Fast Image Restoration for Reducing Blocking Artifacts

Sang Kwang Lee[a], Tae Keun Kim[b], Joon Ki Paik[b], and Yo-Sung Ho[a]

[a]Kwangju Institute of Science and Technology
1 Oryong-Dong Puk-Gu, Kwangju, 500-712, Korea

[b]Department of Electronic Engineering, Chungang University
221 Huksuk-Dong Dongjak-Gu, Seoul, 156-756, Korea

ABSTRACT

DCT-based coding techniques for image data compression are widely used owing to good performance with moderate hardware complexity. In very low bit rate applications, however, block-based image compression techniques usually exhibit significant quality degradation, which is called as the blocking artifact. In this paper, we propose an adaptive fast image restoration method that is suitable for reducing the blocking artifact. The proposed restoration filter is based on an observation that the quantization operation is a nonlinear and many-to-one mapping operator. We have developed an approximated version of the constrained optimization technique for image restoration by removing the nonlinear and space-varying degradation operator. The proposed method can be used as a post-processor at the decoder of video coding systems for digital TV, video on demand (VOD), or digital versatile disc (DVD) applications.

Keywords: Image Restoration, Blocking Artifacts, Edge Classification, Adaptive Constrained Optimization

1. INTRODUCTION

As demands for video communications are increasing enormously, various image compression schemes have been developed and standardized. Especially, image communications at low bit rates gain growing interests in many applications, such as video conferencing, videophone, and interactive TV.

Block discrete cosine transform (BDCT) methods are widely employed for coding of both still and moving images. The main drawback of the BDCT based compression techniques is, however, the blocking artifact that represents the artificial discontinuity between adjacent blocks. The blocking artifact results from the independent processing of the blocks without taking into account of the pixel correlation along the block boundaries.

Recently, several approaches have been proposed to reduce the blocking artifact without increasing the bit rate: (1) lowpass filtering on the boundary region between blocks[1], (2) regularized image restoration methods based on the theory of constrained least squares (CLS) or projections onto convex sets (POCS)[2,3], (3) prediction of AC coefficients using the mean squared difference of the slope (MSDS) between the neighboring pixels on their boundaries[4], and (4) optimization based on the boundary orthogonal function.[5] The lowpass filtering approach does not require any additional operation or any additional information to be transmitted; however, this approach results in image blurring. The methods based on CLS or POCS need more processing time due to their iterative operations; therefore, they are not suitable for real-time video processing. The AC prediction method has a disadvantage of high computational complexity. The optimization method based on the boundary orthogonal function reduces the blocking artifact, but it creates a different type of degradation.

In order to solve the above-mentioned problems, we propose a fast adaptive image restoration filter that can reduce the blocking artifact in BDCT-based compressed images. After classifying image blocks into edge and non-edge blocks to exploit the local image characteristics efficiently, we apply an adaptive CLS algorithm to reduce the blocking artifact for very low bit rate applications.

Correspondence: E-mail: sklee@kjist.ac.kr; Telephone: +82-62-970-2263; Fax: +82-62-970-2204

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2. DEGRADATION MODEL FOR THE BLOCKING ARTIFACT

In order to simplify a derivation of the proposed algorithm, we take a one-dimensional vector representation of the $N \times N$ image $f(m,n)$, where $B \times B$ pixel blocks are used as a processing unit.

$$f = [f_1^T, f_2^T, \cdots, f_{N^2/B^2}^T]^T \tag{1}$$

where f_k represents the lexicographically ordered block of B^2 picture elements.
As shown in Fig. 1, degradation of a BDCT-based compression-reconstruction process can be modeled as

$$g = C^{-1}QCf \tag{2}$$

where g represents the reconstructed image with the blocking artifact due to the quantization of BDCT coefficients. C and C^{-1} are the block-based forward and inverse DCT operations, respectively. Q is the combined quantization and inverse quantization operation. In Fig. 1, the restoration process represents a post-processing operation for reducing the blocking artifact.

