Adaptive Postprocessing Algorithm for Reduction of Blocking Artifacts Using Wavelet Transform and NNF

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Abstract: This paper proposes a novel postprocessing algorithm for reducing the blocking artifacts in low bit rate block-based transform coded images, that use adaptive neural network filter (NNF) in wavelet transform domain. In this algorithm, after performing a 2-level wavelet transform of the decompressed image, the existence of blocking artifacts is determined using statistical characteristic of neighborhood blocks. And then a different one-dimensional (1-D) or 2-D NNF is used to reduce the blocking artifacts according to the classified regions. That is, for HL and LH subbands regions with the blocking artifacts, a different 1-D NNF is used. And 2-D NNF is used in HH subband. Experimental results show that the proposed algorithm produced better results than those of conventional algorithms both subjectively and objectively.

1. Introduction

Block DCT-based coding techniques have been adopted in many international standards, including the still and moving image coding standards JPEG [1], H.263 [2], and MPEG-4 [3]. However, such techniques produce noticeable blocking artifacts along block boundaries in decompressed images at a low-bit-rate, because the DCT coefficients in each block of an image are processed and quantized independently [4]-[9]. Moreover, the discontinuity effect between adjacent blocks in decompressed images is more serious for highly compressed images. Consequently, an efficient blocking artifacts reduction scheme is essential for preserving the visual quality of decompressed images.

A variety of postprocessing schemes for reducing the blocking artifacts have already been proposed to improve the visual quality of block-based coded images at the decoder side, such as adaptive filtering methods in the spatial domain [4],[5], the projections onto convex sets (POCS)-based method [6], estimating the lost DCT coefficients in the transform domain [7], and wavelet transform-based methods [8],[9].

The spatial domain filtering methods [4],[5] have the advantage of simplicity and easy hardware implementtation, but blurred the whole image including the edges. The POCS-based method [6] has produced good results, however, since it is based on an iterative approach, it is computationally expensive and time consuming.

Recently, the wavelet transform modulus maxima (WTMM) representation was used to characterize a signal based on the Lipschitz exponents [8],[9]. It enables local and effective operations on multiscale edges.

Xiong *et al.* [8] proposed an approach to deblocking of JPEG compressed images using overcomplete wavelet representations. By exploiting cross-scale correlations among wavelet coefficients, edge information in the JPEG compressed images is extracted and protected, while blocky noise in the smooth background regions are smoothed out in the wavelet domain. However, this algorithm is unable to accurately classify smooth regions and edge regions. And, since the mean filter is applied to all smooth block boundaries, the whole images are blurred.

Kim *et al.* [9] proposed the 1-D filtering method in wavelet transform domain. In this method, an image is considered a set of one-dimensional signals, and all processing are one-dimensionally executed. This algorithm needs to accurately classify quantization errors in multiscales.

Accordingly, this paper proposes a novel postprocessing algorithm for reducing the blocking artifacts in low-bit-rate block-based transform-coded images, that use adaptive NNF in wavelet transform domain. In this algorithm, after performing a 2-level wavelet transform of the decompressed image, the existence of blocking artifacts is determined using statistical characteristic of neighborhood blocks. And then a different 1-D or 2-D NNF is used to reduce the blocking artifacts according to above classified regions. That is, for HL and LH subbands regions with the blocking artifacts, a different 1-D NNF is used. And 2-D NNF is used in HH subband.

Experimental results show that the proposed algorithm improved the PSNR and visual quality of JPEG decompressed images and produced better results than those of conventional algorithms.

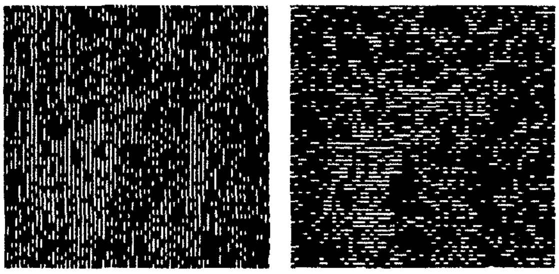
2. The Proposed Algorithm

2.1 Structure of MLP

A multi-layer perceptron (MLP) has already been successfully applied to a variety of difficult and diverse problems based on supervised learning using an error back propagation learning algorithm [11].

