

A Method for Blocking Effect Reduction Based on Optimal Filtering

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Abstract. In block-based coding schemes, the input image is segmented into small blocks that are processed independently; therefore, blocking effects occur along block boundaries. Various methods have been developed to reduce such blocking effects. In this paper, we propose a method for blocking effect reduction based on optimal filtering, and we compare its performance with those of others.

1 Introduction

The objective of image coding is to represent the image with as few bits as possible while retaining sufficient picture quality. Various image compression algorithms have been developed. Some of the more promising involve segmentation of the image into small subimages before coding. In this approach, the original image is divided into subimages, in most cases, square blocks of the equal size, and then each subimage is coded independently of the others. To reproduce the full image, the separated subimage blocks are reassembled by the decoder. The purpose of segmenting the image is to exploit local characteristics of the image and to simplify hardware implementation of the encoding algorithm. The transform coding is a typical example of the coding technique having image segmentation.

One of the fundamental problems of transform coding especially at the low bit rates is so-called the blocking effect. Since each block is processed independently, the reconstructed image at the decoder has discontinuities along block boundaries. This blocking effect is mainly due to independent quantization of transform coefficients in each block. Since the quantization takes place in the transform domain, the effect of quantization error is spread all over the spatial locations within the block. This phenomenon appears very annoying, as the coding bit rate decreases.

In order to reduce the blocking effect, various methods have been developed, such as the lapped orthogonal transform (LOT), the overlapping block method, the interleaving block method and post-filtering. However, each of those approaches has some drawbacks. The overlap method reduces blocking effects well

without degrading image edges, but a major disadvantage of this method is an increase in the bit rate [1,2]. The post-filtering method is easy to implement and it works well. The post-filtering method does not increase the bit rate, but the filter degrades the edge content in the image [2]. The LOT is a popular method for reducing blocking effects. The optimal LOT has a major disadvantage of being highly sensitive to numerical errors, even with double-precision computations [3, 4]. The optimal LOT may not be easily factorable so that a fast algorithm may not exist [3]. The suboptimal LOT which has a fast algorithm, but the approximation for the suboptimal LOT is satisfactory only for the small block sizes. In our simulation for the LOT, we have shown the spread of the discontinuities along the block boundaries to adjacent blocks. The two-stage transform coding method [5] uses the total information of the image to reduce the blocking effect. In this algorithm, the error of each transform coefficient is spread to the entire image. Thus, the quality of image decreases exponentially as the bit rate decrease.

2 Optimal Filtering

In the previous section, we discussed blocking effect reduction algorithms that can be applied within local blocks or along local block boundaries. In this section, we develop a globally optimum filter instead of a locally optimum one. The globally optimum filter considers an entire image. Before we derive a globally optimum filter, let's consider a locally optimum filter to get a concept of the optimal filter.

First, we consider a block processing system with pre- and post-filters, as depicted in Fig. 1. One of the functions of the encoder is to shape the input signal spectrum into some appropriate form that takes into account quantization or noise degradations. At the decoder, an approximate inverse filter is employed to recover the original signal as much as possible.

In Fig. 1, the input noise \mathbf{u} the quantization error \mathbf{d} are stationary, uncorrelated, zero-mean random processes with known spectrum information. Here, the input and reconstructed signals \mathbf{x} and $\tilde{\mathbf{x}}$ are vectors in the N -dimensional real space. We do not assume that \mathbf{F} and \mathbf{G} should be causal. We start by obtaining the optimal \mathbf{G} for a given pre-filter; that allows us to derive an error expression that depends only on \mathbf{F} . If we can find the pre-filter that minimizes the new error function, we can effectively obtain the jointly optimal filter pair. \mathbf{D} and \mathbf{D}^{-1} represent DCT and IDCT, respectively. We here assume that the input noise \mathbf{u} is zero.