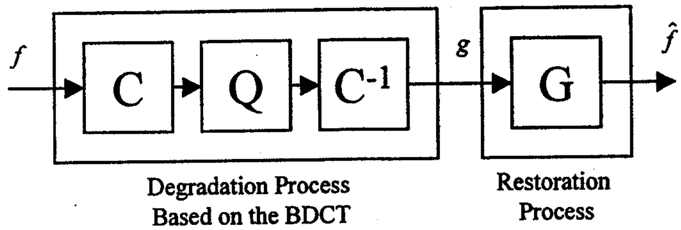

Figure 1. Image Degradation-Restoration Model

For a $B \times B$ image block, the corresponding BDCT coefficient is expressed as[6]

$$D(k,l) = \alpha(k) \cdot \alpha(l) \cdot \sum_{m=0}^{B-1} \sum_{n=0}^{B-1} f(m,n) \cos\frac{\pi}{2B} k(2m+1) \cos\frac{\pi}{2B} l(2n+1) \tag{3}$$

where k and l are the horizontal and vertical frequency indices, respectively, and the constants, $\alpha(k)$ and $\alpha(l)$ are given by

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{B}}, & \text{for } u = 0 \\ \sqrt{\frac{2}{B}}, & \text{for } u = 0,1,2,\ldots,B-1 \end{cases} \tag{4}$$

Using the BDCT coefficients in Eq. (3), C and C^{-1} in Eq. (2) can be represented as

$$C = \begin{bmatrix} [c] & 0 & \cdots & 0 \\ 0 & [c] & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & [c] \end{bmatrix} \text{ and } C^{-1} = \begin{bmatrix} [c]^{-1} & 0 & \cdots & 0 \\ 0 & [c]^{-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & [c]^{-1} \end{bmatrix} \tag{5}$$

where $[c]$ and $[c]^{-1}$ represent the forward and the inverse DCT matrices with size $B^2 \times B^2$, respectively, for lexicographically ordered $B \times B$ image blocks. For the quantization operation Q, we simply use the quantization table[3], which is shown in Fig. 2.

	$j=1$	$j=2$	$\cdots$				$\cdots$	$j=8$
$i=1$	50	60	70	70	90	120	255	255
$i=2$	60	60	70	96	130	255	255	255
$\vdots$	70	70	80	120	200	255	255	255
	70	96	120	145	255	255	255	255
	90	130	200	255	255	255	255	255
	120	255	255	255	255	255	255	255
$\vdots$	255	255	255	255	255	255	255	255
$i=8$	255	255	255	255	255	255	255	255

Figure 2. Quantization Table

3. CONSTRAINED LEAST SQUARES RESTORATION

We consider the CLS restoration problem as one of the minimizing functions. This approach provides considerable flexibility in the restoration process because it yields a different solution with different choice of a highpass filter for incorporating a priori smoothing constraint.

Let $\hat{f}$ be an estimate of the solution to Eq. (2). We derive $\hat{f}$ by solving the following problem:

$$\text{Minimize } \hat{f}' A' A \hat{f} \text{ subject to } (g - H\hat{f})'(g - H\hat{f}) = e'e \tag{6}$$

where f is a vector of dimension MN, and H and A are matrices of size $MN \times MN$. The prime is used to denote the transpose of a vector or a matrix.

A straightforward Lagrangian minimization[7] yields the solution

$$\hat{f} = (H'H + \gamma A'A)^{-1} H' g \tag{7}$$

where $\gamma = 1/\lambda$, and λ is a Lagrange multiplier. The determination of γ is an important issue in image restoration, because it controls the trade-off between the fidelity and smoothness of the solution.

In general, H and A are block circulant matrices. A block circulant matrix can be diagonalized by the two-dimensional discrete Fourier transform.[7] Therefore, the minimization problem of Eq. (7) can be represented in the form of

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)}{\|H(u,v)\|^2 + \gamma \|A(u,v)\|^2} \right] G(u,v) \tag{8}$$

for $u = 0,1,2,\ldots, M-1$ and $u = 0,1,2,\ldots, N-1$, where $\hat{F}(u,v)$, $H(u,v)$, $A(u,v)$, and $G(u,v)$ are two dimensional discrete Fourier transforms of $\hat{f}$, H, A, and g, respectively.

In the two-dimensional discrete frequency domain, Eq. (8) is equivalent to the space domain expression, Eq. (7). More importantly, Eq. (8) can be used in place of Eq. (7) with great savings of computational requirements. Eq. (8) requires only two-dimensional discrete Fourier transforms.

We should notice that the solution obtained by Eq. (8) depends on the choice of the matrix A. We are interested in the feasibility of choosing A so that the ill-posed problem is removed efficiently. One possibility is the Laplacian operator. The Laplacian operator represents the second derivative in the two-dimensional case. [8]

4. A PROPOSED DEBLOCKING METHOD

We describe a fast adaptive image restoration filter for reducing the blocking artifact efficiently in BDCT-based compressed images. Based on edge classification, we can exploit the local image characteristics. Using the classified edge information, we can apply a corresponding highpass filtering operator to the CLS algorithm.

