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Reduction of Blocking Artifact Based on Edge Information in DCT Coded Images

Graduate School of Chosun University
Department of Information and Communications Engineering

Ramesh Kumar Lama

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DCT 변환 영상에서의 에지정보를 이용한 디블록킹 알고리듬

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Advisor: Prof. Goo-Rak Kwon

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Ramesh Kumar Lama

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Acronyms

POCS	:	Projection onto Convex Sets
DCT	:	Discrete Cosine Transform
IDCT	:	Inverse Discrete Cosine Transform
BDCT	:	Block Coded Discrete Cosine Transform
SA-DCT	:	Shape Adaptive Discrete Cosine Transform
LPA-ICI	:	Local Polynomial Approximation – Intersection of Confidence Intervals
ISO/IEC	:	International Organization for Standardization/International Electro technical Commission
IEEE	:	Institute of Electrical & Electronics Engineers
PSNR	:	Peak Signal to Noise Ratio
MSE	:	Mean Square Error
DB	:	Decibel
JPEG	:	Joint Picture Expert Group
MPEG	:	Motion Picture Expert Group
RGB	:	Red Green Blue
HVS	:	Human Visual System
VLC	:	Variable length Code
QP	:	Quantization Parameter
HDTV	:	High Definition Television

초록

DCT 변환 영상에서의 에지정보를 이용한 디블록킹 알고리듬

Ramesh Kumar Lama
지도 교수: 권구락, 교수, **Ph.D.**
정보통신공학과, 대학원 조선 대학교

원영상은 저전송용 멀티미디어 통신을 위해 블록단위로 압축되어 진다. 부호화의 주요한 단점중 하나는 블록 경계면에 artifact 가 보이는 결과가 발생한다. 본 학위논문에서의 블록 경계 주위의 에지 화소수에 의해 두 가지의 모드를 지정하는 것이 제안 알고리듬이다. 에지 화소구는 로버트의 에지 필터를 적용하여 추정한다. 각 모드에서 적절한 필터링은 수평방향과 수직방향으로 수행한다. 첫번째 모드는 부드러운 영역에 할당한다. 변화가 없는 영역은 HVS 에 입각해 더욱 민감한 부분이다. 두번째 모드에서 적응적 저주파 통과필터를 적용한다. 이 필터는 블록 경계 주위의 픽셀 변화도를 기초으로 한다. Artifact 는 영상의 에지 성분을 보존하는 반면, 원하지 않는 왜곡된 부분의 도입없이 제거되어진다. 제안 알고리듬은 간단하고 공간 영역에서 수행하지만 실험 결과로는 여러 특성을 가진 영상의 주관적인/객관적인 화질을 향상하는 결과를 보인다.

I. Introduction

In the field of visual communication, image compression and coding plays key role to overcome the band width limitation of communication medium and storage space. Block Coded Discrete Cosine Transform(BDCT) has been widely used for image coding standards such as JPEG for still images, MPEG [1, 2] for moving pictures and H.26x for video phones and teleconference because much energies are packed into the smallest number of transformed coefficients and these coefficients are deco related with each other. One major drawback of BDCT is the visible degradation on image coded at low bit rate, because the inter block correlation is lost due to transformation and quantization. This annoying degradation is visible in block boundary and referred as blocking artifact. The nature of artifact may be different depending on the pixel characteristics of original image. In monotone region, the artifact called grid noise arises as false edge along the vertical and horizontal direction. Staircase noise occurs in the region with the strong distinguishable edges. During the transformation and quantization, the high frequency coefficients associated with the strong edge components may not be represented adequately. Furthermore, since each block is processed individually the continuity of the strong edge in coded image cannot be guaranteed. As a result the uniform edge in original image becomes visible as irregular appearance in reconstructed image. Textured noise also appears in textured region, such as collection of randomly oriented edges. Post processing is one of the effective solutions to improve the image quality before it is displayed because it can be implemented without any change in existing coding standard.

A. Thesis Motivation and Overview

Compression systems based on the Transform Coding operate on a block by block basis to exploit the spatial redundancy in images. Since each block is coded independently of other blocks, this scheme gives rise to artificial discontinuities often called blocking artifacts, at the block boundaries in low bit rate applications of image and video coding. Even though the overall imagery can easily be understood, the blocking artifact destroy the natural appearance of the image and greatly annoy the human viewer. Therefore, reducing blocking artifact is essential to increase the visual quality.

Reducing blocking artifacts, also called deblocking, is the process of reducing artificial discontinuity between the two blocks below the visibility threshold. This is done by modifying the pixel intensities on the sides of the block boundaries. However, several questions arise. Is the discontinuity at the block boundary completely artificial, or it is part of it also due to original signal in the image. How much reduction in the discontinuity is good? Is it sufficient to modify only pixel next to block boundary or do we also need to change pixel intensities in the interiors of block boundary? Finding answers to all of these questions is difficult if only the image content is not studied prior to deblocking. However, if the edge detail of the image is available, then much better answers can be provided because the type of filter operation can be defined according the nature of the image region.

B. Research Objectives

In real time applications it is difficult or impractical to make the original image available in decoder side to reconstruct the coded image without any error. That is the post processing method is one of best option to reconstruct the coded image without any change in existing coding standard. Since artifact will be visible in block boundary as false edge it is the primary concern to filter these noises.

However, the image contains high frequency components as edge that must be preserved while filtering artifacts. Furthermore edge persevering measures should also be taken into account for more efficient reconstruction of coded images.

The major objective of this carried research is to study the limitations and issues in blocking artifact reduction algorithms and to suggest some techniques and algorithms which could improve the performance in terms of artifact filtering and preserving the original contents of image.

C. Thesis Contribution

In this thesis, a new algorithm for block based DCT coded image is presented. This algorithm is called edge information based algorithm. It was designed to reduce the blocking artifact present in DCT coded images which is caused by the de correlation of DCT coefficient after the quantization process. This thesis surveys algorithms that have already been proposed. Important algorithms that are proposed in the literature and designed for DCT coded image to reduce blocking artifact are identified and explained in this thesis. The main contributions of this thesis are as follows:

New Algorithm: A new algorithm is designed for the DCT coded images with two main features: artifact reduction in block boundary and preserve the original edge information of image.

Design Procedure: A design procedure is given in order to find the important parameters of this algorithm. For a given application with its specifications and requirements, an engineer can follow the steps in this procedure to find the important parameters and also the appropriate number of phases in this algorithm.

Simulation: A simulation code was written in Mat lab R2009a to test the performance of this algorithm and compare with other algorithms.

D. Thesis Organization

The remainder of this thesis is organized in modular chapters. Chapter II presents overview of the image and video coding and the related works that have already been carried out. Chapter III shows the main features and algorithms for this proposed algorithm of this research work. Chapter IV demonstrates the reduction of blocking artifact present in DCT coded image achieved by proposed algorithm through simulation result. Thesis is concluded in the last chapter with wrapping text for the summary of this research.

II. Background

This chapter is devoted to the background necessary for discussing the work in this thesis. Section II.A presents definitions used in image and video coding, and provides the overview of fundamentals of image and video coding. Section II. B summarizes the related works that are done for the reduction of blocking artifacts.