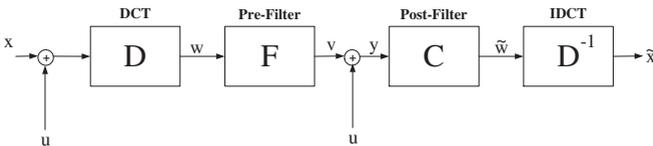


Fig. 1. Pre- and Post-Filter System

The pre-filter generates the intermediate signal \mathbf{v} from \mathbf{w} , which is transformed by the matrix \mathbf{F} and quantized through the quantizer. The post-filter builds an estimate $\tilde{\mathbf{w}}$ of \mathbf{w} , from which the final input estimate $\tilde{\mathbf{x}}$ is generated.

From Fig. 1, it is clear that

$$\mathbf{w} = \mathbf{D}\mathbf{x}, \quad \tilde{\mathbf{w}} = \mathbf{D}\tilde{\mathbf{x}} \tag{1}$$

Since we can assume the DCT and IDCT operations are lossless operations, the absolute mean-square error between \mathbf{w} and $\tilde{\mathbf{w}}$ is the same as that between \mathbf{x} and $\tilde{\mathbf{x}}$, that is given by

$$\xi_w = N^{-1} E[\|\tilde{\mathbf{w}} - \mathbf{w}\|^2] \tag{2}$$

Our problem, therefore, is reduced to find matrices \mathbf{F} and \mathbf{G} in Fig. 1 that minimize ξ_w . This is a typical classical problem in information theory, usually referred to as optimal block quantization or optimal block coding. We can make use of the cross-correlation between \mathbf{v} and \mathbf{d} to derive an expression for the error ξ_w as a function of the matrices \mathbf{F} and \mathbf{G} . However, this would lead to matrix equations that are fairly difficult to manipulate. A much easier approach is to use the 'gain plus additive noise' model of scalar quantization. This model is derived by Malvar [3]. The quantizer output \mathbf{y} is given by

$$\mathbf{y} = \Psi\mathbf{x} + \tilde{\mathbf{d}} \tag{3}$$

where $\tilde{\mathbf{d}}$ is a noise source with no correlations, and Ψ is a diagonal matrix. The elements of Ψ depend on the autocorrelation \mathbf{R}_{vv} [3]. With the relationship between \mathbf{v} and \mathbf{y} , we can modify the block diagram of Fig. 1 to Fig. 2.

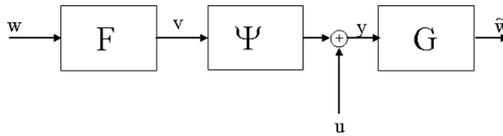


Fig. 2. Subsystem to be Optimized

We can rewrite (2) in the form

$$\begin{aligned} \xi_w &= N^{-1} tr\{E[(\mathbf{G}\Psi\mathbf{F}\mathbf{w} + \mathbf{G}\tilde{\mathbf{d}} - \mathbf{w})(\mathbf{G}\Psi\mathbf{F}\mathbf{w} + \mathbf{G}\tilde{\mathbf{d}} - \mathbf{w})^t]\} \\ &= N^{-1} tr\{\mathbf{\Lambda} + \mathbf{G}\Psi\mathbf{F}\mathbf{\Lambda}\mathbf{F}^t\Psi\mathbf{G}^t + \mathbf{G}\mathbf{R}_{\tilde{\mathbf{d}}\tilde{\mathbf{d}}}\mathbf{G}^t - 2\mathbf{G}\Psi\mathbf{F}\mathbf{\Lambda}\} \end{aligned} \tag{4}$$

For any given \mathbf{F} , the optimal \mathbf{G} can be obtained by setting $\partial\xi_w/\partial\mathbf{G} = 0$, which lead to

$$\mathbf{G}_{opt} = \mathbf{\Lambda}\mathbf{F}^t\Psi(\Psi\mathbf{F}\mathbf{\Lambda}\mathbf{F}^t\Psi + \mathbf{R}_{\tilde{\mathbf{d}}\tilde{\mathbf{d}}})^{-1} \tag{5}$$

For general cases of images coding, \mathbf{F} is the identity matrix. If we assume that DCT and IDCT are lossless operations and DCT is suboptimal to KLT, we can expand the relation of (5) between the coefficients of the decoder and the encoder

