

# IMAGE QUALITY ANALYSIS OF DEBLOCKED IMAGES

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**Abstract**— JPEG compression is the most prevalent technique or method for image codecs. But it suffers from blocking artifacts. In this paper a comparison of the perceptual quality of deblocked images based on various quality assessment metric is done. A proposed PSNR including blocking effect factor is used instead of PSNR. Another quality assessment metric SSIM was used which produces results largely in accordance with PSNR -B. We show the simulation results, which prove PSNR-B produces objective judgments. The efficiency of deblocking algorithms were studied..

**Keywords**---Deblocked images, blocking artifacts, quality assessment, quality metric

## I. INTRODUCTION

Many practical and commercial systems use digital image compression when it is required to transmit or store the image over limited resources. JPEG compression is the most popular image compression standard among all the members of lossy compression standards family. JPEG image coding is based on block based discrete cosine transform. BDCT coding has been successfully used in image and video compression applications due to its energy compacting property and relative ease of implementation. After segmenting an image in to blocks of size  $N \times N$ , the blocks are independently DCT transformed, quantized, coded and transmitted. One of the most noticeable degradation of the block transform coding is the “blocking artifact”. These artifacts appear as a regular pattern of visible block boundaries. This degradation is the result of course quantization of the coefficients and of the independent processing of the blocks which does not take in to account the existing correlations among adjacent block pixels [12]. In order to achieve high compression rates using BTC with visually acceptable results, a procedure known as deblocking is done in order to eliminate blocking artifacts.

In this paper a research has done on quality assessment of deblocked images by estimating various quality metrics and the effect of quantization step of the measured quality of

deblocked image is studied. Simulations are done using quality metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and PSNR-B. PSNR-B is a new quality metric which includes PSNR by a blocking factor. By going through simulation results, it is shown that PSNR-B correlates well with the SSIM index and subjective quality and its performance is much better than the PSNR.

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

## II. DEBLOCKING

To remove blocking effect, several deblocking techniques have been proposed in the literature as post process mechanisms after JPEG compression, depending on the angle from which the blocking problem is tackled. If deblocking is viewed as an estimation problem, the simplest solution is probably just to low pass the blocky JPEG compressed image. More sophisticated methods involve iterative methods such as projection on convex sets [3, 4] and constrained least squares [4, 5]

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

## III. PROPOSED METHOD

Deblocking operation is performed in order to reduce blocking artifacts. Deblocking operation can be achieved by using various deblocking algorithms, employing deblocking filters. The effects of deblocking filters can be analysed by introducing a change in distortion concept.

The deblocking operation results in the enhancement of image quality in some areas, while degrading in other areas.

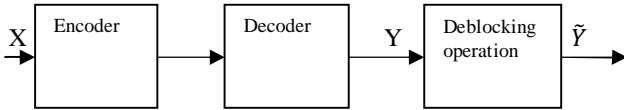


Fig 1 Block diagram showing JPEG compression

Let  $X$  be the reference image and  $Y$  be the test image (decoded image) distorted by quantization errors and  $\tilde{Y}$  be the deblocked image as shown in figure1. Let  $f$  represent the deblocking operation and is given by  $\tilde{Y}=f(Y)$ . Let the quality metric between  $X$  and  $Y$  be  $M(X,Y)$ . For the given image  $Y$ , the main aim of deblocking operation  $f$  is to maximize  $M(X,f(Y))$ .

Let  $\alpha_i$  represent the amount of decrease in distortion in the decrease in distortion region (DDR) and is given by

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

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

$$d(x_i, y_i) = \|x_i - y_i\|^2 \tag{2}$$

$d(x_i, \tilde{y}_i)$  is the distortion between  $i$ th pixels of  $X$  and deblocked image  $\tilde{Y}$ .