A. Overview of Image and Video Coding

One goal of the image compression is to represent an image with as few bits as possible. The reduction in bit rate is achieved by exploiting the redundancy and irrelevancy present in the image. Sources of redundancy are

- Color space: RGB components are correlated among themselves.
- Spatial: Nearby pixels are often correlated with each other.

Among various compression methods, Transform Coding is widely used. In this section we explain how compression system based on Transform Coding exploit the above mentioned redundancies and outline the basic structure of a typical image compression system based on Transform Coding.

The redundancy in the RGB components is exploited by converting RGB values to luminance-chrominance values, such as YIQ. In the YIQ domain there exists less correlation among the components for better approximation of original data upon compression. Furthermore, most of the high frequency content of the image is packed into the luminance component, leaving the chrominance component with significantly smaller amount of high frequency content. Therefore, down sampling the chrominance component does not seriously affect the high- frequency details of a color image and allows coding of a smaller number of samples than in RGB domain.

The redundancy in the spatial domain is evident from the fact that pixel intensities of each of Y, I, Q components in a small spatial region are highly correlated. A transform that decorrelates pixel intensities in this small spatial region (e.g. 8×8 blocks) and packs the energy in as few coefficients as possible would be ideally suited for this task, because in this case a good approximation to the original data would be possible by coding only the few high energy coefficients. The Discrete Cosine Transform (DCT) is widely used in practice. For most of natural images, the DCT is also shown to be very effective for decorrelation and energy compaction. In particular, the DCT results in high energetic low spatial frequency components for most natural images since they group significant low frequency content. Furthermore, fast algorithms for the computation of the DCT are available. The transform idea is the heart of compression systems based on Transform Coding.

After the transformation step, the resulting transform coefficients will have a significant portion of their energy compacted in a small fraction of the coefficients. For compression purposes, not only can we discard low energy coefficients but we can also reduce the representation accuracy of the high energy coefficients. This can be done by quantizing the transform coefficients. Quantization is a lossy operation, that is, it is irreversible. Quantization is an essential part of image compression systems since it also exploit some Human Visual System (HVS) features enabling further compression. In particular, consider the quantization of only one specific transform coefficient; if we go from very fine quantization to very coarse quantization, there will be a specific quantization interval up to which the reconstructed image data will be indistinguishable from the original for the HVS. Hence, by selecting the quantization interval in light of this observation, more compression can be achieved. It should also be noted that different transform coefficients have different perceptual importance for the HVS. As a result, different quantization intervals can be associated with different transform coefficients. For example, high spatial frequency coefficients of the DCT may be quantized more coarsely than low spatial frequency of the DCT.In light of the above discussions, the basic structure of a typical image compression system can be given as follows: first the acquired image in the RGB domain is converted to the YIQ domain and I and Q down sampled by a factor of 2, both in the horizontal and vertical direction. Then, each of the resulting components undergoes block- based DCT with a block size of 8×8 pixels. In other words, each of the components is divided into pieces of 8×8 blocks and each block is transformed using the DCT resulting in 64 DCT coefficients for each block. Let $B(i,j)$ be the block of size 8×8, and then corresponding block of transformed coefficients $T(u,v)$ is given as:

$$T(u,v) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} B(i,j) g(i,j,u,v). \qquad (2.1)$$

for $u, v = 0,1,2 \ldots \ldots \ldots . N-1.$

Where,

$g(i,j,u,v)$ is the forward transformation kernel. This is given by

$$g(i,j,u,v) = \alpha(u)\alpha(v) cos\left[\frac{(2i+1)u\pi}{2N}\right] * cos\left[\frac{(2j+1)v\pi}{2N}\right]. \qquad (2.2)$$

And

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{N}} & for\ u = 0. \\ \sqrt{\frac{2}{N}} & for\ u = 1,2 \ldots . N-1. \end{cases}$$

Next, for each block, quantization of DCT coefficients is performed using a quantization table specifying possibly different quantization intervals for each of the 64 DCT coefficients. The quantization tables used for luminance blocks and chrominance blocks might be different as well. Many of the 64 DCT coefficients in a block may be quantized to zero. Furthermore, for most blocks, the nonzero quantized coefficients will reside in the lower spatial frequency region. To take advantage of these facts and also exploit all remaining statistical redundancy, entropy coding schemes are used. Common practice is to scan one block of quantized DCT coefficient in zigzag fashion starting from lowest spatial frequency coefficient to the highest spatial frequency coefficient. The resulting string of quantized coefficients undergoes run length encoding. Run – length encoding produces symbols that carry two pieces of information: number of zeros in the run, and the nonzero value that terminates the run. These symbols are coded using variable- length-codes (VLC). Huffman codes are the most frequently used VLCs. Arithmetic codes are another choice. Figure 2.1 shows all of these steps graphically. To reconstruct the image at the decoder, reverse of these steps must be performed.

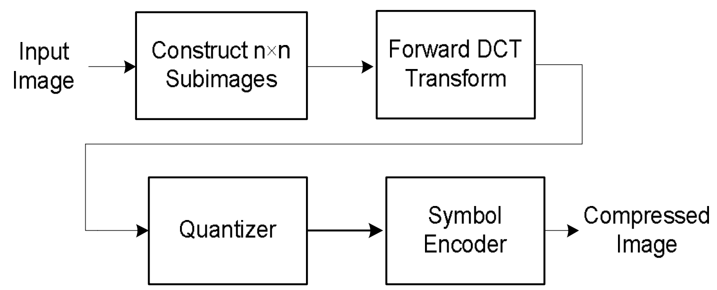


Fig. 2.1 Image compression and coding

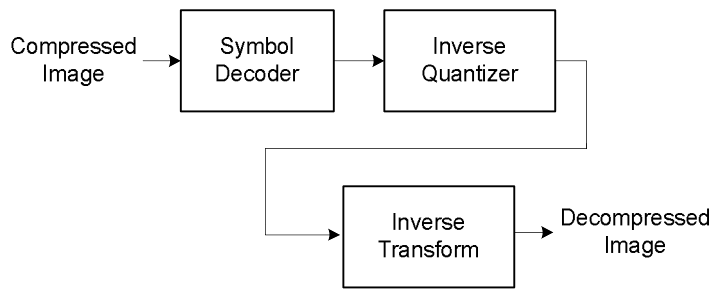


Fig. 2.2 Image Decoding

On the decoder side, the reconstruction of image is performed in three steps: symbol decoding, de quantization, and inverse transform, as given in Fig.2.2, the compressed image is first entropy decoded, then de-quantized by multiplying the coefficient by quantization parameters and inverse transformed to spatial domain by inverse discrete cosine transform (IDCT) defined as:

$$B(i,j) = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} T(u,v)h(i,j,u,v). \tag{2.3}$$

for $u, v = 0,1,2 \dots\dots\dots. N-1.$

Where,

$h(i,j,u,v)$ is the inverse transformation kernel. This can be defined as:

$$h(i,j,u,v) = \alpha(u)\alpha(v)cos\left[\frac{(2i+1)u\pi}{2N}\right] * cos\left[\frac{(2j+1)v\pi}{2N}\right]. \tag{2.4}$$

Now, each block of an image is reconstructed by weighted sum of the DCT coefficients that corresponds to the specific spatial frequency contribution.

