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PERFORMANCE COMPARISION OF BLOCKING ARTIFACT REDUCTION OF COMPRESSED IMAGES USING BILATERAL & BLOCK WIENER FILTER

By

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Recommendation

The undersigned certify that it has been read and recommended to the Department of Electronics and Computer Engineering for acceptance, a thesis entitled **"PERFORMANCE COMPARISON OF BLOCKING ARTIFACT REDUCTION OF COMPRESSED IMAGE BY BILATERAL & BLOCK WIENER FILTER"**, submitted **by Mr. Amar Bahadur Gurung** in partial fulfillment of the requirement for the award of the degree of **"Master of Science in Computer System and Knowledge Engineering"**.

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Abstract

Image compression is a very important issue for several applications in the area of multimedia communications, the objective being reduction of storage and transmission costs. Artifact is a particular class of data error that is usually the consequence of quantization in lossy image compression and often a result of the latent errors inherent in lossy compression. There are different types of artifacts present however effect of blocking artifact is more. Block Wiener filter is a class of optimum linear filter which involve linear estimation of a desired signal sequence from another related sequence and combine with shift weighted average operation. A Bilateral filter depends on the combination of two parameters intensity and spatial distance. Both bilateral and wiener filter is based on enhancement algorithm. The computation of SSIM and PSNR values of de-blocking image after the application of two novel filter can be used to compare filter response for the reduction of blocking artifact.

Keyword: *Artifact, PSNR, SSIM, Block Weiner filter, bilateral filter, DCT*

List of Abbreviation

ASMF	Adaptive Separable Median Filter
BDCT	Block-based Discrete Cosine Transform
DCT	Discrete Cosine Transform
JPEG	Joint Photographic Experts Group
MPEG	Moving Pictures Expert Group
MSDS	Mean Squared Difference of Slop e
POCS	Projection onto Convex Sets
STD	Standard Deviation
MSE	Mean Square Error
PSNR	Peak Signal to Noise Ratio
SSIM	Structural Similarity Index

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1 INTRODUCTION

1.1 Background

As the development of new technology usage of computer grows continuously and size of data storage is increase tremendously therefore we need for efficient ways for storing large amounts of data (images). For example, someone with a web page or online catalog that uses dozens or perhaps hundreds of images will more likely need to use some form of image compression to store those images. This is because the amount of space required for storing unadulterated images can be prohibitively large in terms of cost. Image data compression becomes more important because of the fact that the transfer of uncompressed graphical data requires far more bandwidth and data transfer rate [1]. Most of the coding standards for still images such as JPEG, adopt the Block-based Discrete Cosine Transform (BDCT) as a main coding tool. Image compression suffers from spatial and temporal distortions [2]. Spatial distortion includes blocking and ringing, and typical temporal distortion types are mosquito and flickering artifacts. Blocking artifacts are caused by separate compression of each block, and it occurs both in horizontal and vertical direction of each frame. Ringing artifacts occur when the high frequency transform coefficients obtained from Discrete Cosine Transform (DCT) or wavelet-based coding are quantized or truncated. This causes ripples or oscillations around sharp edges or contours in the image. It is also known as Gibbs Phenomenon. When ringing artifacts are changing from frame to frame as a video sequence is displayed, mosquito artifacts are created. Flickering artifacts [3] appear due to the inconsistency in quality at the same spatial position in adjacent frames. Various approaches have been proposed to reduce the effects of image compression, but in order to utilize standardized compression/decompression techniques and to retain the benefits of the compression (for instance, lower transmission and storage costs), many of these methods have focused on ”post-processing” that is, processing the images when they are received or viewed. No post-processing technique has been shown to improve image quality in all cases consequently, none has garnered widespread acceptance, though some have been implemented and are in use in proprietary systems. The wiener filter transforms images to be smooth, which is highly effective when difference between original images and compressed ones are large. The wiener filter used for decreasing a Gaussian noise, is modified to reduce the blocking artifacts. It consists of the wiener filter per a block, shift and the weighted average operations. The bilateral filter does a weighted spatial averaging, where the weights depend on both spatial distances and intensity distances [4]. In this way, edge preserving smoothing is achieved. Bilateral filtering was recently utilized to reduce compression blocking artifacts. The performance of both filter techniques is then evaluated by calculating the MSE, PSNR and SSIM values.

1.2 Motivation

Image compression is very essential for image processing and since JPEG is used to compress the image for a long period of time. It introduces artifacts over all the digital image [6] where blocking artifact is crucial among them so that it is necessary to remove blocking artifact and further, constantly drives new ideas and implementations in this field. The motivation behind this thesis is to understand the different post processing algorithm for blocking artifact reduction of compressed images. Reduction of the artifacts in compressed images is a very important issue in the area of multimedia communications and storage. Thus, it draws attentions of several researchers, institutions and commercial companies.

1.3 Problem Definition

An Image compression using JPEG is based on principle of block based discrete cosine transform (DCT) and it introduces different artifacts; such as blocking, ringing, mosquito, and flickering, especially at low-bit-rate coding among them blocking artifact is noticeable artifact. In block based DCT separately compressing each block breaks correlation between the pixels at the borders of blocks and causing blocking artifacts. A purpose of data compression is to reduce the storage and transmission costs while maintaining image quality. Therefore, many efficient post image processing techniques have been developed for various applications, and some of them are used as international standard for image communication but still there is limitation in reduction of quality. There are several filters for blocking artifact reduction but wiener and bilateral filter are novel approach and comparison between these two approaches based on different evaluation parameters such as PSNR, MSE and SSIM.

1.4 Objectives

The objectives of this thesis work are given below:

i. To analyze the post processing filter (Bilateral and Block Wiener) for blocking artifacts reduction of reconstructed image.
ii. To compare the performance of two different filters for the reduction of blocking artifacts based on different parameters such as PSNR, MSE and SSIM and suggest efficient filter.

1.5 Overview of Thesis report

This midterm thesis report consists of six parts. In Chapter one covers general introduction of thesis work. Chapter two includes comprehensive literature review, which covers the most popular and advanced researches in this fields. In Chapter three explains the related theory; image compress/decompression, DCT, Bilateral filter etc. Chapter 4 describes the methodology used for the research work. Chapter five includes the experiment results and data for compression blocking artifacts reduction. Summary and conclusion is provided in Chapter six.

2 LITERATURE REVIEW

Over the past several years, many techniques have been applied to reduce the artifacts in block DCT-coded images [9]. Two approaches are generally adopted. In the first approach, the reduction of artifacts is carried out at the encoding side but the methods based on this approach do not conform to the existing standards such as JPEG and MPEG. In the second approach, the reconstructed image is post processed aimed at improving its visual quality without any modification in the encoding or decoding mechanisms, making it compatible with the aforesaid coding standards. Because of this advantage, most of the recently proposed algorithms follow the second approach. In post processing, filter is applied after the decoder and utilizes decoded parameters. It operates on display buffer outside the coding loop. The frame is decoded into reference frame buffer and filtered before passing it to display device [4]. An additional buffer may be required for implementation of post filter. Post processing of the decoded image may be carried out in spatial domain or in frequency domain.

Bilateral filter is firstly presented by Tomasi and Manduchi in 1998. The concept of the bilateral filter was also presented in [5] as the SUSAN filter and in [6] as the neighborhood filter. It is mentionable that the Beltrami flow algorithm is considered as the theoretical origin of the bilateral filter [7], which produces a spectrum of image enhancing algorithms ranging from the $L2$ linear diffusion to the $L1$ non-linear flows.

2.1 Spatial domain techniques

Reeve and Lim proposed a symmetric, two-dimensional 3×3 Gaussian spatial filtering method for the pixels along the block boundaries [10]. However, it causes blurring of the image due to its low-pass nature. Ramamurthi and Gersho proposed nonlinear space-variant filter which adapts to the varying shape of the local signal spectrum, and reduces only the locally out-of-band noise [11].