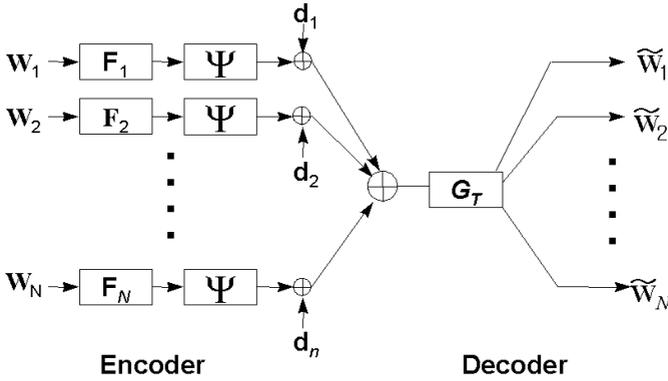


Fig. 3. Globally Optimum Filter G_T

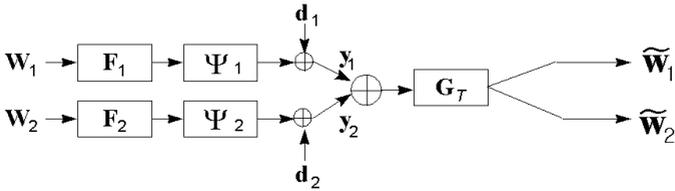


Fig. 4. Reduced System to be Optimized

to that between the original image and the reconstructed one. However, because of the independent block processing, we may have the blocking effect along the block boundaries in the reconstructed image.

In order to reduce the blocking effect, we should design a post-filter that is globally optimal for the entire image, instead of locally optimal for each block. For this work, we consider the system depicted in Fig. 3, where w_i is the input vector in the N -dimensional real space, d_i is the quantization error vector being uncorrelated with the w_i , F_i is preprocessor, and Ψ_i is the diagonal matrix for quantization.

In this scheme, the entire signal is divided into small vectors, and each vector is independently processed in the encoder. At the decoder, we collect each coded vector to find a globally optimum filter G_T .

Without loss of generality, we can simplify the derivation by considering only two blocks, as drawn in Fig. 4. The dimension of each block at the encoder is different from that of the globally optimum filter G_T .

In order to manipulate each block and the global filter, we employ Kronecker product. We define the matrices, K_1 and K_2 , for indicating each block, which is given by

$$K_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad K_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{6}$$

Also, we can write the entire original signal \mathbf{x} and the entire reconstructed signal $\tilde{\mathbf{x}}$ in the form

$$\mathbf{x} = \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix}, \quad \tilde{\mathbf{x}} = \begin{bmatrix} \tilde{\mathbf{x}}_1 \\ \tilde{\mathbf{x}}_2 \end{bmatrix} \quad (7)$$

With (6), we can find the dimension extension of \mathbf{w}_1 and \mathbf{w}_2 , as following:

$$\begin{bmatrix} \mathbf{w}_1 \\ 0 \end{bmatrix} = \mathbf{K}_1 \otimes \mathbf{w}_1, \quad \begin{bmatrix} 0 \\ \mathbf{w}_2 \end{bmatrix} = \mathbf{K}_2 \otimes \mathbf{w}_2 \quad (8)$$

Intermediate vectors, \mathbf{y}_1 and \mathbf{y}_2 , and the quantization error vectors, \mathbf{d}_1 and \mathbf{d}_2 , are represented by

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{w}_2 \end{bmatrix}, \quad \tilde{\mathbf{x}} = \begin{bmatrix} \tilde{\mathbf{x}}_1 \\ \tilde{\mathbf{x}}_2 \end{bmatrix} \quad (9)$$

where

$$\mathbf{y}_i = \Psi \mathbf{F}_i \mathbf{w}_i + \mathbf{d}_i \quad (10)$$

Similarly to the procedure for a locally optimum filter, we can define the error criterion to be minimized, which is given by

$$\xi_w = (2N)^{-1} \left\{ E \left[\|\tilde{\mathbf{x}} - (\mathbf{K}_1 \otimes \mathbf{w}_1 + \mathbf{K}_2 \otimes \mathbf{w}_2)\|^2 \right] \right\} \quad (11)$$