B. Related Works

Numerous post processing techniques have been proposed in order to reduce such blocking artifacts. Fundamentally they are classified into two categories. First one is iterative and the next is non iterative.

The theory of projection onto convex sets (POCS) is the basis for iterative scheme. Zakhor[4] first applied the theory of POCS for the reduction of blocking artifact. In this method, two different convex sets of band limited images and images with block of coefficients lying under the specific quantization intervals are defined. Now iterative procedures are applied the image that lies within the intersection of these two defined convex sets. Each of iteration consists of two steps. In first step, low pass filter is applied. While in the second step, image is divided into N×N blocks and DCT of each block is taken. Now, these DCT coefficients outside their quantization interval are projected onto its appropriate level. If we want the deblocked image to satisfy several properties, we have to define several convex sets. The desired deblocked image can then be found after several iteration of projection. Since convergence of projection is not guaranteed in a single iteration and each of the iteration consists of low pass filtering together with DCT and IDCT operations Iterative based approach requires heavy computational burden. That is why it may not be the appropriate solution in real time image and video processing even though the result is good.

In non iterative approach spatially adaptive low pass filters are used, which are relatively simple to implement and fast however real edges are unnecessarily blurred at the block boundaries. Algorithm [5] applies weighted sums on pixel quartets, which are symmetrically aligned with respect to block boundaries. The weights are obtained from a two dimensional function obeying predefined constraints. This algorithm gives good result in the subjective and objective quality; however it is based on iterative algorithm with requirement of heavy computational cost. [6] is based on edge statistics residing across the neighboring blocks, first block discontinuity is analyzed statistically, the discontinuity is approximated and filtered by controlling the filter strength according to contents of the block. [7]-[8] try to reduce the blocking artifacts in different filtering modes, and the mode of filter is determined in terms of activity across the block boundaries. In former algorithm, filtering is done in three different modes smooth, complex and intermediate. It gives good result in smooth region how ever in complex region, the real edge gets unnecessarily blurred. In later algorithm, filtering is performed in two different modes smooth region mode and default mode. In [9] an adaptive approach is proposed, which performs blocking artifact reduction in both the DCT and spatial domains. It handles the coefficients in both pixel and DCT domain. A given input image needs to be transformed to DCT domain and again back to image space. [11]-[12] suggest the use of rational filter for deblocking. Ratio of polynomials is used to determine the weight of these filters and they are adapted according to local characteristics.

The new technique [16] based on shape adaptive DCT together with anisotropic local polynomial approximation (LPA-ICI) was proposed by A. Foi. For each point in the image, the LPA–ICI provides a set of directional adaptive neighborhood adaptively. Because of the non parametric nature of the procedure, neighborhoods corresponding to adjacent points are usually overlapped. Window size of corresponding neighborhood defines the shape of the transform window in point wise manner. The underlying signal within this neighborhood is uniform in nature. The LPA- IC is based on the convolution and is fastest point wise adaptive methods for robust anisotropic filtering. For each one of these neighborhoods, shape adaptive –DCT is performed. SA-DCT is 2-D ortho normal transform based on 1-D DCT that can be applied on the arbitrarily shaped region. The hard-threshold SA-DCT coefficients are used to construct a local estimate of signal within the adaptive shape support. By using the adaptive neighborhoods as support for SA-DCT that data are represented sparsely in the transform domain, allowing separation of signal effectively from noise. This method for the reduction of blocking artifact is more accurate and allows the adaptation of the finest structure in image, due to which this algorithm has gained superiority in both of the subjective and objective quality of image. However, the algorithm goes though the complex masking operations of LPA–ICI and several iteration of DCT transformation together with thresholding and Weiner filter operations in DCT domain. These operations lead to the huge computational complexity. Due to which this method may not be appropriate for low speed devices.Some methods reduce blocking artifact using the wavelet domain representation of images. These methods start by transforming the compressed image with blocking artifacts to wavelet domain. Then, the wavelet coefficients related to block boundaries with blocking artifact is modified. The algorithms to modify these coefficients differ between the various methods based on wavelets and they are most distinguishing feature between these methods.

In [21], an over complete wavelet representation is used. In other words, wavelet representations in all scales have the same number of coefficients as the image with blocking artifacts. First, an edge map is created using the correlation of wavelet coefficients across the scales. Locations above a threshold are identified as edges. Then, wavelet coefficients at non edge location are set to zero while coefficients are edge locations are untouched. Finally, the low pass component is averaged at the block boundary locations with its neighbor. The inverse wavelet transform using the modified coefficients gives the deblocked image.

III. System to Reduce Blocking Artifacts

In this chapter, we describe a system to reduce blocking artifacts based on edge information. The proposed algorithm attempts to reduce the blocking artifact by studying the pixel behavior around the block boundaries of each region.

A. Overview of the proposed algorithm.

The proposed algorithm performs the deblocking operation on reconstructed image in two separate modes, Smooth and complex mode. A mode decision algorithm is applied according to the nature pixel activity around the block boundary before performing any deblocking operations. The observation illustrates the characteristics of affected local regions by the blocking effect. Based on the information gathered, appropriate type of filtering operation will be selected for each region. Strong filtering is suggested to be applied in the flat area of block boundary, whereas weak filter is to be applied in the complex region. Since, the complex region consists of edge pixels, in order to preserve the original details, statistical behavior of edge pixels around the block boundary is analyzed then the filter appropriate for this region is applied. This algorithm consists of four major functional steps.

1. Edge detection with Roberts’s mask and mode selection.
2. Offset based strong filtering in smooth region and
3. Filtering in complex region.

B. Edge Detection and Mode Selection.

Let **I** be an image of size **R×C,** where **R** and **C** represents the number of rows and columns of image. The given image is divided into 8×8 non overlapping blocks. For simplicity, deblocking operation is explained only for horizontal direction. Let $\mathbf{B_1}$ and $\mathbf{B_2}$ are two adjacent blocks. A new block **B** is constructed by taking right half of block $\mathbf{B_1}$ and left half of block $\mathbf{B_2}$ as shown in Fig.3.1

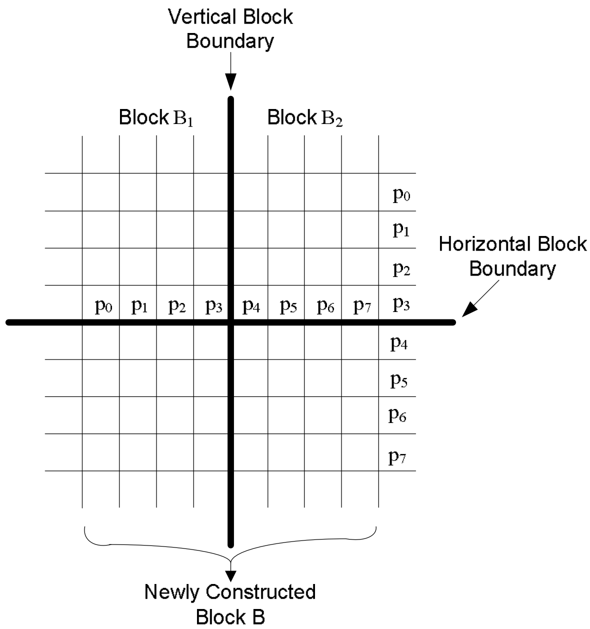


Fig. 3.1 Vertically adjacent blocks $\mathbf{B_1}$, $\mathbf{B_2}$ and newly constructed block **B.**