The algorithm employs a two-dimensional (2-D) filter in the areas away from edges, and for near edges, one-dimensional (1-D) filter aligned parallel to edge so as to minimize the blocking artifacts. Hsu and Chen proposed an adaptive separable median filter (ASMF) [12]. The proposed filter not only reduced the blocking artifacts, but also preserved the edges. Meier et al. presented a region based method for enhancement of images degraded by blocking effects [13]. In this method, the degraded image is segmented by a region growing algorithm, and each region is the filtered using a low-pass filter. It preserves the edges, as filtering is not applied to region boundaries. Lee et al. proposed a post processing algorithm to reduce the blocking artifacts in JPEG compressed images after classifying them into edge area and monotone area according to the edge map which is obtained after thresholding the gradient absolute image [14]. The signal adaptive filtering consists of a 1-D directional smoothing filtering for edge area and 2-D adaptive average filtering for monotone area. A corner outlier detection/replacement scheme is also given to remove the corner outlier. Chou et al. remove blockiness by performing a simple nonlinear smoothing of pixels [15]. They first form the maximum likelihood estimation of quantization noise to differentiate between artificial and actual edges. Many researchers proposed iterative methods based on the theory of projections onto convex sets (POCS) [16]. In these methods, initially closed convex constraint sets are defined which correspond to all of the available data on the original image. Iterative computations of alternating projections onto these convex sets recover the original image from the coded image. However, these methods usually have high computational complexity, and thus are difficult to adapt to real-time image processing applications.

2.2 Frequency domain techniques

Minami et al. gave a new approach for reducing the blocking effect in frequency domain. A new index to measure the blocking effects namely the mean squared difference of slope (MSDS) is introduced. It is shown that the expected value of the MSDS increases after quantizing the DCT coefficients. This approach removes the blocking effect by minimizing the MSDS, while imposing linear constraints corresponding to quantization bounds. Lakhani et al. also reduce blocking effects using MSDS [17]. However, a different solution of minimizing the MSDS is used. Recently, Triantafyllidis et al. have proposed another method of minimizing MSDS, which involves diagonal neighboring pixels in addition to horizontal and vertical neighboring pixels [18]. Liu et al. proposes a DCT domain method for blind measurement of blocking artifacts, by modeling the artifacts as 2-D step functions in shifted blocks [19]. A fast DCT-domain algorithm extracts all the parameters required to detect the presence of blocking artifacts, by using H VS properties. In image processing and computer vision, anisotropic diffusion, also called Perona Malik diffusion, is a technique aiming at reducing the noise without removing essential parts of the image content, such as edges, lines and other details that are important for the interpretation of the image[20].

3 RELATED THEORY

3.1 Image Compression

Technology brings the revolution on all field and we entered into the Digital Age, which means every system is digital & the world has faced a vast amount of information. Dealing with this vast amount of information can often result in many difficulties [1]. We must store, retrieve, analyze and process Digital information in an efficient way, so as to be put to practical use. In the past decade many aspects of digital technology have been developed; specifically in the fields of image acquisition, data storage and image processing. Compressing an image is significantly different than compressing raw binary data. Images have certain statistical properties which can be exploited by encoders specifically designed for them so; the result is less than optimal when using general purpose compression programs to compress images. One of many techniques under image processing is image compression using Block Discrete Cosine Transform (BDCT). Image compression has many applications and plays an important role in efficient transmission and storage of images. The image compression aims at reducing redundancy in image data to store or transmit only a minimal number of samples And from this we can reconstruct a good accession of the original image in accordance with human visual perception [21].

In general image compression means minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk more memory space. It also reduces the time required for image to be sent over the internet or downloaded from web pages. Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and bandwidth. Despite rapid progress in mass storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data transmission bandwidth continues to outstrip the capabilities of available technology. The recent growth of data intensive multimedia based web application have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signal central to storage and communication technology.

3.1.1 Principle of Image Compression

The principles of image compression are based on information theory. The amount of information that a source reduce is Entropy. The amount of information one receives from a source is equivalent to the amount of the uncertainty that has been removed. A source produces a sequence of variables from a given symbol set. For each symbol, there is a product of the symbol probability and its logarithm. The entropy is a negative summation of the products of all the symbols in a given symbol set. Compression algorithms are methods that reduce the number of symbols used to represent source information, therefore reducing the amount of space needed to store the source information or the amount of time necessary to transmit it for a given channel capacity. The mapping from the source symbols into fewer target symbols is referred to as Compression and Vice-versa Decompression. Image compression refers to the task of reducing the amount of data required to store or transmit an image. At the system input, the image is encoded into its compressed form by the image coder. The compressed image may be then subjected to further digital processing, such as error control coding, encryption or multiplexing with other data sources, before being used to modulate the analog signal that is actually transmitted through the channel or stored in a storage medium. At the system output, the image is processed step by the step to undo each of the operations that were performed on it at the system input. At the final step, the image is decoded into its original uncompressed form by the image decoder.

Image Compression addresses the problem of reducing the amount of data required to represent the digital image therefore we can achieve compression by removing of one or more of three basic data redundancies:

i. Spatial Redundancy or correlation between neighboring pixels.
ii. Due to the correlation between different color planes or spectral bands, the Spectral redundancy is founded.
iii. Due to properties of the human visual system, the Psycho-visual redundancy is founded.

3.2 Discrete Cosine Transform

JPEG stands for the Joint Photographic Experts Group, a standards committee that had its origins within the International Standard Organization (ISO). JPEG provides a compression method that is capable of compressing continuous-tone image data with a pixel depth of 6 to 24 bits with reasonable speed and efficiency. It may be adjusted to produce very small, compressed images that are of relatively poor quality in appearance but still suitable for many applications. Conversely, it is capable of producing very high-quality compressed images that are still far smaller than the original uncompressed data. It is primarily a lossy method of compression and was designed specifically to discard information that the human eye cannot easily see. Slight changes in color are not perceived well by the human eye, while slight changes in intensity (light and dark) are perceived. Therefore JPEG lossy encoding tends to be more frugal with the gray-scale part of an image and to be more frivolous with the color [21]. DCT separates images into parts of different frequencies, whereas less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression. Compared to other input dependent transforms, DCT has many advantages: (1) It has been implemented in single integrated circuit; (2) It has the ability to pack most information in fewest coefficients; (3) It minimizes the block like appearance called blocking artifact that results when boundaries between sub-images become visible [22].

The forward 2D-DCT transformation is given by the following equation:

$$(u,v) = D(u)\, D(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) cos\frac{[(2x+1)u]}{2N} \; cos\frac{[2y+1)v}{2N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where, u, v = 0, 1, 2, 3... $N-1$

The inverse 2D-DCT transformation is given by the following equation:

$$(x,y) = D(u)\, D(v)\, \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} D(u,v)\, cos\frac{[(2x+1)u]}{2N} \; cos\frac{[(2y+1)v]}{2N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

Where, D(*u*) = (1/*N*) 1/2 for u =0 and *D*(*u*) = 2(/*N*) 1/2 for ˘=1, 2, 3......., (*N* − 1)

3.3 Artifacts of Compressed/Decompressed Image

The Quality of image degradation of after compression is called artifacts. Block-based discrete cosine transform (BDCT) is adopted by widely used image compression standards, such JPEG, MPEG, and H-263, due to its high energy compaction and low computational complexity. Before BDCT, the image must be split into 8*x*8 blocks of pixels. If the data does not represent an integer number of blocks then the encoder must fill the remaining area of the incomplete blocks with some form of dummy data. Filling the edge pixels with a fixed color (typically black) creates ringing artifacts along the visible part of the border; repeating the edge pixels is a common technique that reduces the visible border, but it can still create artifacts. DCT is applied on such 8*x*8 blocks.

After the DCT, quantization is used to reduce the amount of information in the high frequency components. This is done by simply dividing each component in the frequency domain by a constant for that component, and then rounding to the nearest integer, which is the main lossy operation in the whole process. As a result of this, it is typically the case that many of the higher frequency components are rounded to zero, and many of the rest become small positive or negative numbers, which take many fewer bits to store. When using quantization with block-based coding, several types of artifacts can appear, including staircase noise along curving edges, ”mosquito noise” around edges, and blocking artifact[23].