4.1. Edge Classification of Image Blocks

We employ block-based edge classification using a set of directional masks, which are shown in Fig. 3.

$$\begin{bmatrix} 0 & 0 & 0 \\ 1 & 2 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 1 \\ 0 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(a) 0° (b) 45° (c) 90° (d) 135°

Figure 3. Directional Masks

The edge map is obtained by the Sobel operator. To obtain the edge direction of each pixel, we apply a set of directional masks on the edge map. The edge is determined by the mask that produces the maximum value. Let N_0, N_{45}, N_{90}, and N_{135} denote the counters for 0°, 45°, 90°, and 135° edge directions, respectively. We set a threshold T, to determine edge blocks against monotonous blocks. For each block, the corresponding counter is increased by one according to the edge direction. A block is classified as a monotonous block if

$$Max\{N_0, N_{45}, N_{90}, N_{135}\} \leq T \tag{9}$$

Otherwise, the block is classified as an edge block with the direction of the maximum index.

4.2. Adaptive Constrained Restoration

There is no closed form solution for Eq. (2), since H is a nonlinear operator. With this observation, we propose an approximated version of the constrained optimization with the following assumptions:

Assumption 1: H is a space invariant lowpass filter.
Assumption 2: A is a block-adaptive directional highpass filter determined by the block-classified edge information.

An alternative approach for edge-preserving filtering is the directional filtering approach[9], where we filter along the edges, but not across them. In the directional approach, noise around the edge can be eliminated by filtering along the edges effectively, as opposed to turning the filter off in the neighborhood of edges.

In directional filtering, possible edge orientations are generally quantized into four, 0°, 45°, 90°, and 135°, and five FIR kernels, one for each orientation and one for non-edge regions, are defined, as shown in Fig. 4.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & -1 \\ -10 & 24 & -10 \\ -1 & 0 & -1 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & -1 \\ 0 & 2 & 0 \\ -1 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} -1 & -10 & -1 \\ 0 & 24 & 0 \\ -1 & -10 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & -1 \end{bmatrix}$$

(a) Monotone (b) 0° (c) 45° (d) 90° (e) 135°

Figure 4. Highpass Filtering Operators

Based on the edge classification information, we assign one of the different highpass filters to each block. We then implement an adaptive CLS restoration filter using the following lowpass filter. Fig. 5 summarizes the proposed deblocking method.

$$\hat{H} = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 10 & 2 \\ 1 & 2 & 1 \end{bmatrix} \quad (10)$$

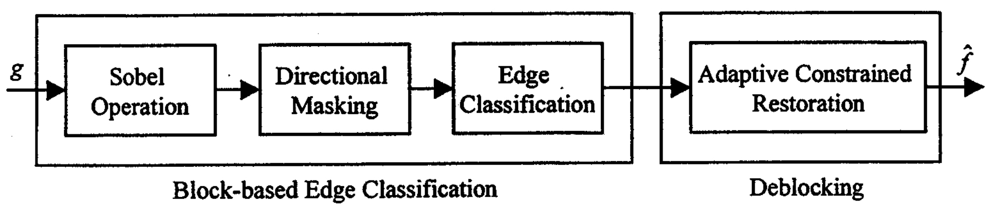

Figure 5. Proposed Deblocking Method

5. EXPERIMENTAL RESULTS

For the computer simulation, we have used LENA and PEPPERS images of 512 × 512 pixels. Decoded images with the blocking artifact are obtained with the quantization table of Fig. 2. We have set $T = 1$ for blocks of 8 × 8 pixels. Fig. 6 and Fig. 8 show the results of edge classification for each image, respectively, where we can observe that the proposed edge classification works very well.

We compare the performance of the proposed algorithm with those of two conventional deblocking algorithms. Using the edge variance σ^2_{edge}, which is defined in Eq. (11), we measure the image blockiness.

$$\sigma^2_{edge} = \sum (f_1 - f_2)^2 \quad (11)$$

where f_1 and f_2 represent intensity values of two pixels that are adjacent to each other in neighboring blocks along block boundaries.

Table 1 summaries edge variances of the original image, the decoded image with no deblocking operation, and restored images with deblocking algorithms. As shown in Table 1, we can observe that the proposed method shows significant improvement of reducing the blocking artifact over the lowpass filtering method[1]. Although the proposed method has similar edge variances as the POCS method[3], the computational complexity is significantly reduced in our algorithm.