Since, the proposed algorithm is based on the edge information. An edge is a set of connected pixels that lie on the boundary between two regions with relatively distinct gray levels. Edge components present in any image can be detected by the computation of derivatives or the gradients. The common method used for the computation of gradient is Roberts's operator. Roberts's operator can be defined by two kernels, $M_h(i,j)$for horizontal direction and $M_v(i,j)$ for the vertical direction. Horizontal and vertical gradient images $G_h(i,j)$ and $G_v(i,j)$ are obtained by linear convolution of given image with Roberts kernels as.

$$G_h(i,j) = B(i,j) * M_h(i,j). \tag{3.1}$$

$$G_v(i,j) = B(i,j) * M_v(i,j). \tag{3.2}$$

$$G = |G_h| + |G_v| \tag{3.3}$$

Here, G gives the edge magnitude or the maximum rate of increase of $B(i,j)$ per unit distance.

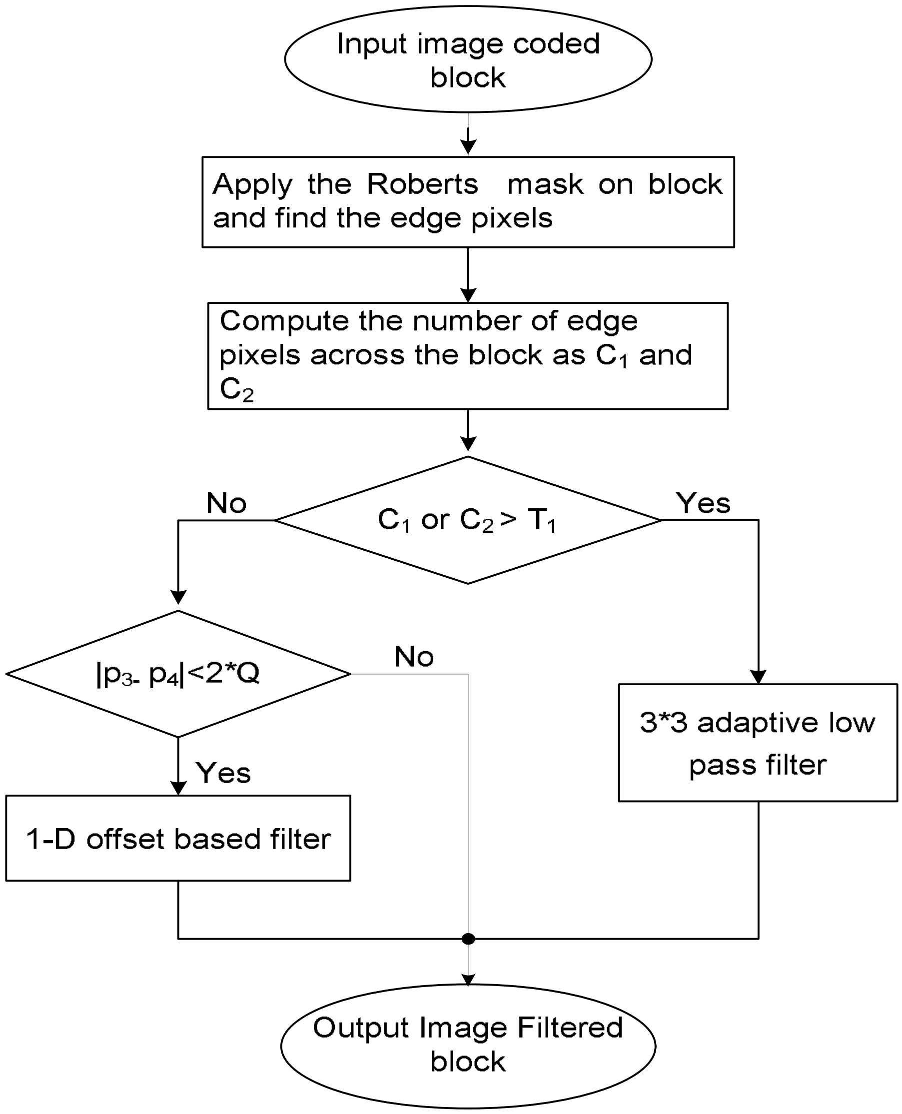


Fig. 3.2 Flow chart of the proposed algorithm.

Appropriate pixels are selected as edge pixels if they satisfy the edge magnitude consistency. That is, we compare the gradient pixel G with a threshold value T and the pixel is selected as edge pixel if it is greater than or equal to T. The numbers of edge pixels on either side of block are counted by edge counters C_1 and C_2. C_1 represents the number of edge pixels in block B_1 and C_2 represents for block B_2. The computation of C_1 and C_2 is given as follows.

$$C_1 = \sum_{i=0}^{\left(\frac{N}{2}\right)-1} \emptyset(G_i). \tag{3.4}$$

$$C_2 = \sum_{i=\frac{N}{2}}^{N-1} \emptyset(G_i). \tag{3.5}$$

Where, G_i represents the gradient pixel obtained after the Roberts filer operation in i direction and the function $\emptyset$ represents the comparison operation of gradient pixel with threshold value T, which can be described as:

$$\emptyset(G) = \begin{cases} 1\ if & G \geq \mathrm{T} \\ 0, & otherwise. \end{cases} \tag{3.6}$$

The major operation performed for the reduction of blocking artifact is smoothing operation. Different types of smoothing operations are performed on each block based on the nature of the pixel activity inside the block. The nature of smoothing operation is determined according to number of edge pixels C_1 and C_2 residing across the block boundaries. If both side of the block B contains edge pixels less than certain threshold value T_1 then this region is assumed as the monotone region.

C. Filtering in Smooth Region

Since the blocking artifact is more visible in smooth region as false edge along the vertical and horizontal directions. The human eye is more sensitive to such discontinuities, so the deblocking filter is designed to improve the visual quality of image. The pixel intensity is abruptly changed in this region which can be modeled as shown in Fig, 3.3(a). In order to reduce such artifacts simple offset based filter is used. The coefficients of the filter are shown in Fig. 3.3(b).

