168 dB</td>
</tr>
<tr>
<td>Bird</td>
<td>0.9241 dB</td>
<td>33.86942595 dB</td>
<td>44.01041474 dB</td>
<td>10.14098879 dB</td>
</tr>
<tr>
<td>Wiring</td>
<td>0.2461 dB</td>
<td>13.13769584 dB</td>
<td>33.64454968 dB</td>
<td>20.50685384 dB</td>
</tr>
</tbody>
</table>

The results obtained are plotted graphically showing the difference between the proposed PSNR-B metric and various other quality metrics in Figure 5.13.
Figure 5.13 Comparison of SSIM, PSNR and PSNR-B

5.3 CONCLUSION

The proposed block-sensitive image quality index PSNR-B for quality assessment of deblocked images modifies the conventional PSNR by including an effective blocking effect factor. 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 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. Selection of proper mode like Dc offset mode and default mode are corresponding filtering to provide improvement of PSNR and also minimizing computational complexity of one dimensional filtering with separate mode.