Table 1. Edge Variances, σ^2_{edge}

	LENA	PEPPERS
Original image	2.08×10^6	2.47×10^6
Decoded image	3.51×10^6	3.79×10^6
Lowpass filtering method	2.22×10^6	2.42×10^6
POCS method	1.19×10^6	1.17×10^6
Proposed method	1.25×10^6	1.19×10^6

Restored images by the lowpass filtering method are shown in Fig. 7(c) and Fig. 9(c), where we can see that the blocking artifact is not completely removed because the filtering area is restricted to block boundaries. In comparing the subjective quality of images shown in Fig. 7(c) and Fig. 7(d), and Fig. 9(c) and Fig. 9(d), we can observe that the proposed algorithm reduces the blocking artifact, while preserving edge details inside each block.

6. CONCLUSIONS

In this paper, we proposed a fast adaptive image restoration filter for reducing the blocking artifact in BDCT-based compressed images. Although the proposed restoration filter can reduce the blocking artifact efficiently, the quality of the processed images cannot completely be equal to that of original one owing to missing information in the quantization process and the inherent lowpass characteristics in the proposed filter. The major contribution of this paper is that it is a fast adaptive image restoration for reducing the blocking artifact by using block-based edge classification method. In comparing the proposed algorithm with conventional iterative algorithms that have been proposed mainly for still image, the computation time is greatly reduced. Therefore, the proposed method can be used as a post-processor at the decoder of video coding systems for very low bit rate applications.

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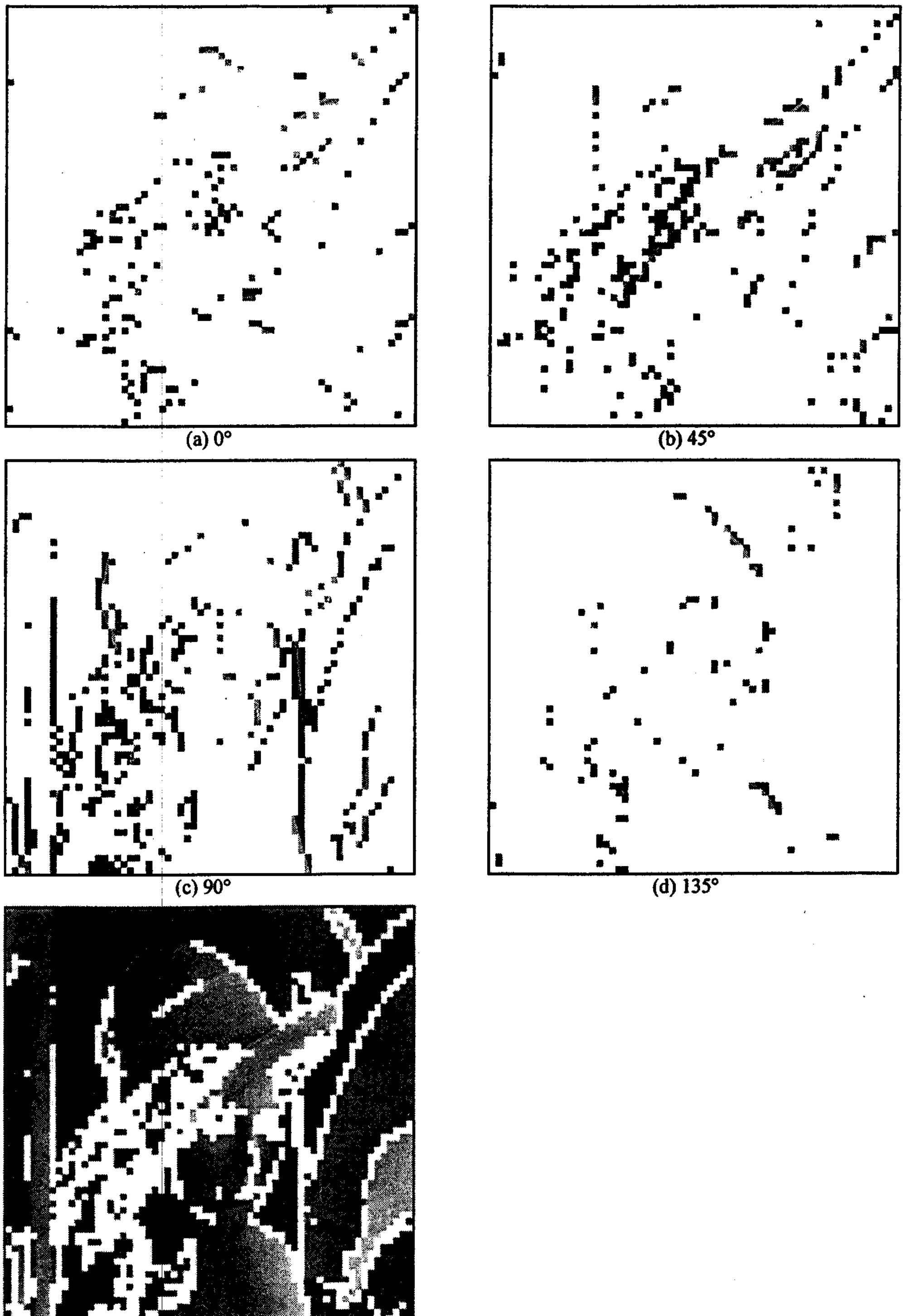