The blocking effect is the most noticeable artifact associated with both JPEG and MPEG compression standards, which use the discrete cosine transform (DCT) coding. Other coding techniques that involve block partitioning, such as vector quantization, block truncation coding, and fractal-based compression also suffers from this artifacts. In block based coding schemes, blocking artifact arises since each block is encoded without considering the correlation between adjacent blocks.

3.4 Selection of Filter

The purpose of this work was to gain some insight into the process of filtering in compressed image. Filtering image data is a standard process used in almost all image processing systems. The goals vary from noise removal to feature abstraction and improvement of image quality. Linear and nonlinear filters are the two most utilized forms of filter construction. Knowing which type of filter to select depends on the goals and nature of the image data however; post processing algorithms are used to reduce the artifact present in compressed image. Both Block wiener filter and bilateral filters are used after image compression. In wiener filtering consist of filtering per a block, shift and the weighted average operations. Current research suggest that block based application of wiener filter reduce the blocking artifact of compressed image more efficiently. The block wiener filtering also has powerful results for smoothing the rough parts of the compressed image. Thus I choose bilateral and block wiener filter for the performance analysis in case of reduction of blocking artifact present in compressed image.

3.4.1 Bilateral Filter

The bilateral filter is a nonlinear filter that does spatial averaging without smoothing edges. It has shown to be an effective image denoising technique. It also can be applied to the blocking artifacts reduction. An important issue with the application of the bilateral filter is the selection of the filter parameters, which affect the results significantly. Another research interest of bilateral filter is acceleration of the computation speed.

The bilateral filter takes a weighted sum of the pixels in a local neighborhood; the weights depend on both the spatial distance and the intensity distance [1]. The bilateral filter is a filter used for artifact reduction and removal of blocking artifacts in compressed images. Bilateral filtering is done by calculating the weighted averaging of its neighboring pixels and modifies the current pixel values. The weights can be determined by using two parameters intensity and spatial distance. At a pixel location X = (x1, x2), the output of a bilateral filter can be formulated as follows:

$$\hat{I}\,(x) = \frac{1}{C}\ \sum_{y \in N(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}}\ e^{\frac{-||I(y)-I(x)||^2}{2\sigma_i^2}}\ I(y) \quad \ldots\ldots\ldots\ldots (3.3)$$

Where, σ_d and σ_i controls weighting average in spatial and intensity domain, N(x) is a spatial neighborhood of pixel I(x) and C is the normalization constant:

$$C = \sum_{y \in S(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}}\ e^{\frac{-||I(y)-I(x)||^2}{2\sigma_i^2}} \quad \ldots\ldots\ldots\ldots (3.4)$$

There are two parameters σ_d and σ_i that control the behavior of the bilateral filter. In case of compression artifact reduction, these parameters should be chosen carefully. When the σ_i value is less than the discontinuity amount, the filter is basically useless against eliminating the discontinuity. When σ_i is larger than the discontinuity amount, the discontinuity can be eliminated.

These observations tell us to measure the discontinuity amount along the block boundaries and adapt the value of σ_i accordingly. On the other hand, we would like to avoid over-smoothing texture regions. This could be done by first estimating the texture regions (through, for example, estimating the local variances), and then control the extent of smoothing by adapting the σ_d value. For a smooth region, the value of the σ_d can be large; otherwise, it should be small.

3.4.2 Block Wiener Filter

Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. Block based application of wiener filter become block wiener filter. In the statistical approach to the solution of the linear filtering problem, we assume the availability of certain statistical parameters (e.g. mean and correlation functions) of the useful pixel values of compressed image and blocking artifact. The wiener attenuation coefficients are given based on the estimated error in a block unit [24]. The wiener filter transforms images to be smooth, which is highly effective when difference between original images and compressed ones are large. In the proposed algorithm, the block wiener filter, used for decreasing a Gaussian noise, is modified to reduce the blocking artifacts. Our proposed method consists of the wiener filtering per a block, shift and the weighted average operations. The block wiener filtering has powerful results for smoothing the rough parts of the compressed image. The block wiener filtering also prevents losses on texture information. The dissipation of block boundary occurs by a combination of the shift and average operations. Accordingly, this de-blocking algorithm works well for the de-blocking of compressed image. The Block wiener coefficients are computed in 2D transform domain as follows:

$$W_m(x_n, y_n) = \frac{||C_m^{wie}(x_n,y_n)||^2}{||C_m^{wie}(x_n,y_n)||^2\ n + \sigma_{m,n}^2} \quad \text{(3.5)}$$

$C_m^{wie}(x, y) = H_m \hat{X}(x, y)$ ………………………..……………………………..……….. (3.6)

Where $\hat{X}(x, y)$ is de-blocked image, *Hm* denotes shifting DCT and is x_n and y_m $(0 \leq xn \leq 8, 0 \leq yn \leq 8)$ are ordinate and abscissa in n^{th} block of m^{th} *shifted* image. $\sigma_{m,n}$ is a variable depending on amount of the error in n^{th} block of m^{th} shifted image. In this filtering method, $\sigma_{m,n}$ is decided by the local error estimation. An error in the DCT encoded images differ appreciably from one block to another. The estimated error E(x, y) is calculated from the first denoised image as $E(x, y) = |\hat{X}(x, y) - Y(x, y)|$. $\sigma_{m,n}$ is defined as

$\sigma_{m,n} = \sum_{x_n=1}^{8} E_m(x, y)$ ……………………………………………….…………… (3.7)

Where $E_m(x_n, y_n) = Shift_{(i, j)}(E(x, y))$. The index m and selected pairs (i, j) are the same with $H_m(.)$.

3.5 Performance Analysis Tools

For the performance analysis of two filters, we consider the class of quality assessment (QA) methods that are full-reference (FR) QA, which compares the blocking artifact reduced (filtered) image with a reference (original) image.

3.5.1 Mean Square Error (MSE)

Mean square error measures the cumulative square error between the original and the compressed image. MSE has its merits and is widely accepted in image processing research, it only measures gray-level difference between pixels of the ideal and the distorted images without considering correlation between the neighboring pixels. Distorted images with equal MSE may have significantly different visual quality. A human observer always views an image as an entirety, rather than just a collection of isolated pixels, therefore correlation between neighboring pixels plays a role in the subjective judgment of image quality. As a result it, different type of signal processing procedures and noise interference can cause different perceptual effects, and the visual judgment is sometimes heavily dependent upon the degree of distortion.

Let I and I' be the original and the decompressed filtered images respectively, size of image is M×N then MSE is defined as:

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[I'(i,j) - I(i,j)]^2 \quad \text{(3.8)}$$

Where I'(i , j) and I(i , j) are the matrix element of the decompressed filtered and the original image at (i , j) pixel.

3.5.2 Peak Signal to Noise Ratio (PSNR)

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. PSNR is most commonly used to measure the quality of reconstruction of lossy image compression codecs. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. PSNR is basically a logarithmic scale of the mean squared difference between two sets of values (pixel values).so, define as:

$$PSNR = 10\log_{10}\left[\frac{max^2}{MSE}\right] \quad \text{(3.9)}$$

Where, max is the maximum pixel value of image and MSE is a Mean Square Error.

3.5.3 Structural Similarity (SSIM)

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. The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong interdependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. Therefore, a measurement of structural information change or structural similarity (or distortion) should provide a good approximation to perceived image quality. The SSIM metric is calculated on various windows of an image. The measure between two windows and of common size *N* is:

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad \text{...} (3.10)$$

Where, μ_x is an average of x, μ_y is an average of y, σ_x^2 is a variance of x, σ_y^2 is a variance of y, σ_{xy} is a covariance of x and y, C_1 and C_2 are two variables to stabilize the division with weak denominator. $C_1 = 0.01 \times M^2$ and $C_2 = 0.03 \times M^2$ where M is maximum pixel value.

4 METHODOLOGY

The main outcome of this project is to analyze the performance level of two different filters (Wiener Filter and Bilateral Filter) for the reduction of blocking artifacts present in lossy compression. We design the Wiener filter and bilateral filter as per their characteristics and optimized performance level.