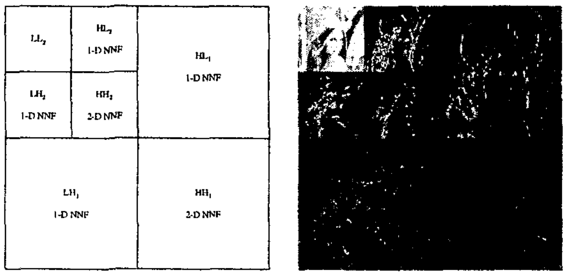
We use NNFs rather than adaptive linear filters because compression and decompression are highly nonlinear and complex and NNFs have been proven effective in finding nonlinear mappings between inputs and outputs. After training the NNFs, the final synaptic weights of the NNFs are used as the processing filters to reduce the blocking artifacts.

2.2 Determination of the Blocking Artifacts



(a) (b)

Fig. 1. The results of the blocky or non-blocky regions in the (a) HL_1 subband and (b) LH_1 subband on a JPEG decoded LENA image with a bit rate of 0.271 bpp.



(a) (b)

Fig. 2. (a) Two-level wavelet decomposition and (b) result of two-level wavelet decomposition on a JPEG decoded LENA image with a bit rate of 0.271 bpp.

In this algorithm, we use two characteristics, knowing the positions of the blocking artifacts in each band and discriminating between the horizontal and vertical blocking artifacts by using the wavelet transformed signal. At first, we perform a 2-level wavelet transform of the decompressed, and determination of the boundary regions occurring to the blocking artifacts using the statistical characteristics of four pixels within a block boundary. That is, if $m_1 - m_2 = 0$, then those regions are non-blocky regions, and if $m_1 - m_2 \neq 0$, then those regions are blocky regions. Where, m_1 and m_2 are formed as follows:

$$m_1 = \frac{\tilde{c}_0 + \tilde{c}_1}{2} \tag{1}$$

$$m_2 = \frac{\tilde{c}_2 + \tilde{c}_3}{2} \tag{2}$$

The results of the blocky or non-blocky regions in the HL1 and LH1 subbands on a JPEG decoded LENA image with a bit rate of 0.271 bpp are shown in Fig. 1.

2.3 Inter-block Filtering Using Adaptive NNF

For above detected blocky regions, a different 1-D or 2-D NNF is used to reduce the blocking artifacts according to the characteristics of each level, as shown in Fig. 2 and Fig. 3.

As shown in Fig. 2 (b), in the HL_1 and HL_2 subbands, block discontinuities appear significantly in vertical blocking artifacts, and in the LH_1 and LH_2 subbands, block

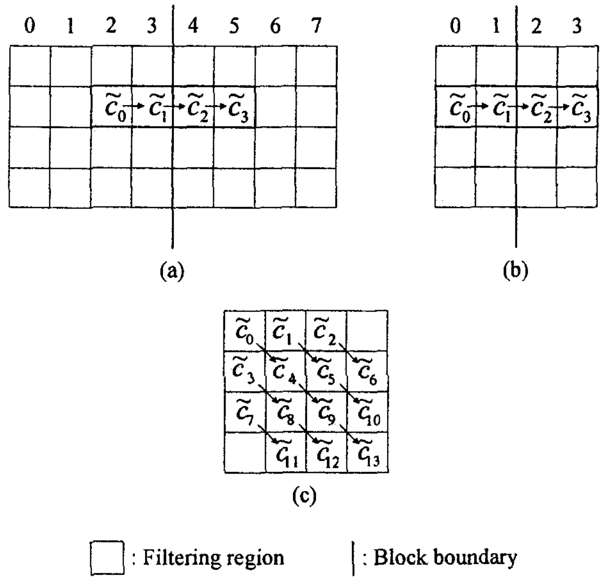


Fig. 3. (a) HL_1 subband, (b) HL_2 subband, and (c) HH_1 and HH_2 subbands filtering methods.

discontinuities appear significantly in horizontal blocking artifacts. So we use 1-D NNF in the horizontal direction for HL_1 and HL_2 subbands, and 1-D NNF in the vertical direction for LH_1 and LH_2 subbands. The LL_2 subband does not processed because it has the important information of the image. And the HH_1 and HH_2 subbands reduce the blocking artifacts using 2-D NNF because they cannot be classified the horizontal and vertical blocking artifacts and appeared the horizontal and vertical blocking artifacts simultaneously.

The NNFs in each band are designed using MLP with an EBP learning algorithm. The structures of the NNFs to process the HL_1, LH_1, HL_2, and LH_2 subbands are the same. In each band, the number of the input and output nodes of the MLP have three and four, respectively. For the HH_1, and HH_2 subbands, 2-D NNFs, with the number of the input and output nodes of the MLP have nine, are designed. Each NNF was trained with a training rate of 0.05. The initial synaptic weights were initialized with a floating point interval between 0 to 0.00001.

