IMAGE DEBLOCKING USING DUAL ADAPTIVE FIR WIENER FILTER IN THE DCT TRANSFORM DOMAIN

Renqi Zhang, Wanli Ouyang, Wai-Kuen Cham

Dept. of EE, the Chinese University of Hong Kong

ABSTRACT

Blocking artifacts exist in images and video sequences compressed to low bit rates using block discrete cosine transform (DCT) compression standards. In order to reduce blocking artifacts, a novel DCT domain technique is presented in this paper. Firstly, a new FIR Wiener filter which exploits the dependence of neighboring DCT coefficients based on the linear minimum mean-square-error (LMMSE) criterion is proposed. Then we apply the new FIR Wiener filter twice in a dual adaptive filtering structure to restore each quantized DCT coefficient. In addition, an efficient parameter estimation method is proposed for the designed filter. Experimental results show that the performance of the proposed method is comparable to the state-of-the-art methods but has low computational complexity.

***Index Terms*—**Blocking artifacts, FIR Wiener filter, DCT coefficient, dual adaptive filtering, parameter estimation

1. INTRODUCTION

Block based discrete cosine transform (BDCT) coding is adopted in several industry standards, such as JPEG, MPEG-4 and H.264/AVC, for image and video compression. In a BDCT based scheme, an image is firstly divided into non-overlapping blocks and pixels in each block are transformed into the DCT coefficients which are then quantized. At low bit rates, blocking artifacts will be visible because quantization is performed independently at each block.

The use of a post-processing technique on a decoded image is a common strategy to reduce blocking artifacts, as it does not require changing of existing standards. A number of post-processing techniques were proposed in recent years [1]-[10]. Therein, post-filtering in the DCT domain for the restoration of the DCT coefficients [9][10] has been shown to be a promising deblocking technique, since quantization of the DCT coefficients is the sole error source.

Our proposed method aims to reduce blocking artifacts based on the restoration of quantized DCT coefficients in the DCT domain. We designed a new FIR Wiener filter which exploits the correlation between neighboring DCT coefficients based on the linear minimum mean-square-error (LMMSE) criterion. Then we apply the proposed filter twice in a dual adaptive Wiener filtering structure. Experimental results show that the proposed method offers excellent deblocking performance, not only on objective measure, but also on subjective visual quality. Another advantage of the proposed method is its low computational complexity, making it suitable for real-time applications.

2. THE PROPOSED FIR WIENER FILTER

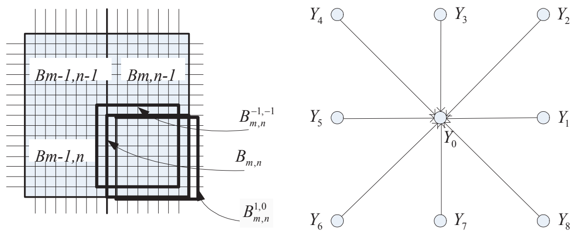
2.1. Quantization Model

Suppose X represent the DCT coefficients of the original image and Y represent the quantized DCT coefficients, so we have $Y=X+N$, where N is the additive zero-mean noise introduced by the quantizers and contributes to the blocking artifacts in the coded image. The additive noise model is frequently used before and proves to be reasonable for quantization noise. The problem here is to estimate X from Y and the quantizer information.

2.2. The Context Window

Let $B_{m,n}$ be an 8×8 block at the *mth* block row and *nth* block column in an image, and $B_{m,n}^{k,l}$ be the block with k shifts in the horizontal direction and l shifts in the vertical direction, relative to the block $B_{m,n}$. Fig.1(a) gives two examples with $k=-1, l=-1$ and $k=1, l=0$ respectively.

When $|k| \le 1$ and $|l| \le 1$, there will be 8 shifted blocks $B_{m,n}^{k,l}$ neighboring to the block $B_{m,n}$. We apply the DCT on each of the shifted blocks. Hence, for each coefficient in $B_{m,n}$, there will be 8 neighboring coefficients from the 8 shifted blocks $B_{m,n}^{k,l}$ as shown in Fig. 1(b). We call this 3×3 context window. While $B_{m,n}^{k,l}$ represents $B_{m,n}$ shifted in the spatial domain, the DCT coefficients of $B_{m,n}^{k,l}$ can be computed using a fast algorithm [11] directly from the DCT coefficients of $B_{m,n}$. In other words, the conversion processes back and forth between the DCT domain and the spatial domain can be eliminated.