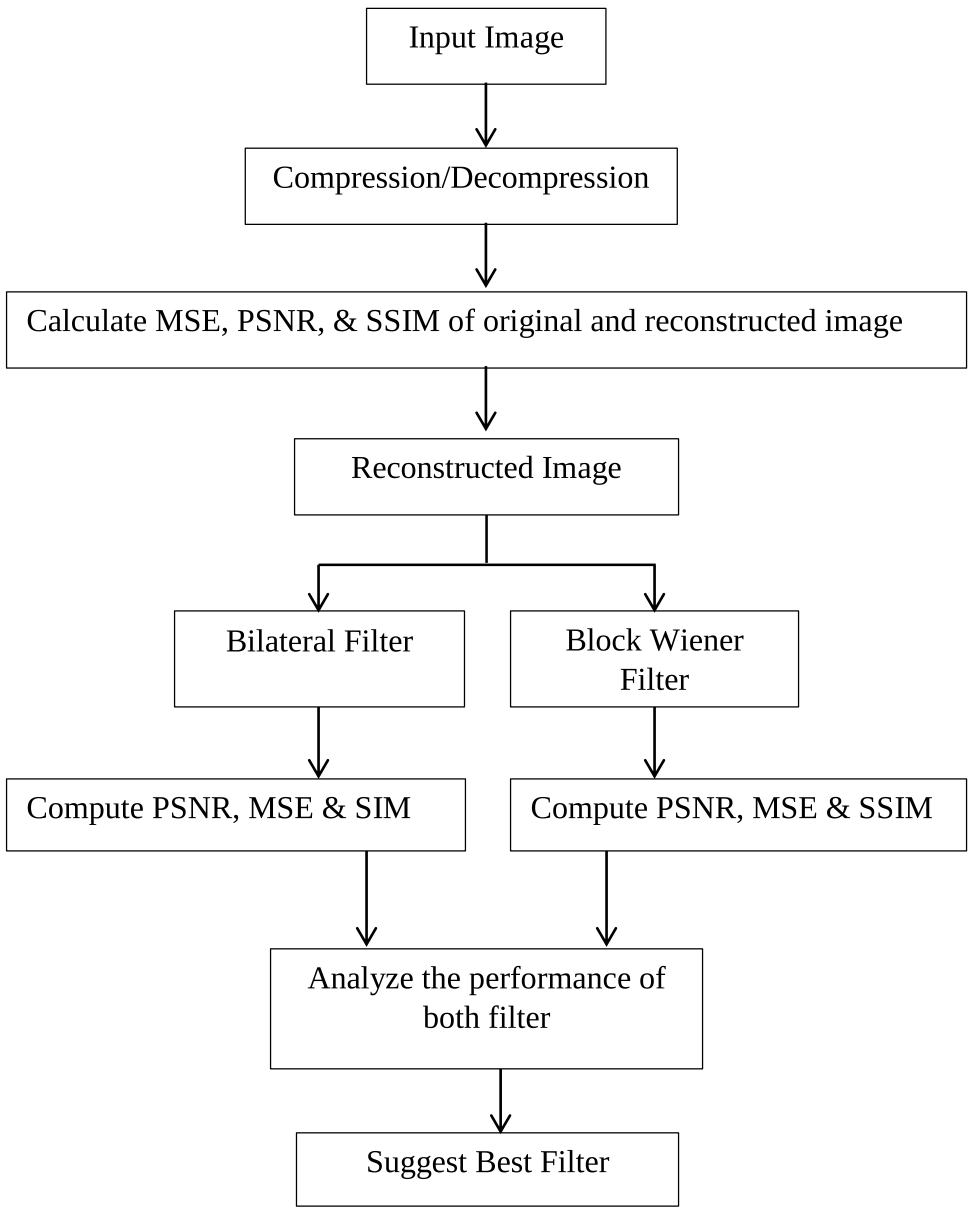

Figure 4.1 Functional flow diagram of methodology

First image is taken as input image then compressed/decompressed using JPEG method which use block based discrete cosine transform (DCT). In decompressed image present different type of artifact however blocking artifact is most crucial thus, it degraded the image quality. Now, blocking artifact present in image is reduced by Wiener filter and Bilateral Filter separately. Generally reconstructed image quality is evaluate using different tools such as PSNR and SSIM. The output of these two filters is analyzed using different tools such as Mean Square Error (MSE) Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM). Finally, comparing the result of two filtered (reconstructed) image, we got the best filter for reduction of blocking artifact.

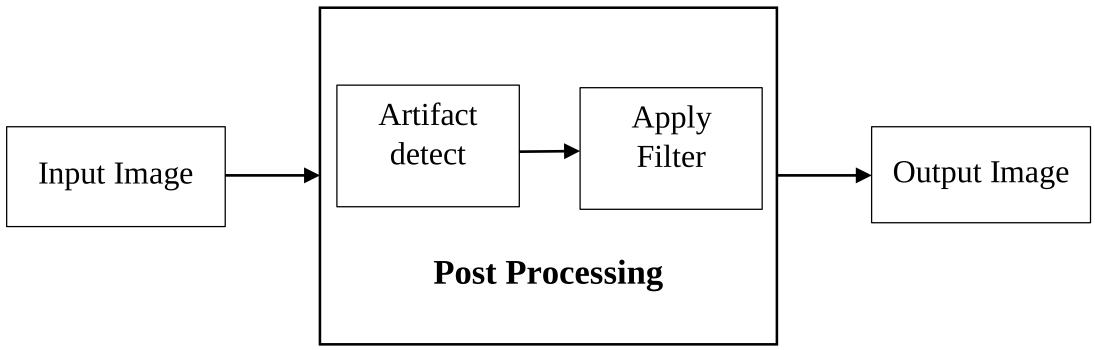

Figure 4.2 Block diagram of artifact reduction of compressed image

The post processing algorithm improves the image quality with reduction of different types of artifact present in compressed image. In general blocking artifact is most visible artifact present in block based compressed image. To reduce distortion of image due to compression use enhancement algorithm. Filtering method is post processing technique used in reduction of artifact.

4.1 Process of Image compression and decompression

At compression section each component is divided into 8x8 blocks, the value 128 is subtracted from each pixel and each block is transformed by DCT. The next step is quantization. The JPEC quantization is a sophisticated process that can effectively use a different quantizer for each coefficient in the 8x8 array. This process is one of the most significant contributor to the power of JPEC.