DDR  $\mathcal{A}$  is defined as the decrease in distortion region composed of those pixels where the deblocking operation decreases the distortion

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

Now the mean distortion decrease (MDD) is given by

$$\bar{\alpha} = \frac{1}{N} \sum_{i \in \mathcal{A}} (d(x_i, y_i) - d(x_i, \tilde{y}_i)) \tag{4}$$

The amount of distortion increase (DIR) for the  $i$ th pixel  $\beta_i$  is given by

$$\beta_i = d(x_i, \tilde{y}_i) - d(x_i, y_i) \tag{5}$$

(DIR)  $\mathcal{B}$  defines the distortion increase region given as

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

Now the mean distortion increase (MDI) is given as

$$\bar{\beta} = \frac{1}{N} \sum_{i \in \mathcal{B}} (d(x_i, \tilde{y}_i) - d(x_i, y_i)) \tag{7}$$

The difference between MDD and MDI can be represented as Mean distortion change (MDC)  $\bar{\gamma}$  and is given by

$$\bar{\gamma} = \bar{\alpha} - \bar{\beta} \tag{8}$$

From this it can be stated that the deblocking operation is likely successful if  $\bar{\gamma} > 0$ .

This is because the mean distortion decrease is larger than the mean distortion increase. Nevertheless, the level of perceptual improvement or loss does not meet these conditions. Based on these conditions, the effect of deblocking filters can be analyzed.

1) *Lowpass filter* : A simple  $L \times L$  lowpass deblocking filter can be represented as

$$g(N(x_i)) = \sum_{k=1}^{L^2} h_k \cdot x_{i,k} \tag{9}$$

Where  $N(x_i)$  represent Neighborhood of pixel  $x_i$

$g$  represents deblocking operation function

$h_k$  represents Kernel for the  $L \times L$  filter

$x_{i,k}$  represents the  $k$ th pixel in the  $L \times L$  neighborhood of pixel  $x_i$

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

2) *POCS*: Deblocking algorithms based upon projection onto convex sets (POCS) have demonstrated good performance for reducing blocking artifacts and have proved popular [3]-[8]. In POCS Projection operation is done in the DCT domain and lowpass filtering operation is done in the spatial domain. Forward DCT and inverse DCT operations are required because the lowpass filtering and the projection operations are performed in various domains. Convergence require Multiple iterations and the lowpass filtering, DCT, Projection, IDCT operations require one iteration. POCS filtered images converge to an image that does not exhibit blocking artifacts under certain conditions [3], [6], [7]. But computational complexity is more as it requires more iterations.

#### IV. ESTIMATION OF QUALITY METRICS

To Measure the quality degradation of an available distorted image with reference to the original image, a class of quality assessment metrics called full reference (FR) are considered.

Full reference metrics perform distortion measures having full access to the original image. The quality assessment metrics are estimated as follows

A. 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  $l(X, Y)$  is defined as below

$$l(X, Y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \quad (10)$$

Where  $\mu_x$  and  $\mu_y$  are the mean values of X and Y respectively and  $C_1$  is the stabilization constant

Similarly the contrast comparison function  $c(X, Y)$  is defined as

$$c(X, Y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \quad (11)$$

Where the standard deviation of X and Y are represented as  $\sigma_x$  and  $\sigma_y$  and  $C_2$  is the stabilization constant.

The structure comparison function  $s(X, Y)$  is defined as

$$s(X, Y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \quad (12)$$

Where  $\sigma_{xy}$  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

$$SSIM(X, Y) = [l(X, Y)]^\alpha \cdot [c(X, Y)]^\beta \cdot [s(X, Y)]^\gamma \quad (13)$$

The parameters are set as  $\alpha = \beta = \gamma = 1$  and  $C_3 = \frac{C_2}{2}$  as in[2]

From the above parameters the SSIM index can be defined as

$$SSIM(X, Y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (14)$$

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].

$$SSIM(X, Y) = \frac{1}{M} \sum_{j=1}^M SSIM(X_j, Y_j) \quad (15)$$

Where  $X_j$  and  $Y_j$  are image patches covered by the jth window and the number of local windows over the image are represented by M

B. PSNR

Peak Signal-to-Noise Ratio (PSNR) and mean –Square error are most widely used full reference (FR) QA metrics [2], [15]. 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

$$MSE(X, Y) = \frac{1}{N} \sum_{i=1}^N e_i^2 = \frac{1}{N} \sum_{i=1}^N (x_i^2 - y_i^2) \quad (16)$$

$$PSNR(X, Y) = 10 \log_{10} \frac{255^2}{MSE(X, Y)} \quad (17)$$

Where N represent Number of pixels in an image. However, The PSNR does not correlate well with perceived visual quality [2], [15]-[18].