Using (8), (9), and (10), we can rewrite (11) as

$$\begin{aligned} \xi_w &= (2N)^{-1} tr \left\{ E \left[\mathbf{K}_1 \otimes \mathbf{w}_1 \mathbf{K}_1^t \otimes \mathbf{w}_1^t + \mathbf{K}_1 \otimes \mathbf{w}_1 \mathbf{K}_2^t \otimes \mathbf{w}_2^t \right. \right. \\ &\quad \left. \left. + \mathbf{K}_2 \otimes \mathbf{w}_2 \mathbf{K}_2^t \otimes \mathbf{w}_2^t + \mathbf{K}_2 \otimes \mathbf{w}_2 \mathbf{K}_1^t \otimes \mathbf{w}_1^t \right] \right. \\ &\quad \left. - 2\mathbf{G}_T^t E \left[\mathbf{K}_1 \otimes \mathbf{w}_1 \mathbf{K}_1^t \otimes \mathbf{y}_1^t + \mathbf{K}_1 \otimes \mathbf{w}_1 \mathbf{K}_2^t \otimes \mathbf{y}_2^t \right. \right. \\ &\quad \left. \left. + \mathbf{K}_2 \otimes \mathbf{w}_2 \mathbf{K}_1^t \otimes \mathbf{y}_1^t + \mathbf{K}_2 \otimes \mathbf{w}_2 \mathbf{K}_2^t \otimes \mathbf{y}_2^t \right] \right. \\ &\quad \left. + \mathbf{G}_T^t E \left[\mathbf{K}_1 \otimes \mathbf{y}_1 \mathbf{K}_1^t \otimes \mathbf{y}_1^t + \mathbf{K}_1 \otimes \mathbf{y}_1 \mathbf{K}_2^t \otimes \mathbf{y}_2^t \right. \right. \\ &\quad \left. \left. + \mathbf{K}_2 \otimes \mathbf{y}_2 \mathbf{K}_1^t \otimes \mathbf{y}_1^t + \mathbf{K}_2 \otimes \mathbf{y}_2 \mathbf{K}_2^t \otimes \mathbf{w}_2^t \right] \mathbf{G}_T^t \right. \\ &\quad \left. = (2N)^{-1} tr \left\{ \mathbf{G}_T \mathbf{R}_{yy} \mathbf{G}_T^t - 2\mathbf{G}_T \mathbf{R}_{xy} + \mathbf{R}_{xx} \right\} \right\} \quad (12) \end{aligned}$$

where \mathbf{R} represents a correlation function. For any given \mathbf{F}_i , assumed $\mathbf{F}_1 = \mathbf{F}_2$, the optimal \mathbf{G}_T can be get by setting $\partial \xi_w / \partial \mathbf{G}_T = 0$, which leads to

$$\mathbf{G}_{T\text{opt}} = \mathbf{R}_{xy} (\mathbf{R}_{yy})^{-1} \quad (13)$$

Here, we have assumed that \mathbf{F} is the identity matrix as in the local optimum filter, and we have assumed that DCT and IDCT are lossless operations. We can extend this relation to the original input signal at the encoder and the reconstructed signal at the decoder. By such an extension, we can see that (13) is in the form of the optimal Wiener filter. It is not strange because the Wiener filter is known as the optimal solution for many restoration problems.

Fig. 5(a) shows the reconstructed image before the blocking effect is reduced. Fig. 5(b) is the output image with the globally optimum filter. This technique



Fig. 5. Results for LENA

has the best performance among all the methods discussed in this paper. This technique shows higher SNR about 1 dB than the other algorithms at 0.98 bpp.

We assumed the pre-filter is identity matrix. However, if we employ a pre-filter, we can get better performance than the scheme without the pre-filter. A disadvantage of this scheme is that we should know the information about the spectrum of the input signal.

3 Simulation Results

In this section, we compare various algorithms designed to reduce the blocking effect. For a fair comparison, each method should generate the same number of coding bits. It is important because some methods, such as overlap method, can generate more bits than other methods. Thus, the quantizer, with the bit allocation according to the variances of transform coefficients, can generate the same number of bits for various algorithms. Here, the optimized bit allocation table depends on the encoding algorithm, but the total number of bits in the bit allocation table should be independent of the employed algorithms. Since we do not use entropy coding, which is lossless coding, to make a fair comparison, our results have higher bit rate than those of standards.