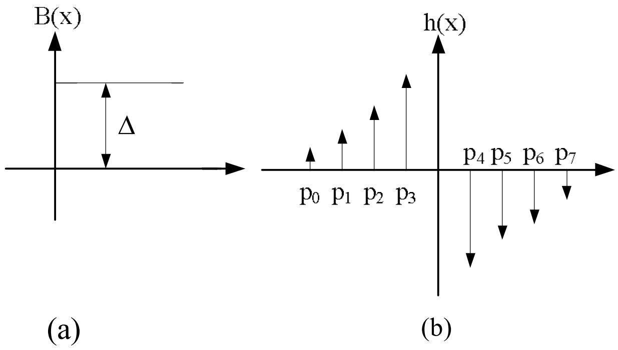


Fig. 3.3 Blocking artifact and it’s deblocking. (a) Blocking artifact in smooth region. (b) Filter coefficients applied in smooth region.

First, offset Δ is determined by taking the difference between two pixels across the block boundary. Since this offset significantly influences the blocking effect. Pixels are updated based on the offset values and the filter coefficients. The value of filter coefficients h = [0, 1/8, 1/4, 1/2,-1/2,-1/4,-1/8, 0] as shown in Fig. 3.3(b). Steps involved in filtering in horizontal direction are as following equation.

$$
\begin{aligned}
\Delta &= |p_3 - p_4|. \\
p_{1,j} &= p_{1,j} + (\Delta/8). \\
p_{2,j} &= p_{2,j} + (\Delta/4). \\
p_{3,j} &= p_{3,j} + (\Delta/2). \\
p_{4,j} &= p_{4,j} - (\Delta/2). \\
p_{5,j} &= p_{5,j} - (\Delta/4). \\
p_{6,j} &= p_{6,j} - (\Delta/8).
\end{aligned}
\tag{3.7}
$$

Total six pixels are updated across the block boundary. The block boundary may also contain the original edge. In order to preserve the original edge from unnecessary blurring, smoothing operation is performed only if Δ is less than a minimum value quantization parameter Q, which ranges from (50 –110) in our simulation. It is because the offset related to blocking artifact is smaller than quantization parameter. Newly computed pixel values are adjusted between 0 and 255. Smoothing operation in vertical direction can be done in the same way as horizontal direction. Only the difference is computation is performed in vertical direction.

D. Filtering in Complex Region

After the deblocking operation in smooth region, our next task is to reduce the artifact in complex region. Any region in image is identified as complex region containing edge pixels, if either side of the block boundary consists of edge pixels greater than threshold value T_1. In order to preserve the original edge from unnecessary blurring and enhance details and reduce the noise, the statistical behavior of the edge pixels is analyzed first then appropriate filter is applied. Since, the noise produced in the complex region varies according to pixel characteristics in original image. The regions containing strong edges are suffered from corner outlier and staircase noise. On the other hand, regions with the random distribution of pixel intensities are suffered from textured noise. The filter designed for corner outlier may not produce the good result for textured noise and vice versa, so an adaptive low pass filter based on bilateral filter is designed with the consideration of preserving the original edge content and enhancing the details of original image while reducing the artifact.

D.i. Bilateral Filter

Bilateral filter is a nonlinear filter that smoothes the noise while preserving edge of an image. The shift-variant filtering operation of the bilateral filter is described as.

$$P'(p_0) = C^{-1} \sum_{p \epsilon N(p)} e^{\frac{-|p-p_0|^2}{2\sigma_d^2}} e^{\frac{-|I(p)-I(p_0)|^2}{2\sigma_r^2}} P(p) \tag{3.8}$$

Where σ_d and σ_r are parameters to determine the smoothness. If σ_r is set to zero, the bilateral filter is reduced to a simple Gaussian smoothing filter. $N(p)$ is a spatial neighborhood of pixel p_0 , and C is the normalization constant to maintain zero-gain for the output image.

$$C = \sum_{p \epsilon N(p)} e^{\frac{-|p-p_0|^2}{2\sigma_d^2}} e^{\frac{-|I(p)-I(p_0)|^2}{2\sigma_r^2}} \tag{3.9}$$

The basic idea underlying bilateral filtering is to do in the range of an image what traditional filters do in its domain. Two pixels can be close to one another, that is, occupy nearby spatial location, or they can be similar to one another, that is, have nearby values, possibly in a perceptually meaningful fashion. A low pass filter of 3×3 window size is applied based on the fundamental idea of bilateral filter is applied in the complex region. With the application of this filter pixels around the block boundary are filtered with the minimal lose of original detail. The filter specifications are as follows. First the coefficients of mask are computed. Let $P_{i,j}$ be the pixel to be filtered and $S_{k,l}$ represents the coefficient of mask. Before the computation of filter coefficients, gradient of pixels within the region of mask is determined as:

$$d_{i,j} = \left| p_{i,j} - p_{i+m,j+n} \right|_{\mathrm{m}=-1 \text{ to } 1,\ \mathrm{n}=-1 \text{ to } 1.} \tag{3.10}$$

In a discrete image, the difference of the gray values on pixels in outer area is larger than that in inner area. In same area, the change on centre pixels is smaller than that on edge pixels. The gray gradient is direct ratio to the gray difference in vicinity. That is, where the gray change is slower, the gradient is smaller. A function whose value reduces with the increase of the gradient is adopted, and it is chosen as the weight of the window. So, the smoothing contribution is mainly coming from the same area. Accordingly the edge and the detail cannot be lost apparently after image smoothing. In designing gradient-selected filters, power and exponential function are often chosen as weighting function. Especially when the power is equal to –1, the filtering is called gradient reciprocal weighting filtering. When the function is the exponential one, the filtering is called adaptive filtering. When we extract lines from remote sensing images, the adaptive filtering is often adopted in pre-processing to realize the aim of noise removal and edge enhancement. It can be described as:

$$S_{k,l} = \beta . e^{-(d_{i,j}^2/K^2)} \tag{3.11}$$

Where, K is the constant value and it is determined based on the experimental results. In our experiment its value is set to be 30.

$$\beta = \begin{cases} 1 \ \ if \ \ d_{i,j} < Th. \\ 0 \ \ otherwise. \end{cases} \tag{3.12}$$

$$Th = 33 - Q/3.$$

Since, this filter is more sensitive to preserve the original edge of image; the filter coefficient $S_{k,l}$ is set to zero, if the deviation of pixels is above or equal to the threshold value $Th.$ as given in (3.12). The value of threshold $\boldsymbol{Th}$ is set according to the JPEG quality factor (Q) which lies between 0 and 100. Finally, the filtered pixel $P'_{i,j}$will be computed by the weighted average of the neighboring pixels. The filtered pixel $P'_{i,j}$will be computed by the weighted average of the neighboring pixels.

$$P'_{i,j} = \frac{1}{M}\sum_{k=-1}^{1}\sum_{l=-1}^{1} S_{k,l} \cdot P_{i+k,j+k}. \tag{3.13}$$

$$M = \sum_{k=-1}^{1}\sum_{l=-1}^{1} S_{k,l}. \tag{3.14}$$

Only four pixels around the block boundary are selected inside the filtering window. The threshold *Th* is adjusted between (0 to 30) according to the quantization parameter Q which ranges between 50 and 110. The newly calculated pixels are adjusted between the range of 0 and 255.