(a) (b)

Fig.1 Shifted blocks representation and 3×3 context window

2.3. The Designed FIR Wiener Filter Using LMMSE

For each coefficient in the 8×8 block $B_{m,n}$, we denote it as Y_0. Let its neighboring coefficients from shifted blocks $B_{m,n}^{k,l}, |k| \le 1, |l| \le 1$ be Y_i, $i=1,2,\dots,K$. Let the FIR filter coefficients be H_i, $i=0,1,\dots,K$, then the estimated coefficient $\hat{y}_0$ is given by $\hat{Y}_0 = \sum_{i=0}^{K} H_i Y_i$.

According to the linear minimum mean-square-error (LMMSE) criterion, the filter coefficients are:

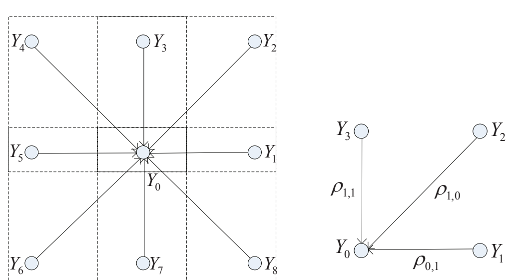
$$H_i = \arg\min E\{[\hat{Y}_0 - X_0]^2\} = \arg\min E\{[\sum_{i=0}^{K} H_i Y_i - X_0]^2\}, \quad (1)$$

where X_0 is the original DCT coefficient before quantized. Let $R_Y(i,j) = E[Y_i Y_j]$ be the autocorrelation of the quantized DCT coefficients and $R_{YX}(i,j) = E[Y_i X_j]$ be the cross-correlation between the quantized DCT coefficients and the original DCT coefficients. After some derivation, we have:

$$\sum_{i=0}^{K} H_i R_Y(i,j) = R_{YX}(0,j),\ j = 0,1,\dots,K. \quad (2)$$

Thus, the FIR filter coefficients H_i, $i=0,1,\dots,K$ can be determined from (2).

If we build the FIR filter on basis of the 3×3 context window, then we have a 9th order Wiener filter, i.e. $K=8$. Because of symmetric property of the context window as shown in Fig. 2(a), the 9th order Wiener filter can be simplified and its output will be represented as the average output of four 4th order Wiener filters.



(a) (b)

Fig. 2. Symmetric property of 3×3 context window

We assume that quantization noise N has a zero-mean uniform distribution which can be determined from the quantization table. We also assume the DCT coefficients and quantization noise are uncorrelated.

$$R_Y(i,j) = R_X(i,j) + R_N(i,j) \quad R_{YX}(i,j) = R_X(i,j). \quad (3)$$

If the DCT coefficients also have zero mean, then (2) can be expressed as:

$$\begin{bmatrix} 1+\frac{\sigma_N^2}{\sigma_X^2} & \rho_{0,1} & \rho_{1,0} & \rho_{1,1} \\ \rho_{0,1} & 1+\frac{\sigma_N^2}{\sigma_X^2} & \rho_{1,1} & \rho_{1,0} \\ \rho_{1,0} & \rho_{1,1} & 1+\frac{\sigma_N^2}{\sigma_X^2} & \rho_{0,1} \\ \rho_{1,1} & \rho_{1,0} & \rho_{0,1} & 1+\frac{\sigma_N^2}{\sigma_X^2} \end{bmatrix} \begin{bmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{bmatrix} = \begin{bmatrix} 1 \\ \rho_{0,1} \\ \rho_{1,0} \\ \rho_{1,1} \end{bmatrix}, \quad (4)$$

where σ_N^2 is the quantization noise variance. We use the uniform distribution variance model $\sigma_N^2 = Q^2/12$, where Q is the quantization step; σ_X^2 is the priori variance of the original DCT coefficients; $\rho_{0,1}$,$\rho_{1,0}$,$\rho_{1,1}$ are the normalized correlation coefficients between Y_0 and Y_1,Y_2,Y_3 separately as shown in Fig. 2(b).