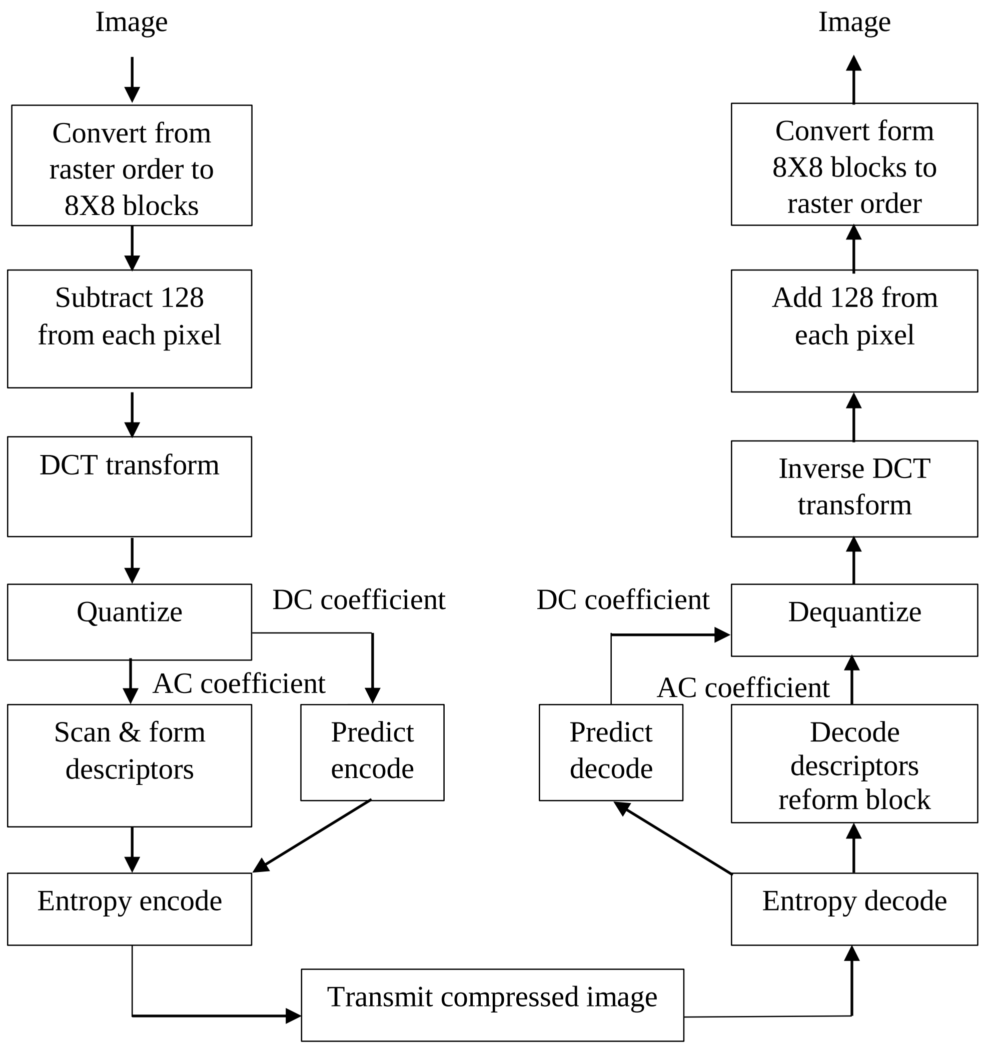

Figure 4.3 Simplified block diagram of image compression and decompression

The quantized DC coefficient is separated from the AC coefficients, and the sequence of DC coefficients is predictively encoded, and then entropy encoded. The quantized AC coefficients from a block are arranged and grouped to form descriptors. Like entropy encoding, this process is statistical, but at higher level. The process uses the known characteristics of DCT and the quantization matrix to arrange and group the coefficients into units that area particularly suited to entropy encoding. These units are given descriptors (which are just like symbols, but we usually use this word to form the alphabet of a DMS, which is fed to the entropy encoder. Together the descriptors from the alphabet of a DMS, which is fed to the entropy encoder.

The data stream form the entropy encoder is combined with various markers to indicate data types and boundaries; these also serve to aid resynchronization at the receiver in the event of data errors.

At the decompression section, the data stream is parsed to separate the different types of data. The entropy encoded data from each pixel block is decoded into descriptor which, together with the known descriptor definitions, allows the block of AC DCT coefficients to be reassembled. Separately, the stream of data representing the DC coefficients is decoded first by the entropy decoder, then by the predictive decoder, and the appropriate DC coefficient is associated with each group of AC coefficients. The next step is dequantization. As previously noted, this is poor name, as the process does not undo the effects of quantization. It does replace each quantized coefficient with the appropriate reconstruction value, taking into account the quantizer used for each individual coefficient.

All the coefficients of the block are now back in the correct range, the inverse DCT transform is applied, and 128 is added to each value to generate the block of received pixel values. These are reordered into the correct scan or file format, along with any other color components, and the process is complete.

4.2 An algorithm of Block Wiener Filter

step1:

Obtain a first de-blocked image for the wiener filter using DCT compression with its shifted cutdown version. The DCT transformed coefficients of m^{th} alignment are quantized as:

$$C_m\,(x,y) = H_m\,Y(x,y \qquad \text{……………………………………………….. (4.1)}$$

$$\hat{C}_m\,(x,y) = q(C_m\,(x,y)) \qquad \text{……………………………………………….. (4.2)}$$

$$\hat{X}_m\,(x,y) = H_m^{-1}\,\hat{C}_m\,(x,y) \qquad \text{……………………………………………….. (4.3)}$$

$$\hat{X}(x,y) = \frac{1}{M}\sum_{m=1}^{M}\hat{X}_m(x,y) \quad \text{……..……………………………….……….. (4.4)}$$

Where $C_m(x,y)$, $\hat{C}_m(x,y)$ and $\hat{X}(x,y)$ are respectively the transform coefficients due to H_m , the quantized coefficients and the m^{th} de-blocked estimate of X(x, y). Then we average all estimates so that the secondary blocking is diffused over all pixels.

step2:

Second step is almost same as Step 1 however, the quantization processing is replaced with the Wiener filtering which is derived from the first de-blocking image. The weighted average operation composes the final de-blocked image form combination of estimated images. It can be expressed as:

$$C_m^{wie}(x,y) = H_m\hat{X}(x,y) \quad \text{……………………………………….……….. (4.5)}$$

$$\hat{C}_m(x,y) = W_m(x,y)C_m^{wie}(x,y) \quad \text{……………………………………………… (4.6)}$$

$$\hat{X}_m^{wie}(x,y) = H_m^{-1}\hat{C}_m^{wie}(x,y) \quad \text{…………………………….……….. (4.7)}$$

The wiener filter uses the frequency of first de-blocking image $\hat{X}(x,y)$, and performs on block unit of 8 × 8 pixels.

4.3 Algorithm of Bilateral Filter

Bilateral filter is combination of two Gaussian filter. It does a weighted spatial averaging, where the weights depend on both spatial distances and intensity distances. There are two parameters which decide the performance of filter.

1. Parameter σ_i is linearly related average of the first 3x3 values from quantization table so, σ_i is calculated using empirical formula:

   $$\sigma_i = (Q_{av} * 0.3241) + 3.1530 \quad \text{…………………………….…….. (4.8)}$$

   Where Q_{av} is the average of first 3x3 values from the quantization table.

2. We set the value of σ_d at 2.0.

3. Calculate the normalization constant C from square window centered at given pixel location using formula:

$$C = \sum_{y \in S(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}} e^{\frac{-||I(y)-I(x)||^2}{2\sigma_i^2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.9)}$$

4. Finally determine the pixel value of Image using formula:

$$\hat{I}\,(x) = \frac{1}{C} \sum_{y \in N(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}} e^{\frac{-||I(y)-I(x)||^2}{2\sigma_i^2}} I(y) \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(4.10)}$$

4.4 Filter Parameters

In bilateral filter intensity parameter σ_i is calculated using empirical formula given in equation (4.8) where Qav is average value of first 3x3 window of quantization table and spatial parameter is σ_d set to be 2 as fixed value; this value is set after the experiment for different condition. Normalization parameter C is calculated using equation (4.9) taking square window centered at given pixel value.

In Block wiener filter, wiener filter coefficient $W_m(x_n, y_n)$ is calculated using equation (3.5) and $\sigma_{m,\,n}$ is decided by the local error estimation. The estimated error E(x, y) is calculated from the first denoised image as $E(x, y) = |\hat{X}\,(x, y) - Y(x, y)|$. Thus, $\sigma_{m,\,n}$ is aslo calculated using equation (3.7)

4.5 Data Collection and Analysis

Three different images (Lena, Cameraman and Buddha) were collected form internet as input image for simulation and analysis. These images were 256 x256 grayscale image. After the implementation of filters; compressed image has been filtered. A reduction of blocking artifact and improvement of image quality has been analyzed using different analysis tools (MSE, PSNR and SSIM). A higher value of PSNR means good quality of image and lower PSNR means worse quality of image, therefore calculation of PSNR provides information about image quality. In general image is combination of pixel values and their structure. The structural information is measured by SSIM.

5 RESULT, ANALYSIS AND COMPARISON

Bilateral and Wiener filter has been successfully simulated using MATLAB and demonstrate the performance of these two filter. It has been compared the output result of two filter using different (MSE, PSNR and SSIM) analyzing tools. The test images are Lena, Cameraman and Buddha which was taken from internet having 256 X 256 [pixel] 8-bit gray scale standard. For simulation propose, these images has been compressed using JPEG standard in different quantization level.