C PSNR-B

A new quality metric called PSNR-B which includes ordinary PSNR by blocking 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.

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

Fig. 2 Example for 8x8 pixel block

For an image I, let  $N_H$  and  $N_V$  be the horizontal and vertical dimensions .The horizontal neighbouring pixel pairs in I are represented as  $\mathcal{H}$  and the set of horizontal neighbouring pixels that lie across the boundary as  $\mathcal{H}_B$  and  $\mathcal{H}_B \subset \mathcal{H}$  .The set of horizontal pixel pairs other than that lie across the boundary are represented as  $\mathcal{H}_B^C$  and is given as  $\mathcal{H}_B^C = \mathcal{H} - \mathcal{H}_B$ .Similarly the set of vertical neighbouring pixels are represented as  $\mathcal{V}$  and the set of vertical neighbouring pixels that lie across the boundary as  $\mathcal{V}_B$  and  $\mathcal{V}_B \subset \mathcal{V}$  .The set of vertical neighbouring pixels that does not lie across boundary are represented as  $\mathcal{V}_B^C$  and  $\mathcal{V}_B^C = \mathcal{V} - \mathcal{V}_B$ .

$$N_{H_B} = N_V \left( \frac{N_H}{B} \right) - 1 \quad (18)$$

$$N_{H_B^C} = N_V(N_H - 1) - N_{H_B} \quad (19)$$

$$N_{V_B} = N_H \left(\frac{N_V}{B}\right) - 1 \quad (20)$$

$$N_{V_B^C} = N_H(N_V - 1) - N_{V_B} \quad (21)$$

Where  $N_{H_B}$ ,  $N_{H_B^C}$ ,  $N_{V_B}$ ,  $N_{V_B^C}$  are the number of pixel pairs in  $\mathcal{H}_B$ ,  $\mathcal{H}_B^C$ ,  $\mathcal{V}_B$  and  $\mathcal{V}_B^C$  respectively and B is the block size. Fig 2 shows the example for  $8 \times 8$  pixel block with  $N_H = 8$ ,  $N_V = 8$  and  $B=8$ . In the above example  $N_{H_B} = 8$ ,  $N_{H_B^C} = 48$ ,  $N_{V_B} = 8$  and  $N_{V_B^C} = 48$ . The set of pixel pairs are represented as follows

$$\mathcal{H}_B = \{(y_{25}, y_{33}), (y_{26}, y_{34}), \dots \dots \dots (y_{32}, y_{40})\} \quad (22)$$

$$\mathcal{H}_B^C = \{(y_1, y_9), (y_9, y_{17}), \dots \dots \dots (y_{56}, y_{64})\} \quad (23)$$

$$\mathcal{V}_B = \{(y_4, y_5), (y_{12}, y_{13}), \dots \dots \dots (y_{60}, y_{61})\} \quad (24)$$

$$\mathcal{V}_B^C = \{(y_1, y_2), (y_2, y_3), \dots \dots \dots (y_{63}, y_{64})\} \quad (25)$$

For image Y the mean boundary pixel square difference  $D_B$  and the mean non boundary pixel square difference  $D_B^C$  is given by

$$D_B(y) = \frac{\sum_{(y_i, y_j) \in \mathcal{H}_B} (y_i - y_j)^2 + \sum_{(y_i, y_j) \in \mathcal{V}_B} (y_i - y_j)^2}{N_{H_B} + N_{V_B}} \quad (27)$$

$$D_B^C(y) = \frac{\sum_{(y_i, y_j) \in \mathcal{H}_B^C} (y_i - y_j)^2 + \sum_{(y_i, y_j) \in \mathcal{V}_B^C} (y_i - y_j)^2}{N_{H_B^C} + N_{V_B^C}} \quad (28)$$