With these statistical parameters, FIR Wiener filter coefficients H_0,H_1,H_2 and H_3 can be determined. Because of the symmetric property, parameters of the four 4th order Wiener filters are approximately the same, thus we only need to compute once to obtain these filter coefficients. Thus, the estimated DCT coefficient $\hat{Y}_0$ is given below:

$$\hat{Y}_0 = H_0 Y_0 + \frac{H_1}{2}(Y_1+Y_5) + \frac{H_2}{2}(Y_3+Y_7) + \frac{H_3}{4}(Y_2+Y_4+Y_6+Y_8). \quad (5)$$

The derivation above assumes that the DCT coefficients have zero mean. Suppose the priori mean of the original DCT coefficients X are $\overline{X}$, then DCT coefficients will be zero-mean after subtracting the priori mean. Thus, with the estimated priori mean $\overline{X}$, the restored DCT coefficients $\hat{Y}$ can be obtained using

$$\hat{Y} = \overline{X} + H(Y - \overline{X}), \quad (6)$$

where H is the proposed FIR Wiener filter applied on the 3×3 context window. We shall explain how to estimate the parameters of the proposed filter and the priori mean in section 3.

3. THE DUAL ADAPTIVE WIENER FILTERING STRUCTURE

3.1. The Proposed Structure Description

We apply the new FIR Wiener filter twice in a dual adaptive filtering structure as shown in Fig 3. The first filtered result is taken as the pilot information, from which parameters are estimated for the second FIR Wiener filter. It is our prior knowledge that the original DCT coefficients must lie within the quantization intervals determined by the quantization step. So in our proposed structure, "restriction" should be imposed after each filtered DCT coefficient.

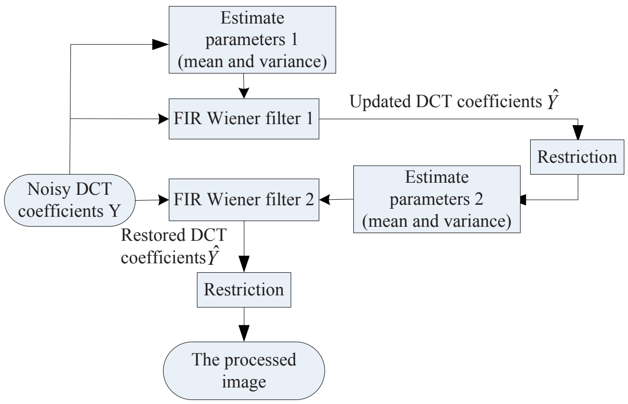


Fig. 3. The proposed dual adaptive Wiener filtering structure

3.2. Parameter Estimation

a. Prior mean $\overline{X}$ and variance σ_X^2 of the original DCT coefficients

As an approximation in practical realization, they are computed as the local mean and variance based on local statistics, given that the DCT coefficients are locally independent and identically distributed (i.i.d). The larger the size of the local window to estimate statistical parameters is, the more reliable this estimation is because of more samples to be used. However, the locally i.i.d assumption becomes inaccurate as the window size grows. This suggests the existence of a proper local neighborhood for parameter estimation.

A number of methods based on varying local windows have been reported. Our novel window selection approach is based on feature matching .If the shifted block $B_{m,n}^{k,l}$ has similar feature with that of block $B_{m,n}$, we can say that the DCT coefficients $X_{m,n}^{k,l}(u,v)$ and $X_{m,n}(u,v)$ obtained from the two blocks are identically distributed, where $u,v=0,\ldots,7$. In order to measure feature similarity of two 8×8 blocks, we introduce the following criterion:

$$\sum_{u=0}^{7}\sum_{v=0}^{7}\left|X_{m,n}^{k,l}(u,v)-X_{m,n}(u,v)\right|^2 < T, |k| \le L, |l| \le L, \tag{7}$$

where L is the maximal block shift and T is the maximal distance for which two blocks are considered similar. If the criterion is satisfied, the neighboring coefficient $X_{m,n}^{k,l}(u,v)$ from this shifted block $B_{m,n}^{k,l}$ can be admitted in the local window for the estimation of mean and variance.