Figure 5.1 Test images (a) Lena, (b) Cameraman and (c) Buddha

5.1 Block Weiner Filter Response

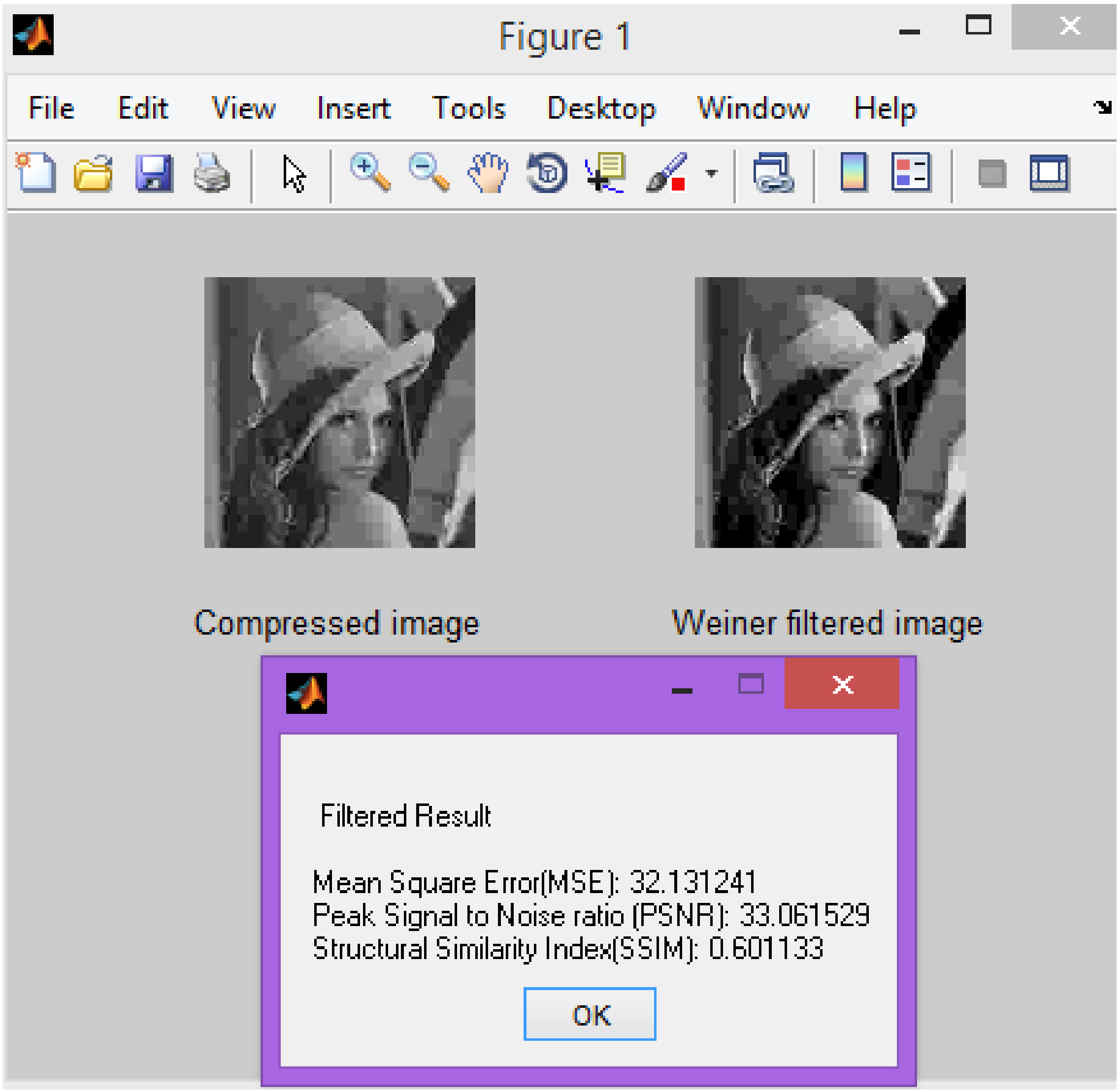

Figure 5.2 De-blocking results for Lena image at QF = 10

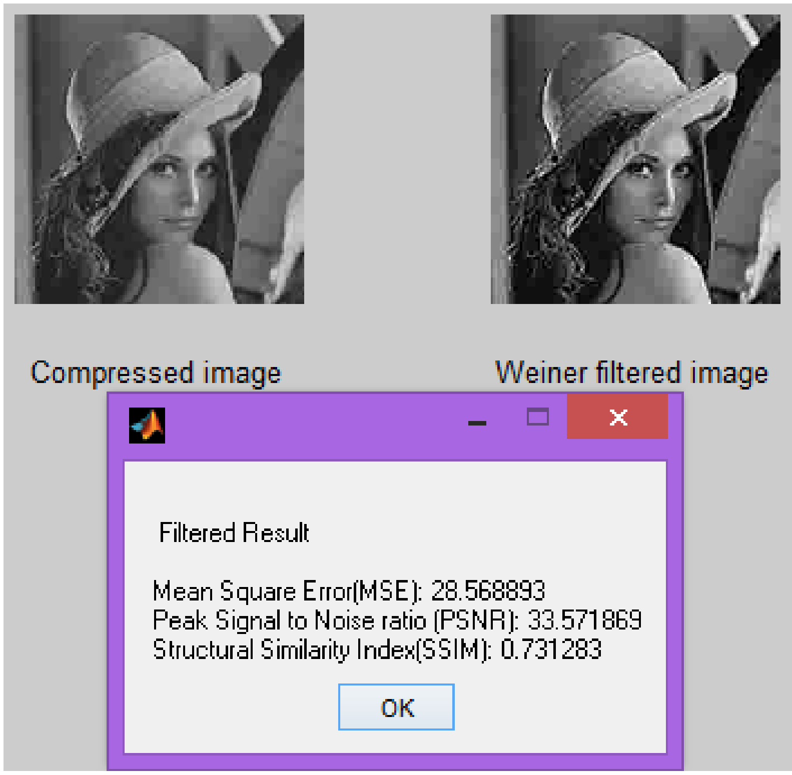

Figure 5.3 De-blocked results for Lena image at QF = 30

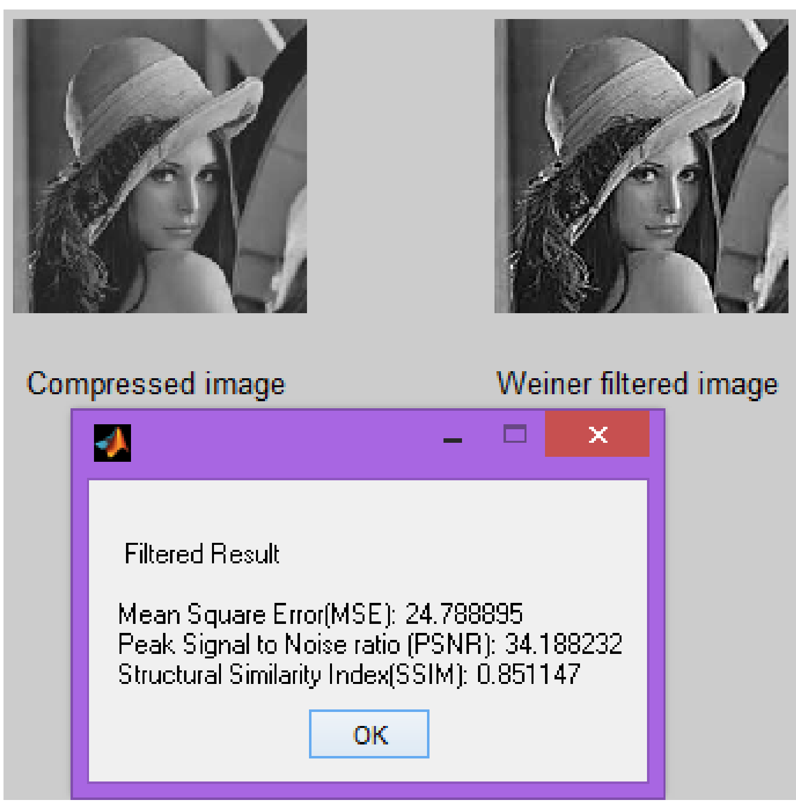

Figure 5.4 De-blocked result for Lena image at QF = 50

Table 5.1 PSNR, MSE and SSIM values of reconstructed image applying Block Wiener filter

Image	QF	MSE	PSNR	SSIM
Lena	10	41.187225	31.983178	0.629238
	30	36.004028	32.567293	0.766687
	50	33.118637	32.930079	0.841680
Cameraman	10	102.247223	28.034288	0.616205
	30	60.844284	30.288606	0.685022
	50	39.407608	32.175003	0.794491
Buddha	10	159.768997	26.095879	0.552449
	30	139.730545	26.677890	0.646723
	50	88.188217	28.676698	0.684611

Three different images Lena, Cameraman and Buddha has been taken for the experiment. All these image has been compressed at different quantization label 10, 30 and 50. The compressed images has been filtered using block wiener filter and Finally MSE, PSNR and SSIM values has been calculated using simulation tool; which are shown in Table 5.1 above.