IV. Performance Evaluation

This chapter presents results obtained using the proposed algorithm described in chapter III and IV together the analysis of performance by comparing the output with baseline algorithms. Experiments are performed on 512×512 JPEG coded images. Images of different class with high frequency and low frequency contents are selected for experiment. Two different experiments are performed separately. First, only low pass adaptive filter is applied then combination of both adaptive and offset filters is applied. In this experiment threshold values are set as T = 67 and T_1= 1.Images are coded with the quantization parameters shown in Table 4.1. Coded images are reconstructed and post processed in order to improve the visual quality of image. Performance of the proposed algorithm is evaluated in three different metrics.

- Objective Quality.
- Subjective Quality.
- Computational Cost Analysis.

A. Objective Quality

To evaluate the objective quality of images, PSNR is used. PSNR is defined as

$$PSNR = 20log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{4.1}$$

Here, MSE is the averaged mean square error between the original image and the filtered image. Since PSNR is not directly corelated with the quality of the human visual system however it is taken into account for the evaluation of performance of algorithms. Table 4.2 shows PSNR values of coded images and filtered images. Similarly, Table 4.1 shows the qunatization table which us the 8×8 matrix of step sizes - one element for each DCT coefficient. It is usually symmetric in nature. Step sizes are small in the upper left (low frequencies), and large in the upper right (high frequencies); a step size of 1 is the most precise. The quantizer divides the DCT coefficient by its corresponding quantum, then rounds to the nearest integer. Large quantums drive small coefficients down to zero. The result: many high frequency coefficients become zero, and therefore easier to code. The low frequency coefficients undergo only minor adjustment. Fig 4.1 shows the graphical representation of PSNR corresponding to Table 4.2.

Table. 4.1 Quantization Tables.

50	60	70	70	90	120	255	255
60	60	70	96	130	255	255	255
70	70	80	120	200	255	255	255
90	96	120	200	255	255	255	255
90	130	200	255	255	255	255	255
120	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

(a)

86	59	54	86	129	216	255	255
64	64	75	102	140	255	255	255
75	70	86	129	216	255	255	255
75	91	118	156	255	255	255	255
97	118	199	255	255	255	255	255
129	189	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

(b)

110	130	255	255	255	216	255	255
130	150	255	255	255	255	255	255
150	192	255	255	255	255	255	255
192	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

(c)

Table. 4.2 Competitive Results.

	PSNR[db]				
Image	***JPEG***	***Proposed***	***Adaptive***	***Chen's***	***Zhai's***
Lena	30.67	31.19	30.91	30.73	30.80
Barbara	25.75	25.83	25.82	25.32	25.82
Boat	28.33	28.67	28.56	28.16	28.34
Baboon	23.34	23.37	23.35	22.99	23.34
Pepper	30.40	31.10	30.50	30.50	30.65

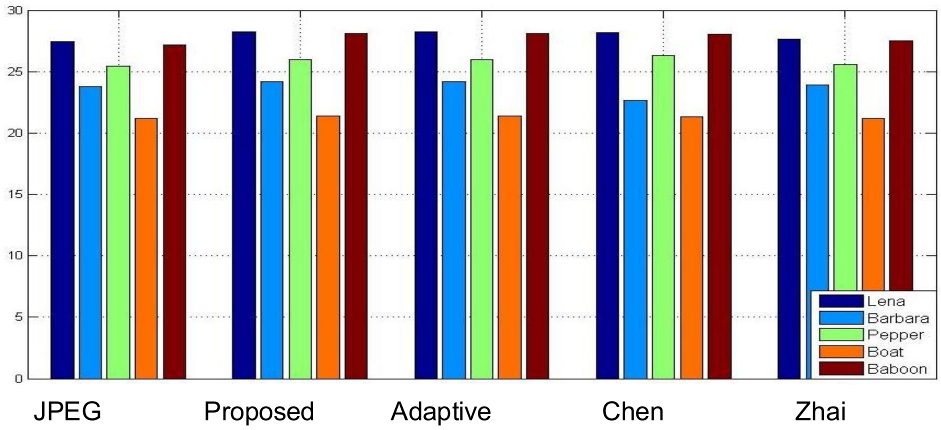
(a)

	PSNR[db]				
Image	***JPEG***	***Proposed***	***Adaptive***	***Chen's***	***Zhai's***
Lena	30.08	30.70	30.30	30.28	30.31
Barbara	25.47	25.56	25.52	25.10	25.56
Boat	27.86	28.26	28.10	27.81	27.94
Baboon	23.24	23.30	23.27	22.92	23.25
Pepper	29.82	30.58	29.93	30.08	30.16

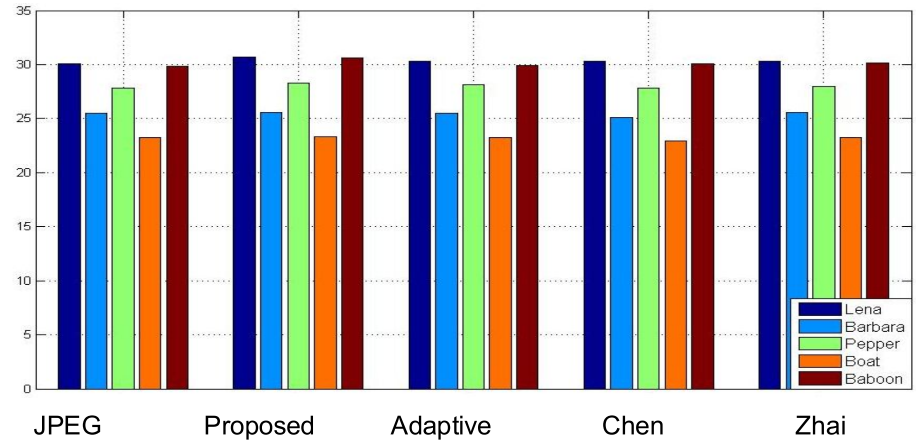
(b)

	PSNR[db]				
Image	***JPEG***	***Proposed***	***Adaptive***	***Chen's***	***Zhai's***
Lena	27.42	28.23	28.23	28.20	27.64
Barbara	23.80	24.15	24.15	22.67	23.90
Boat	25.44	25.99	25.99	26.28	25.57
Baboon	21.16	21.41	21.41	21.34	21.20
Pepper	27.19	28.13	28.13	28.06	27.52

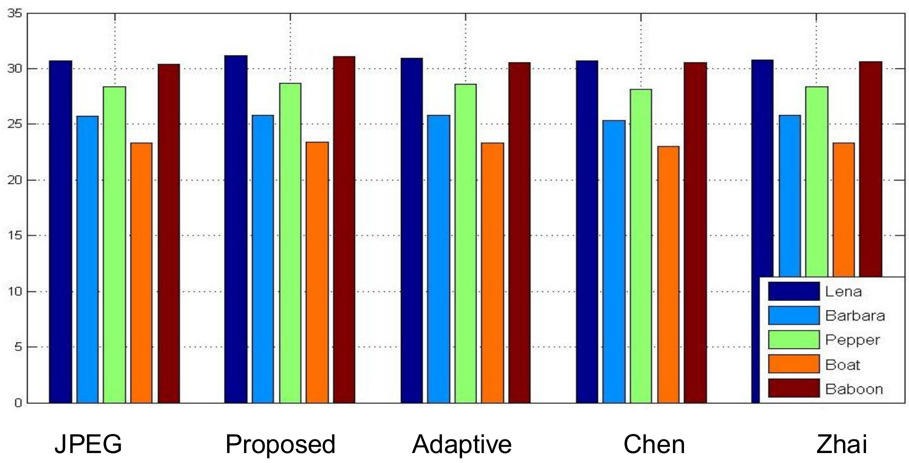
(c)



(a)



(b)



(c)

Fig. 4.1 Graphical Comparison in terms of PSNR obtained from table (a) 4.2.a , (b) 4.2.b, (c) 4.2.c.