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

$$BEF(Y) = \eta [D_B - D_Y^C] \quad (29)$$

Where

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

A decoded image may contain multiple block sizes like  $16 \times 16$  macro block sizes and  $4 \times 4$  transform blocks, both contributing to blocking effects. Then the blocking effect factor for kth block is given by

$$BEF_k(Y) = \eta_k [D_{B_k}(Y) - D_{B_k^C}(Y)] \quad (30)$$

For overall block sizes BEF is given by

$$BEF_{Tot}(Y) = \sum_{k=1}^K BEF_k(Y) \quad (31)$$

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

$$MSE - B(X, Y) = MSE(X, Y) + BEF_{Tot}(Y) \quad (32)$$

Finally the proposed PSNR-b is given as,

$$PSNR - B(X, Y) = 10 \log_{10} \frac{255^2}{MSE - B(X, Y)} \quad (33)$$

#### V. EFFECT OF QUANTIZATION STEP SIZE.

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  $L \times L$  block transfer codes. The transformed DCT coefficient block from input block b is given by

$$B = T b T^t \quad (34)$$

Where T is transform matrix and  $T^t$  is the transpose matrix of T

A scalar quantizes that transform coefficients

$$\tilde{B} = Q(B) = Q(T b T^t) \quad (35)$$

The output of the decoder is given by

$$\tilde{b} = T^t \tilde{B} T = T^t Q(T b T^t) T \quad (36)$$

Quantization step is represented by  $\Delta$ . As quantization step increases, the structural difference between reference and test

image also increases hence PSNR and SSIM index are monotonically decreasing functions of quantization step size  $\Delta$

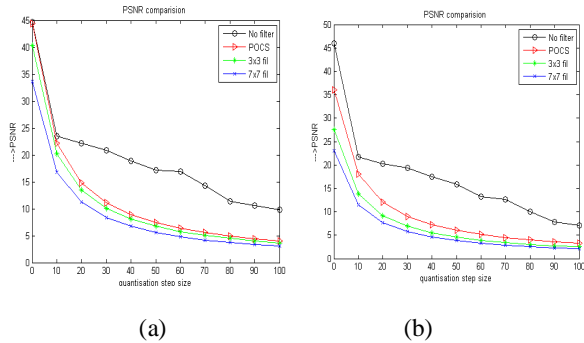


Figure 3 PSNR comparisons of images (a) Leopard (b) cameraman

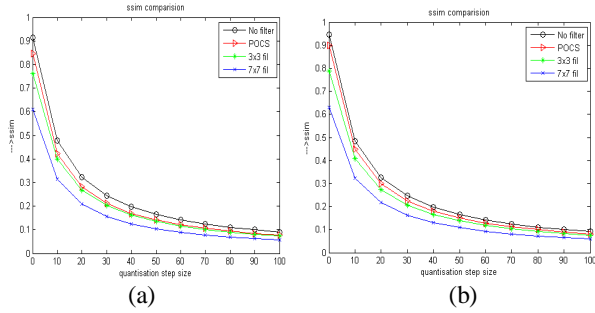


Figure 4 SSIM comparisons of images (a) Leopard (b) cameraman

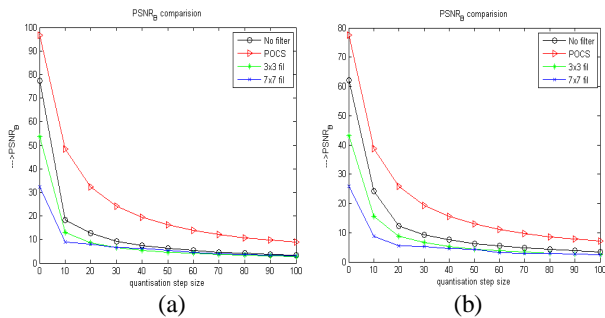


Figure 5 PSNR-B comparisons of images (a) Leopard (b) cameraman.