As to the first FIR Wiener filter, because the original DCT coefficients are not available, we can estimate the priori mean and variance from local statistics of the quantized coefficients and quantization noise. The DCT coefficients and quantization noise are approximately uncorrelated, so $\overline{X}=\overline{Y}, \sigma_X^2=\sigma_Y^2-\sigma_N^2$. With the estimated priori mean and variance above, the DCT coefficients will be updated into $\hat{Y}$ using $\hat{Y}=\overline{X}+H(Y-\overline{X})$ which is the first Wiener filter procedure. After that, the priori mean and variance will be estimated more accurately from the updated DCT coefficients $\hat{Y}$ as: $\overline{X}=\overline{\hat{Y}}, \sigma_X^2=\sigma_{\hat{Y}}^2$ for the second FIR Wiener filter.

b. Normalized correlation coefficients $\rho_{0,1},\rho_{1,0},\rho_{1,1}$

The DCT coefficients at 64 different frequencies for each block have their specific autocorrelations. The autocorrelations can be estimated from the original DCT coefficients using the definition of normalized correlation coefficients between two random variables r and s:

$$\rho=\frac{E[(r-\overline{r})(s-\overline{s})]}{\sqrt{E[(r-\overline{r})^2]E[(s-\overline{s})^2]}}. \tag{8}$$

The autocorrelations can be trained from sample images and then used as a table to look up.

5. EXPERIMENTAL RESULTS AND ANALYSIS

Three quantization tables Q1, Q2, and Q3 corresponding to 0.24, 0.189 and 0.15 bits per pixels (bpp) are used for the experiments. Table 1 summarizes the PSNR results of our method and other popular deblocking methods. In most cases, the proposed method has the highest PSNR gain except the image "Lena" using the quantization tables Q1 and Q2 for which Sun's method [7] is slightly better. We have also provided the visual comparison of different deblocking methods through the image "Lena" shown in Fig. 4. We can find that the proposed method effectively removes most of annoying artifacts and preserves edges and texture well. The results of MPEG4-2, $POCS_Y$, WT_X, $POCS_P$, and WT_L leave some artifacts unprocessed, while the processed images of Sun's method and our method give the best visual quality improvement.

In the proposed technique, the computational complexity is mainly introduced by the computation of the DCT coefficients from shifted blocks. The author in paper [11] proposed a fast algorithm to obtain the DCT coefficients of new shifted blocks directly from the DCT coefficients of original blocks. The complexity depends on the number of zero DCT coefficients in each block, which is related to the compression ratios of the input images. Since we process low-bit-rate coded images with very high compression ratios, the fast algorithm is supposed to save much computational cost. It should be noted that the performance of our method is comparable to Sun's method, but as to the latter one, MAP criterion is adopted to minimize the energy function which requires iterations to obtain the optimal results, therefore, our method has a much lower computational complexity than Sun's.

6. CONCLUSIONS

In this paper, a DCT domain algorithm is proposed to reduce blocking artifacts for low bit rate coded images. We propose to design a new FIR Wiener filter with an effective parameter estimation strategy and apply a dual adaptive Wiener filtering structure to restore each DCT coefficient. Experimental results on some images have demonstrated the effectiveness of the proposed DCT domain method. From the comparison with the other deblocking methods, we can say that the performance of our method is comparable to the state-of-the-art methods but has low computational complexity.

7. REFERENCES

[1]MPEG4 Verification Model, VM 18.0, 2001. pp. 271-275.

[2]Y. Yang, N. Galatsanos, and A. Katsaggelos, "Projection-based spatially adaptive reconstruction of block-transform compressed images," *IEEE Trans. on Circuits Syst. Video Technol*., vol. 4, no. 7, pp. 896–908, July 1995.

[3]H. Paek, R.-C. Kim, and S.-U. Lee, "On the POCS-based postprocessing technique to reduce the blocking artifacts in transform coded images," *IEEE Trans. on Circuits Syst. Video Technol*., vol. 3, no. 3, pp. 358–367, June 1998.

[4]M. Robertson and R. Stevenson. DCT quantization noise in compressed images. *IEEE Trans. Circuits Syst. Video Technol*., 15(1):27–38, Jan.2005.

[5]Z. Xiong, M. T. Orchard, and Y. Q. Zhang, "A deblocking algorithm for JPEG compressed images using overcomplete wavelet representations," I*EEE Trans. Circuits Syst. Video Technology*, vol. 7, pp. 692–695, Aug. 1999.

[6]A. Liew and H. Yan, "Blocking artifacts suppression in block-coded images using overcomplete wavelet representation," *IEEE Trans. on Circuits Syst. Video Technol*., vol. 14, no. 4, pp. 450–461, April 2004.