To process the HL_1 and HL_2 subbands, as shown in Fig. 3, the input vectors for the NNF are formed as follows:

$$x_n = | \tilde{c}_{n+1}(u,v) - \tilde{c}_n(u,v) |, \quad n = 0, 1, \cdots, m \tag{3}$$

where $\tilde{c}_n(u,v)$ and m denote the wavelet coefficients of the decompressed image and number of the NNF's input, respectively. And u and v represent the horizontal and vertical frequency coordinates, respectively. The corresponding desired output vectors are formed based on the difference between the wavelet coefficients of the original image and the wavelet coefficients of the decompressed image as

$$t_n = c_n(u,v) - \tilde{c}_n(u,v), \quad n = 0, 1, \cdots, m+1 \tag{4}$$

where $c_n(u,v)$ denote the wavelet coefficients of the original image. That is, the proposed NNFs produce the difference between the wavelet coefficients of the original image and the wavelet coefficients of the decompressed image. So the blocking artifacts are removed by adding the outputs of the NNFs to the wavelet coefficients of the decompressed image. That is, the postprocessed image $\hat{I}(i,j)$ is formed as follows:

$$\hat{I}(i,j) = W^{-1}[\tilde{c}_n(u,v) + y_n] \tag{5}$$

for $i = 0, 1, \cdots, M$, $j = 0, 1, \cdots, N$ and $n = 0, 1, \cdots, m+1$. Where W^{-1} denotes inverse wavelet transform, M and N denotes the horizontal and vertical image size, respectively and y_n denotes the outputs of the NNF.

After the HL_1 and HL_2 subbands are processed, the LH_1 and LH_2 subbands are processed in a similar manner with a different NNF of the same size.

As shown in Fig. 3 (c), the HH_1 and HH_2 subbands are processed using 2-D NNF to reduce the blocking artifacts as follows:

$$x_n = |\tilde{c}_{n+4}(u,v) - \tilde{c}_n(u,v)|, \quad n \in \{0, 1, 2, 3, 4, 5, 7, 8, 9\} \tag{6}$$

The corresponding desired output vectors are formed as

$$t_n = c_{n+4}(u,v) - \tilde{c}_n(u,v), \quad n \in \{0, 1, 2, 3, 4, 5, 7, 8, 9\} \tag{7}$$

After training the MLP for the HH_1 and HH_2, each subband is processed in a similar manner in the above.

3. Experimental Results

To evaluate the performance of the proposed algorithm, computer simulations were performed using JPEG decompressed images. The NNFs were trained using five training images (BANK, F-16, GIRL, MAN, and TIFFANY) due to the generalization capability of the NNFs. Another five images (LENA, BOAT, PEPPERS, BABOON, and BARBARA) were then used as the test images. Each image was 512×512 in size with 256 gray levels and compressed by JPEG at various bit rates. The peak signal-to-noise ratio (PSNR) was used to measure the performance of the reduction algorithms. We used 9/7-tap biorthogonal filter, proposed by Antonini *et al.* [10].

To compare the proposed algorithm with other conventional algorithms, the PSNR performances of the proposed algorithm and those of the five conventional algorithms [4]-[6],[8],[9] are presented in Table I. The proposed algorithm improved the PSNR by 0.30 dB to 0.71 dB in the JPEG decoded images, and the PSNR was roughly the same or better than the performances of the conventional algorithms.

Magnified portions of the LENA image decoded by JPEG with a bit rate of 0.271 bpp, and the postprocessed images are shown in Fig. 4. The proposed algorithm effectively reduced the blocking artifacts and preserved the original high-frequency components, such as edges. But, spatial domain filtering methods [4],[5] have been blurred the whole image, including the edges.

4. Conclusions

A new postprocessing algorithm that can reduce the blocking artifacts in block-based coded images by using adaptive NNF in wavelet transform domain. In this algorithm, we use two characteristic, knowing the positions of the blocking artifacts in each band and discriminating between the horizontal and vertical blocking artifacts by using the wavelet transformed signals. At first, after performing a 2-level wavelet transform of the decompressed image, the existence of blocking artifacts is determined using statistical characteristics of neighborhood blocks. And then a different 1-D or 2-D NNF is used to reduce the blocking artifacts according to the classified regions. That is, for the detected blocky regions, we use 1-D NNF in the horizontal direction for HL_1 and HL_2 subbands, and 1-D NNF in the vertical direction for LH1 and LH_2 subbands. The LL_2 subband does not processed because it has the important information of the image. And the HH_1 and HH_2 subbands reduced the blocking artifacts using 2-D NNF because they don't classify the horizontal and vertical blocking artifacts. Experimental results showed that the proposed algorithm improved the PSNR from 0.30 dB to 0.71 dB in JPEG decoded images, and the PSNR was roughly the same or better results than the performances of the conventional algorithms, thereby effectively reducing the blocking artifacts and preserving the original high-frequency components, including the edges.