vi.RESULTS AND DISCUSSIONS

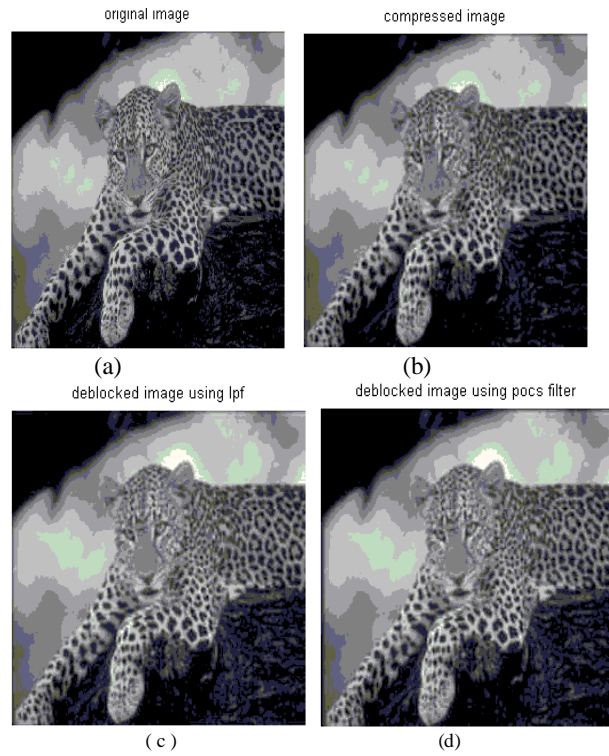
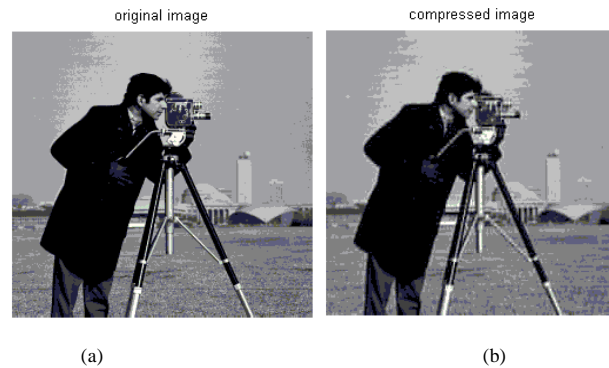


Figure 6 at Quantization step  $\Delta=50$   
 (a) Original Image  
 (b) compressed Image (PSNR=40.4182, SSIM=0.0122, PSNR-B=56.5088)  
 (c) Deblocked Image using LPF (PSNR=40.4397, SSIM=0.0122, PSNR-B=56.818)  
 (d) Deblocked Image using POCS (PSNR=40.4240, SSIM=0.0133, PSNR-B=58.5718)





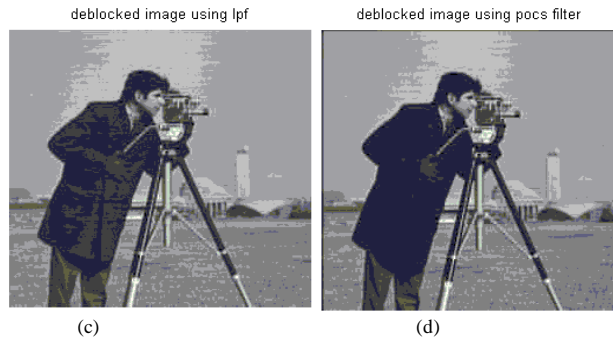


Figure 7 at Quantization step  $\Delta=50$

- (a) Original Image
- (b) compressed Image (PSNR=27.6356, SSIM=0.0127, PSNR-B=51.6224)
- (c) Deblocked Image using LPF (PSNR=27.6360, SSIM=0.0127, PSNR-B=51.6353)
- (d) Deblocked Image using POCS (PSNR=27.6385, SSIM=0.0137, PSNR-B=51.7019).

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

**A. PSNR Analysis:**

Figure 3 shows that when the quantization step size was large ( $\Delta \geq 80$ ), the  $3 \times 3$  filter,  $7 \times 7$  filter and POCS methods resulted in higher PSNR than the no filter case on both the images. All the deblocking methods produced lower PSNR when the quantization step size was small ( $\Delta \leq 30$ ).

**B. SSIM Analysis :**

Figure 4 shows that when the quantization step was large ( $\Delta \geq 80$ ), on the two images, all the filtered methods resulted in larger SSIM values. The  $3 \times 3$  and  $7 \times 7$  lowpass filters resulted in lower SSIM values than the low 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 two images by employing lowpass filtering methods. The POCS resulted in improved PSNR-B values compared to the no filtered case, even at small quantization step size.

**VII. CONCLUSION**

We have tested our algorithm on few natural images. Those sample images are shown in above figure. We have found that the better quality metric is obtained at quality factor 70 for JPEG compression. This Analysis will bring out a new trend in the quality metrics of the image and proves to be efficient than the conventional metrics.

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