(a) 0°
(b) 45°
(c) 90°
(d) 135°
(e) Monotone

Figure 6. Edge Classification (LENA)

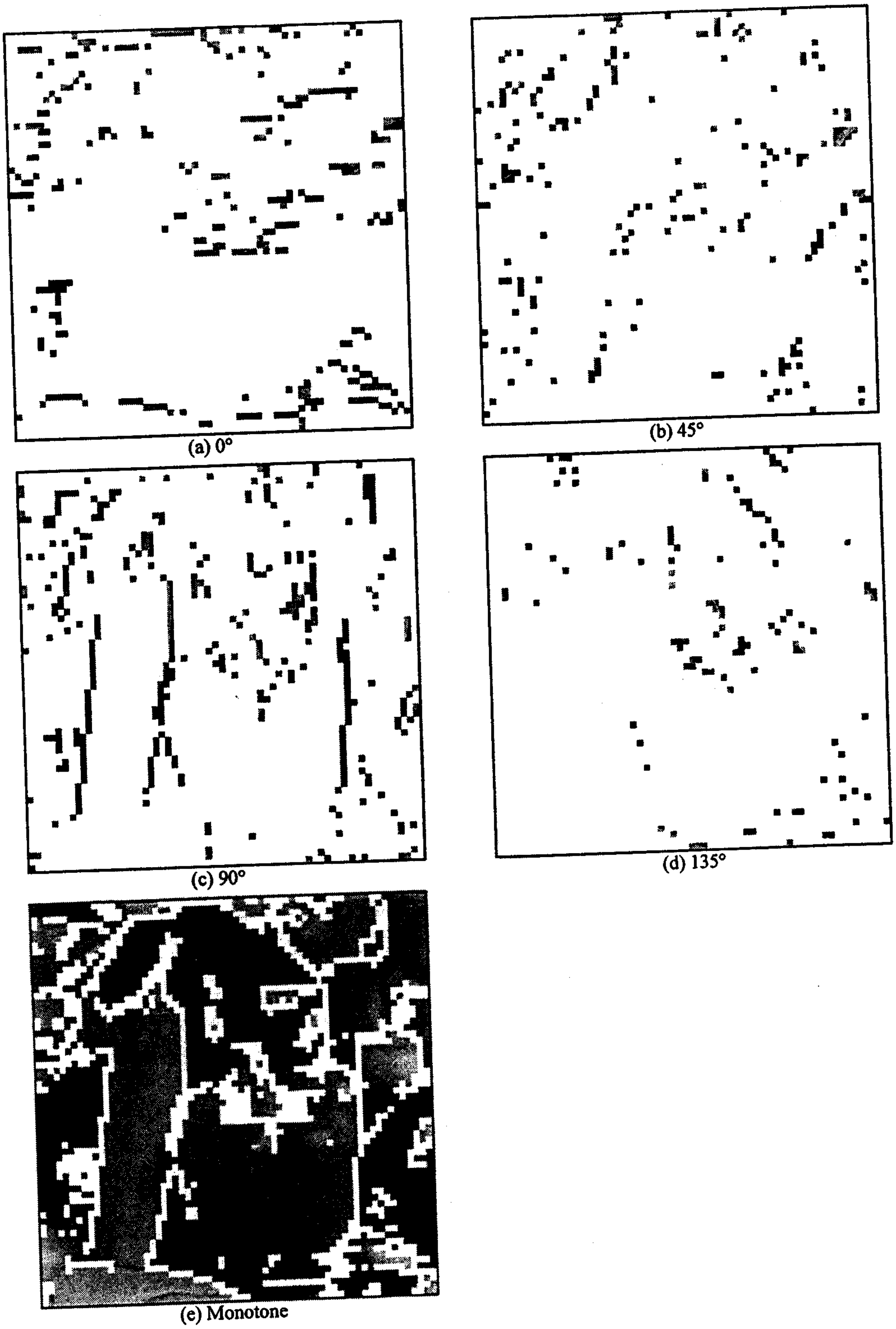
(a) Original Image

(b) Decoded Image

(c) Lowpass Filtering Method

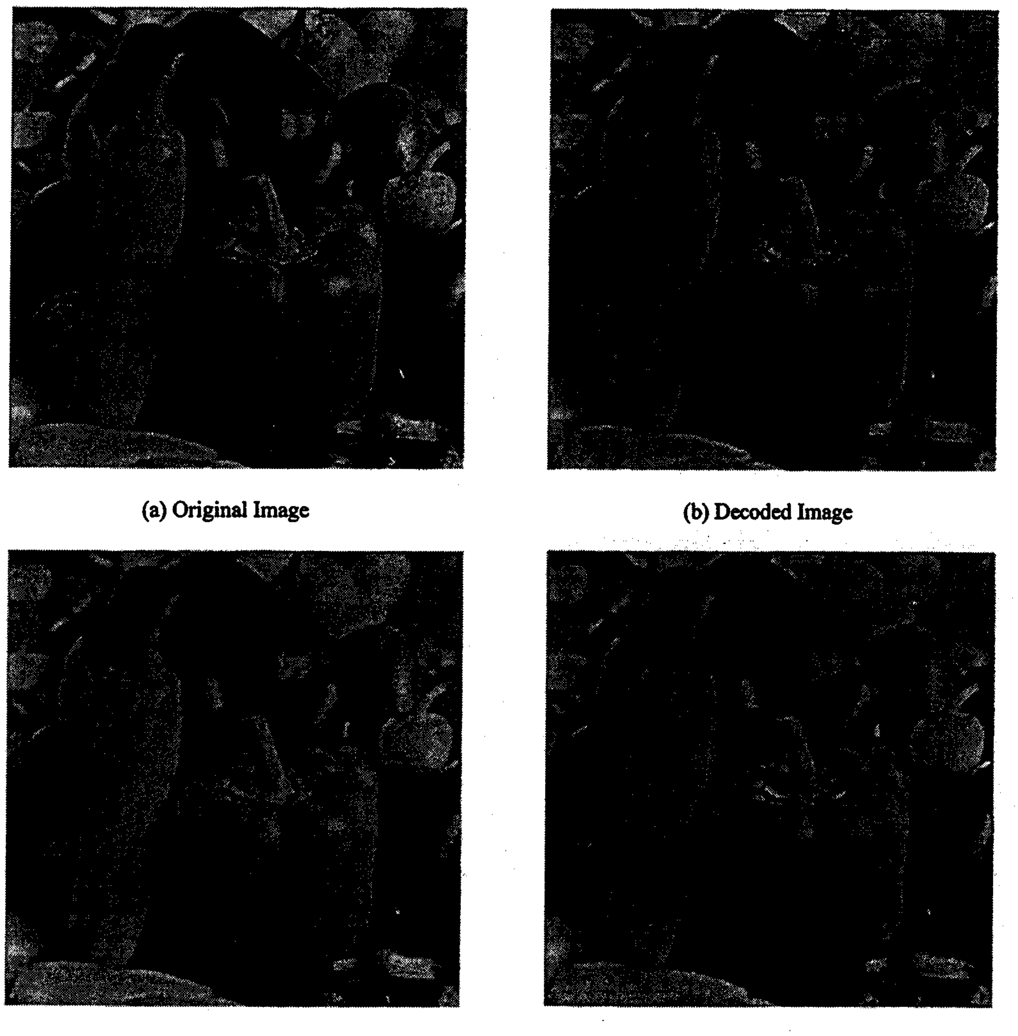
(d) Proposed Method

Figure 7. Original and Restored Images (LENA, 512 × 512)



(a) 0° (b) 45° (c) 90° (d) 135° (e) Monotone

Figure 8. Edge Classification (PEPPERS)



(a) Original Image

(b) Decoded Image

(c) Lowpass Filtering Method

(d) Proposed Method

Figure 9. Original and Restored Images (PEPPERS, 512 × 512)