B. Subjective Quality

Fig. 4.2 shows the Lena image obtained after filtering operation with the proposed algorithm and Chen's algorithm with the images coded with quantization values in Table 4.1. Similarly, Fig. 4.3 shows 512×512 Barbara image obtained after deblocking by the proposed algorithm and Chen's algorithm. Here, the blocking artifact is reduced in smooth region as well as in complex region while preserving the original edge of image. The experimental results show that the proposed algorithm has outperformed the baseline algorithm in subjective quality as well as in objective quality. Fig. 4.4 shows the image of pepper. The pepper image contains mostly the low frequency components. Human eyes are more sensetive to artifacts present in such regions. Effective reduction of such blocking artifacts by proposed algorithm can be seen in Fig. 4.2(c).

(a) (b)

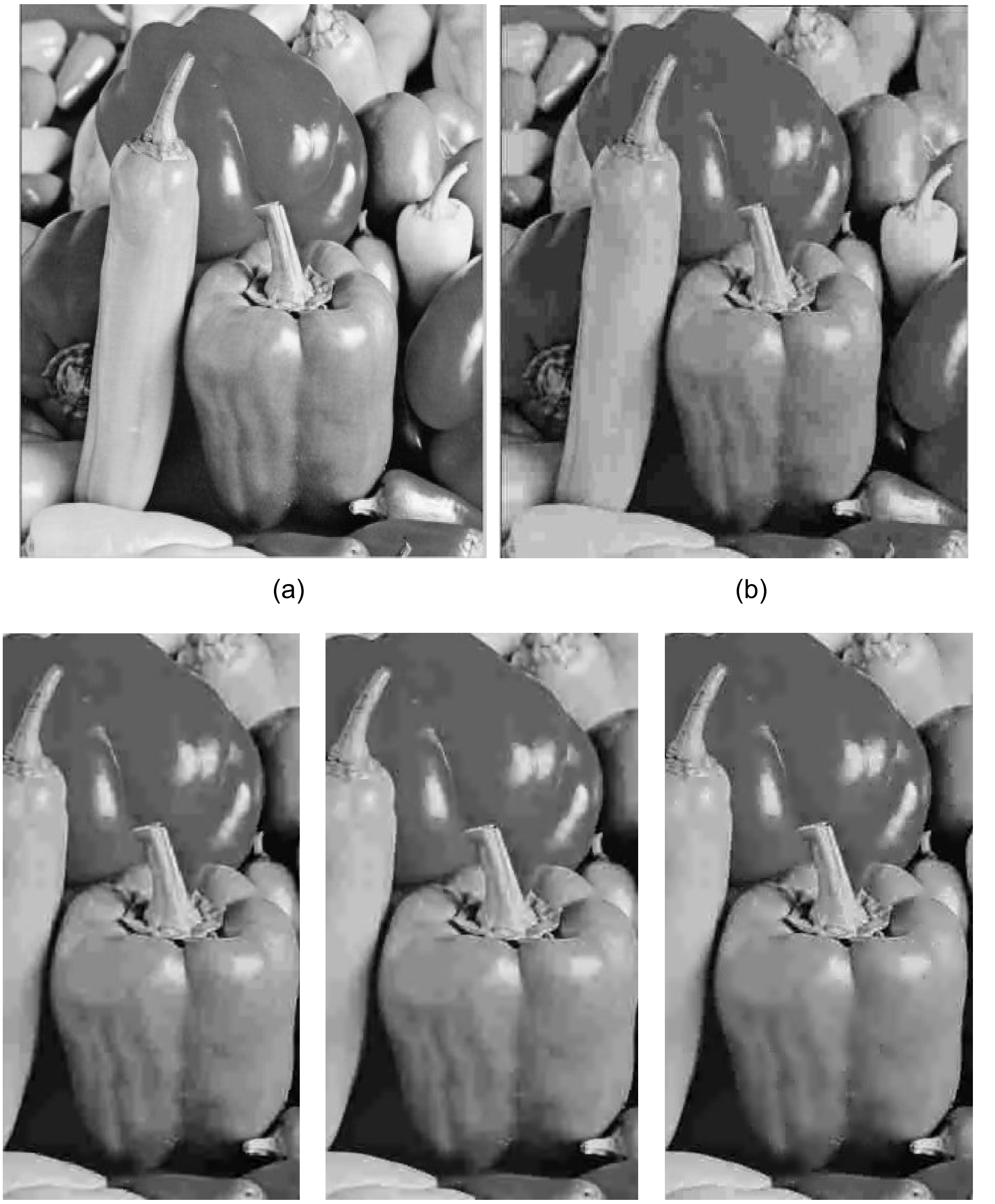
(c) (d) (e)

Fig. 4.2 Deblocking of Lena image in smooth region. (a) Original image. (b) Compressed image. (c) Deblocked image by the proposed algorithm. (d) Deblocked image by Chen’s algorithm. (e) Deblocked image by Zhai’s algorithm.

(a) (b)

(c) (d) (e)

Fig. 4.3 Deblocking of Barbara image. (a) Original image. (b) Compressed image. (c) Deblocked image by the proposed algorithm. (d) Deblocked image by Chen's algorithm. (e) Deblocked image by Zhai's algorithm.



(a) (b)