[7]D. Sun and W.K. Cham. Postprocessing of Low Bit-Rate Block DCT Coded Images Based on a Fields of Experts Prior**.** *IEEE Trans. Image Processing*,vol.16,pp 2743-2751,Nov.2007.

[8] Zhen Li, and Edward J. Delp, "Block Artifact Reduction Using a Transform-Domain Markov Random Field Model," *IEEE Trans. Circuits Syst. Video Technology*, vol.15,No 12,pp 1583-1593, December 2005.

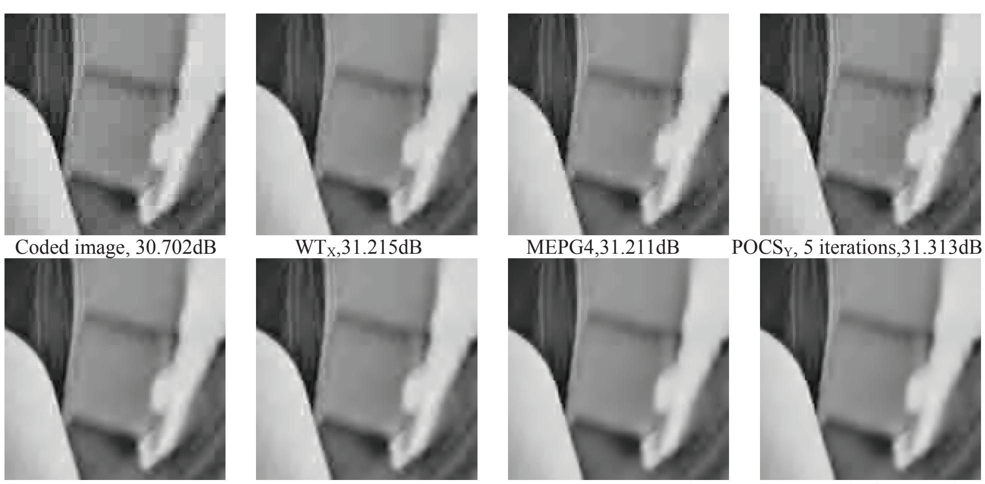
[9]Tao Chen, Hong Ren Wu, and Bin Qiu, "Adaptive postfiltering of transform coefficients for the reduction of blocking artifacts, " *IEEE Trans. Circuits Syst. Video Technology*, vol.11, No. 5, pp 594-602, May 2001.

[10] Shizhong Liu and Alan C. Bovik, "Efficient DCT-domain blind measurement and reduction of blocking artifacts," *IEEE Trans. Circuits Syst. Video Technology*, vol.12, No. 12, pp 1139-1149, December 2002.

[11] S.-F. Chang and D. G. Messerschmitt, "Manipulation and compositing of MC-DCT compressed video," *IEEE J. Select. Areas Commun*., vol. 13, pp. 1–11, Jan. 1995.

	Lena			Barbara			Baboon		
Quantization Table	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
Coded Image	30.702	30.091	27.382	25.939	25.591	24.028	24.320	24.143	22.133
WT_X[5]	31.215	30.758	28.315	26.226	25.070	24.100	24.240	24.125	22.476
MPEG4[1]	31.211	30.694	28.095	26.092	25.774	24.367	24.451	24.293	22.401
$POCS_Y$[2]	31.313	30.739	28.292	26.400	26.052	24.454	24.545	24.387	22.415
$POCS_P$[3]	31.629	31.020	28.513	26.689	26.321	24.746	24.631	24.469	22.522
MAP_R[4]	31.592	31.128	28.642	26.125	25.860	24.478	24.504	24.429	22.573
WT_L[6]	31.612	31.187	28.654	26.374	26.043	24.660	24.591	24.450	22.558
Sun's[7]	**31.963**	**31.435**	28.806	26.655	26.320	24.869	24.774	24.623	22.618
The proposed method	31.955	31.342	**28.885**	**26.831**	**26.598**	**24.973**	**24.793**	**24.636**	**22.622**

Table 1. PSNR results(db) processed by different methods using Q1,Q2,Q3.



Coded image, 30.702dB | WT_X,31.215dB | MEPG4,31.211dB | $POCS_Y$, 5 iterations,31.313dB

$POCS_P$, 5 iterations,31.629dB | WT_L,31.612dB | Sun's, 31.963dB | Our method, 31.955dB

Fig. 4.The processed result using different methods for "Lena"