5.2 Bilateral Filter Response

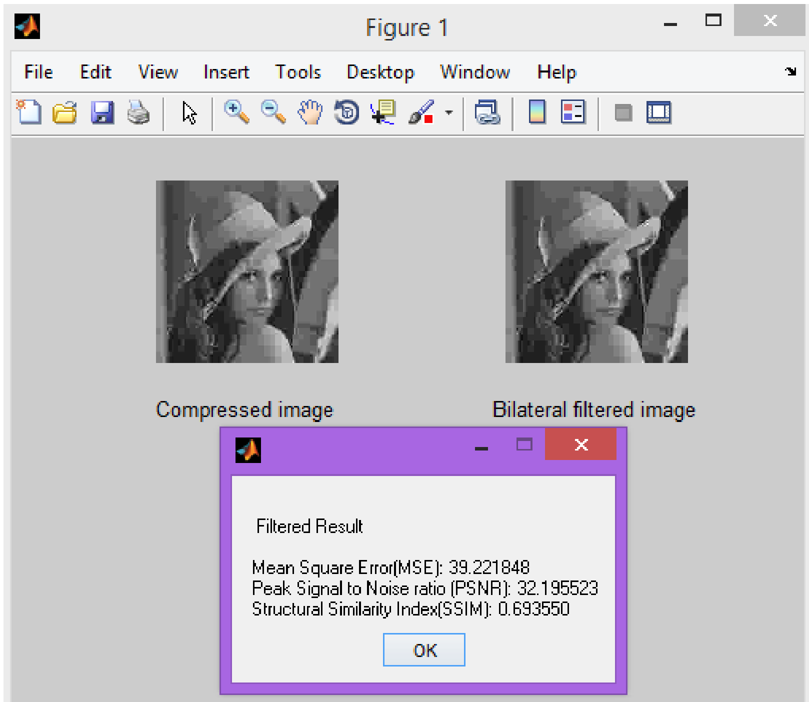

Figure 5.5 De-blocked result for Lena image at QF = 10

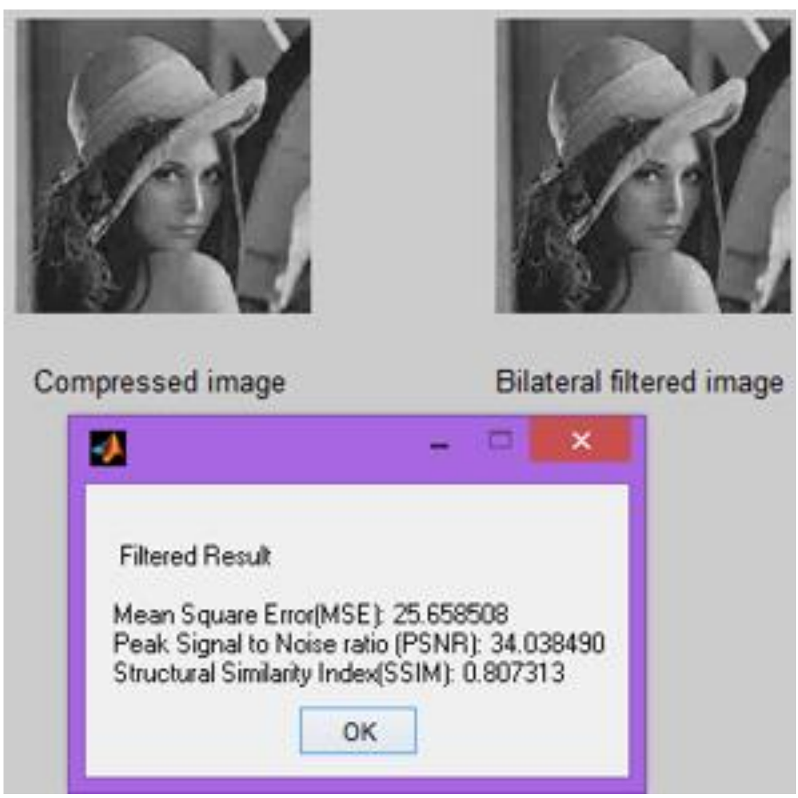

Figure 5.6 De-blocked result for Lena image at QF = 30

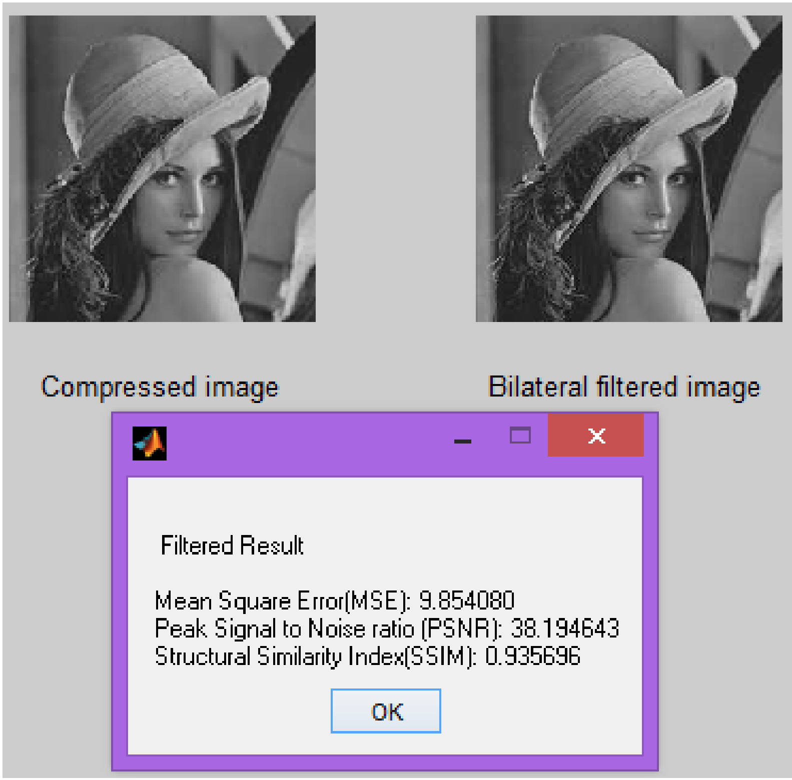

Figure 5.7 De-blocked result for Lena image at QF = 50

Table 5.2 PSNR, MSE and SSIM values of reconstructed image applying bilateral filter

Image	**QF**	**MSE**	**PSNR**	**SSIM**
Lena	10	39.221848	32.195523	0.693550
	30	26.478851	33.901812	0.798687
	50	9.854080	38.194643	0.935696
Cameraman	10	35.751602	32.597849	0.754431
	30	26.444229	33.907494	0.818560
	50	21.829971	34.740272	0.857831
Buddha	10	58.023972	30.494729	0.566994
	30	51.602783	31.004072	0.650549
	50	46.278290	31.477031	0.692033

Three different images Lena, Cameraman and Buddha has been taken for the observation. First all there images were compressed at different quantization label 10, 30 and 50. The compressed images have been filtered using bilateral filter. MSE, PSNR and SSIM values of filtered image has been computed using simulation tools and results are shown in Table 5.2 above.