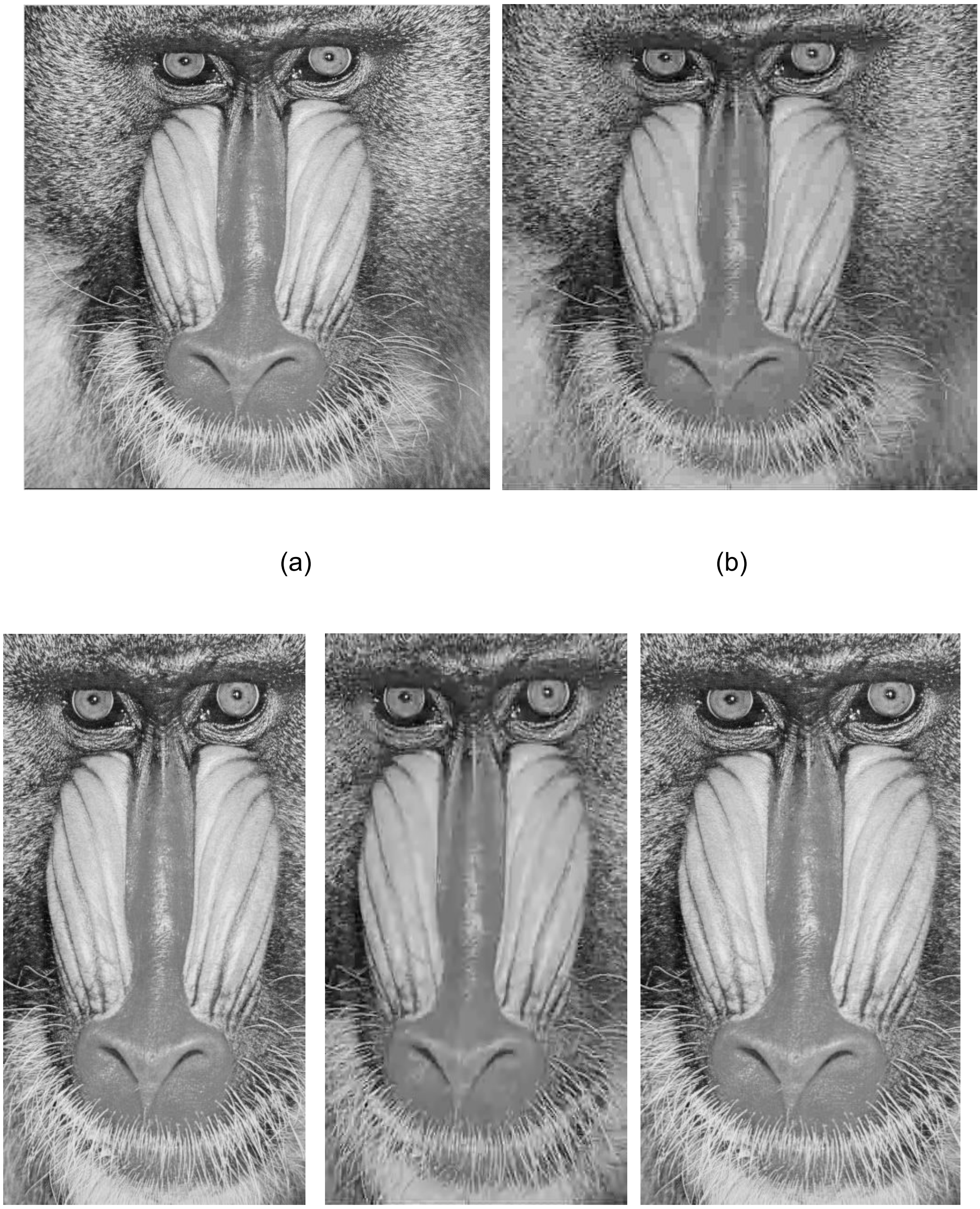
(c) (d) (e)

Fig. 4.4 Deblocking of Pepper image. (a) Original image. (b) Compressed image. (c) Deblocked image by the proposed algorithm. (d) Deblocked image by Chen's algorithm. (e) Deblocked image by Zhai's algorithm.

(a) (b)

(c) (d) (e)

Fig. 4.5 Deblocking of Boat image. (a) Original image. (b) Compressed image. (c) Deblocked image by the proposed algorithm. (d) Deblocked image by Chen's algorithm (e) Deblocked image by Zhai's algorithm.



(a) (b)

(c) (d) (e)

Fig. 4.6 Deblocking of Baboon image. (a) Original image. (b) Compressed image. (c) Deblocked image by the proposed algorithm. (d) Deblocked image by Chen's algorithm (e) Deblocked image by Zhai's algorithm.

C. Computational Cost Analysis.

In this section, we analyze the complexity of the proposed algorithm with that of [7]'s Scheme. Table 4.3 provides the number of mathematical operations required to execute different procedures employed for the reduction of blocking artifact for each newly constructed block. Table shows that the total number of addition and subtraction is greater than that of Chen's algorithm. However, the number of multiplication and division in Chen's is greater that of the proposed algorithm. This indicates that the proposed method gives better reconstruction quality in comparison with [7]'s method at the minimal computational cost.

Table. 4.3 Comparison of complexity

	Chen [7] 's Algo.		Zhai[17]'s Algo.		Proposed Algo.	
	Mode Decision	Filter Operation	Mode Decision	Filter Operation	Mode Decision	Filter Operation
Addition	$5n^2N^2$	$8n^2N^2$	$7n^2N^2$	$63n^2N^2$	$16n^2N^2$	$5n^2N^2$
Subtraction	$5n^2N^2$	$7n^2N^2$	$63n^2N^2$	0	$16n^2N^2$	$5n^2N^2$
Multiplication	n^2N^2	$3n^2N^2$	$(n^2+3n/8)N$	n^2	0	n^2N^2
Division	0	$4n^2N^2$	n^2	n^2	0	0
Comparison	n^2N^2	$3n^2N^2$	n^2	0	$8n^2N^2$	n^2N^2

V. Discussion

Image compression plays significant role in reduction of bandwidth requirement and the storage space. In modern multimedia communication image coding with the minimum bit rate has become mandatory process. So an efficient post processing method is required to reduce the artifact generated by low bit rate coding. While applying filter to reduce the artifacts special concern should be taken so that the original edge contents of the image should not be lost.

VI. Conclusion

This thesis paper presented a new class of algorithm for reducing blocking artifacts in low bit rate coded images. The proposed algorithm reduces the blocking artifacts by properly analyzing the pixel statistics. Analysis of the pixels are carried out by reading the edge information of image. Appropriate filters are then applied on pixels of different class reconstructed image. 1-D offset based filter is applied on the smooth region since the false edges caused by blocking artifact are more visible in the this region. While, the gradient based filter is applied on the complex region. Since filter coefficients are varied according to the gradient of pixels, filter strength is week in more complex region while strong in smooth region. That is why artifacts in edge region are filetered while original edge details of image are preserved.

Experimental results have shown that this algorithm has excellent performance interms of both subjective and objecitve qualities. Moreover, due to non iterative nature of filters used, the compuational complexity of the proposed algorithm is alsominimum as compared to conventional algorithms. Because of this low complexity property, the proposed algorithm can be applied for the post processing of real time images and video sequences coded in low bit rate in low speed devices.

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ABSTRACT

Reduction of Blocking Artifact Based on Edge Information in DCT Coded Images

Ramesh Kumar Lama
Advisor: Prof. Goo-Rak Kwon, Ph.D
Department of Information and Communications Engineering,
Graduate School of Chosun University

For low bit rate multimedia communication, the original image is compressed by block based DCT coding. One of the major drawbacks of this coding scheme is that they may result to visible artifacts in block boundaries. In this thesis, a new algorithm is proposed based on two separate modes in terms of number of edge pixels around the block boundary. The number of edge pixels is estimated by applying the Robert's edge filter. In each mode, proper filtering operation is carried out in both horizontal and vertical direction. The first mode is associated with smooth region. Since flat regions are more sensitive to human visual system, strong filtering operation is applied. In second mode an adaptive low pass filter is applied. This filter is based on pixel gradient around the block boundaries. Artifacts are reduced without introducing undesired distortion while preserving the original edge of image. Although the proposed approach is simple and operates on spatial domain, the experimental results show that it improves both the subjective and objective quality of images with various features.

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