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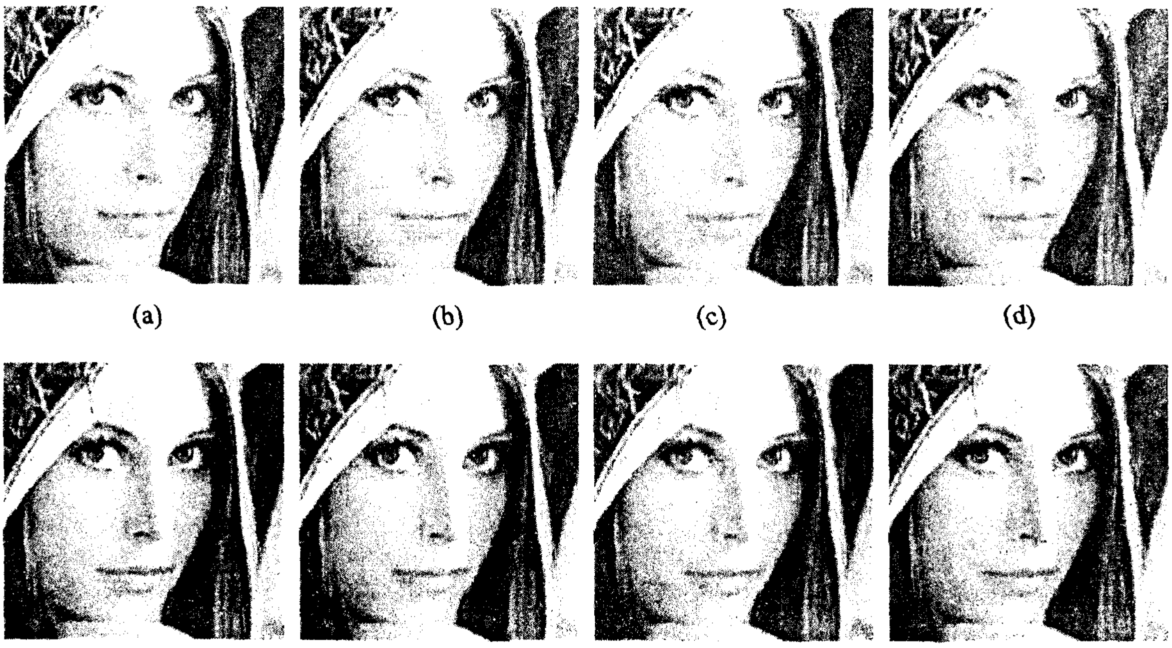
Table I. PSNR of postprocessing on JPEG decoded images.

Test images	Bit rate [bpp]	PSNR [dB]						
		JPEG	S. Kim	G. Qui	Y. Yang	Z. Xiong	N. Kim	Proposed
LENA	0.208	30.41	30.72	30.94	31.05	31.22	31.15	31.12
	0.271	31.95	32.15	32.36	32.45	32.57	32.49	32.64
	0.324	32.96	33.03	33.23	33.34	33.39	33.33	33.53
BOAT	0.258	28.13	28.32	28.57	28.57	28.62	28.64	28.62
	0.350	29.53	29.66	29.87	29.88	29.80	29.90	29.98
	0.420	30.49	30.56	30.73	30.76	30.60	30.74	30.86
PEPPERS	0.212	30.13	30.49	30.55	30.62	30.75	30.87	30.75
	0.272	31.53	31.77	31.80	31.88	31.80	32.05	32.07
	0.325	32.43	32.54	32.58	32.66	32.64	32.82	32.88
BABOON	0.420	23.42	23.44	23.50	23.60	23.53	23.51	23.75
	0.585	24.50	24.51	24.41	24.62	24.39	24.47	24.81
	0.720	25.26	25.26	25.03	25.36	24.95	25.12	25.52
BARBARA	0.273	25.60	25.70	25.97	26.00	25.51	26.71	26.21
	0.380	27.14	27.21	27.46	27.52	26.52	27.09	27.82
	0.471	28.34	28.38	28.60	28.71	27.24	28.22	28.98



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 4. A magnified portions of (a) original LENA image, (b) JPEG decoded image with a bit rate of 0.271 bpp, and postprocessed images by (c) S. Kim's method, (d) G. Qui's method, (e) Y. Yang's method, (f) Z. Xiong's method, (g) N. Kim's method, and (h) proposed method.