After observing the results of Table 5.1 and 5.2 we came to conclusion that the performance of bilateral filter was better compared with wiener filter in all different quantization level of compressed image. Which has been demonstrated in bar chart given below:

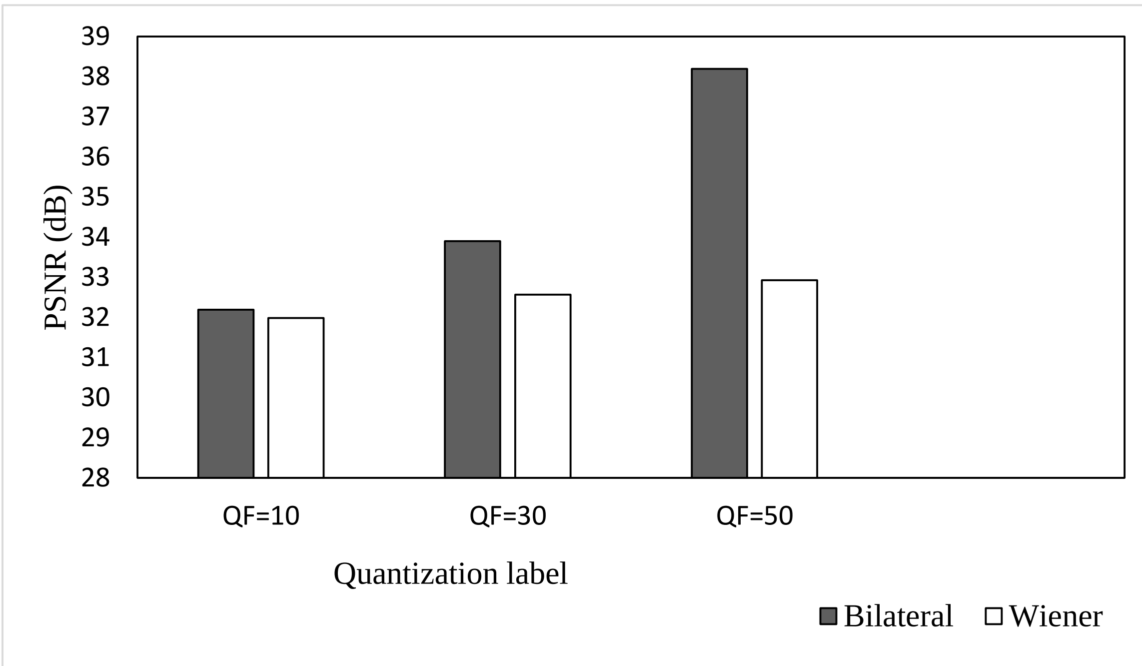

Figure 5.8 Bar diagram Showing PSNR value of reconstructed image (Lena) after applying filter

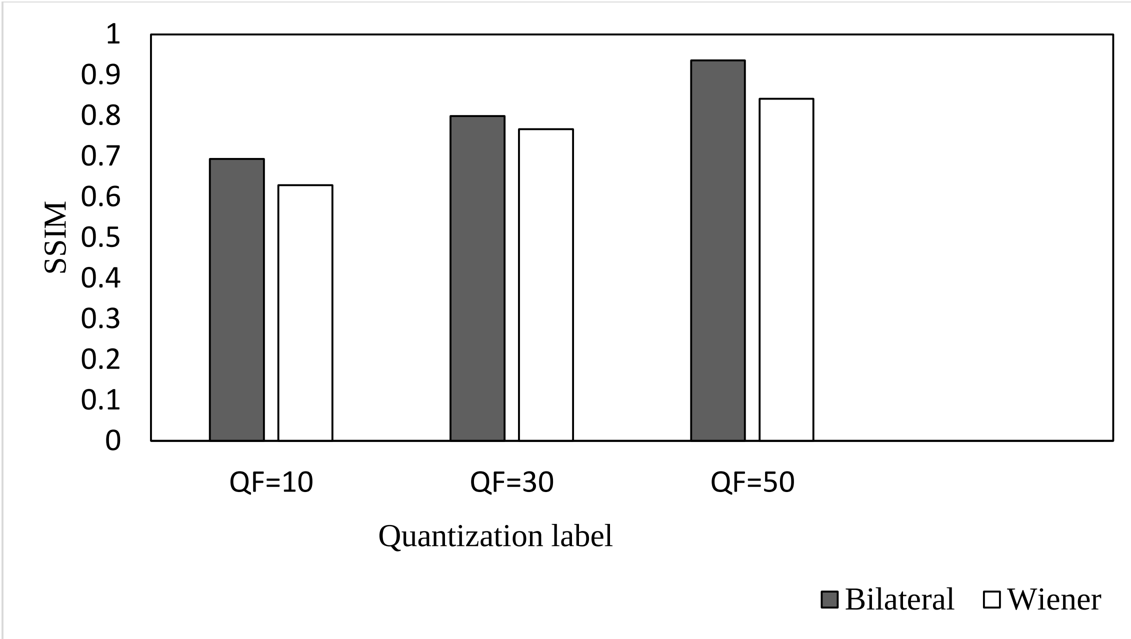

Figure 5.9 Bar diagram showing SSIM value of reconstructed image (Lena) after applying filter

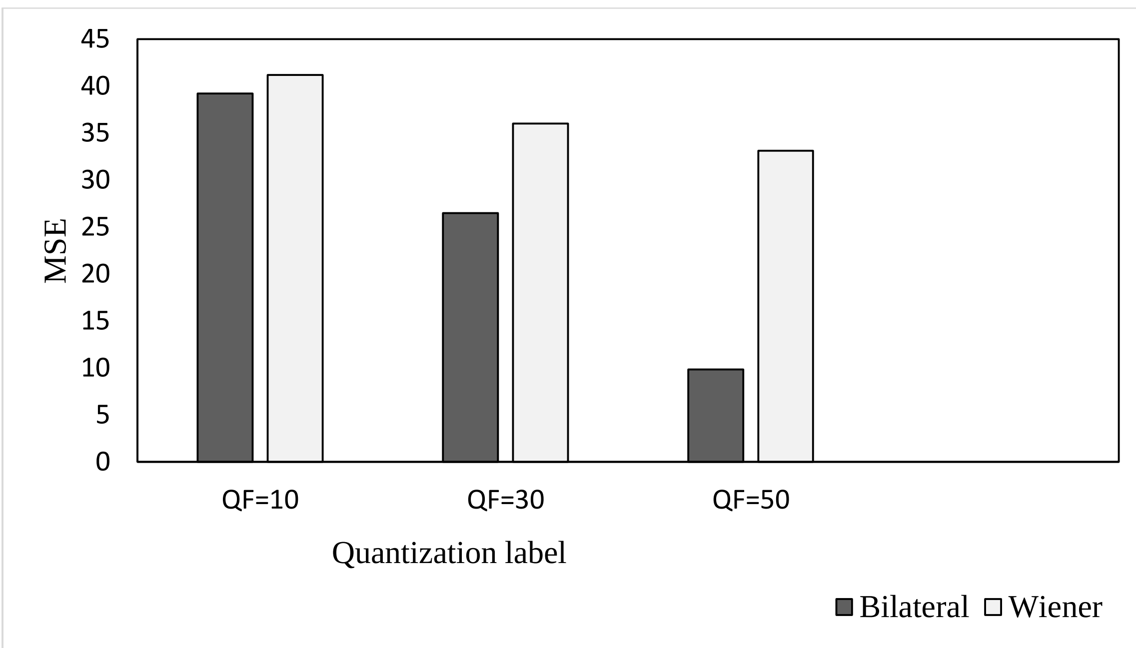

Figure 5.10 Bar diagram showing MSE value of reconstructed image (Lena) after applying filter

Here Figure 5.8, 5.9 and 5.10 shows the performance of two filter when input image Lena has been taken. From this bar diagram clearly shows that bilateral filter performance is better than block wiener filter.

6 EPILOGUE

6.1 Conclusion

The goal of this thesis is to explore the efficient blocking artifact reduction filter for reconstructed image. The two filter algorithm has been implemented and a blocking artifact present in the compressed image quality has been analyzed using two filtering method; first is a bilateral filter and second is a wiener filter. The MSE, PSNR and SSIM values for both filtering algorithm has been computed and plotted. From this result better performance has been given by bilateral filter compared with Block Wiener filter.

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