Fig. 6 shows the SNR plot resulting from applying various algorithms to LENA. In Fig. 6, there are two reasons of the small difference in SNR. One is that SNR is not a good measure for the blocking effect, and the other is that we assign bits by the amount of energy. The globally optimum filter has the highest SNR value.

We define the discontinuity as the sum of absolute values of the differences taken along the block boundaries. The discontinuity along the block boundaries can represent the degree of the blocking effect. However, if we consider only the

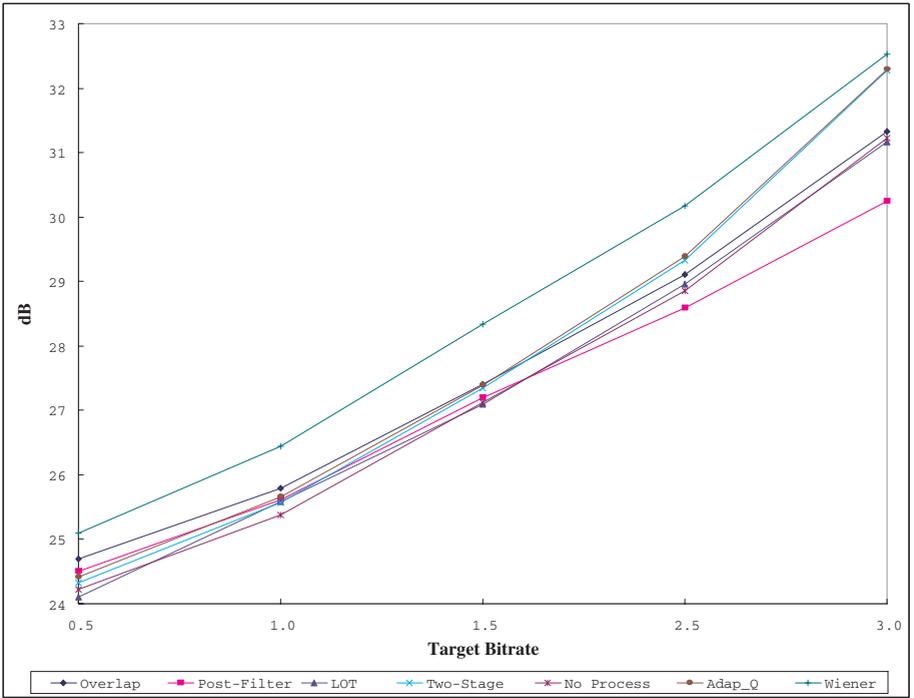


Fig. 6. Reduced System to be Optimized

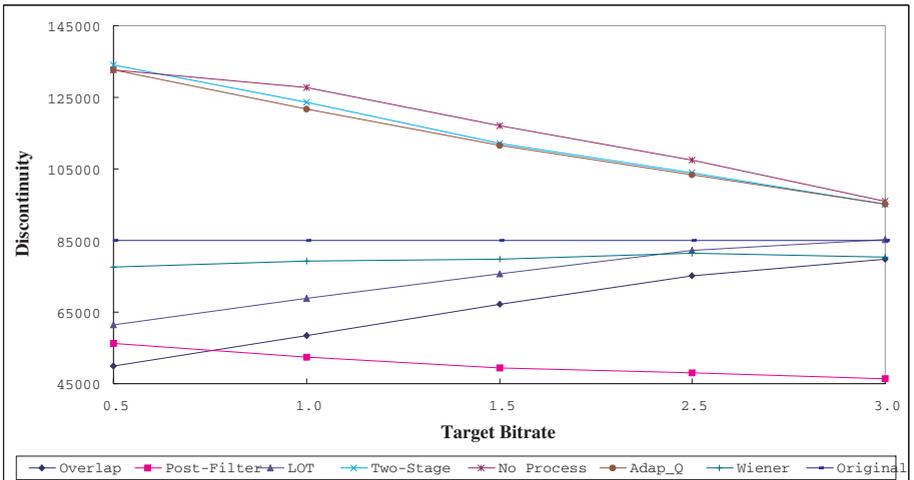


Fig. 7. Reduced System to be Optimized

method to minimize the discontinuity, some methods such as low-pass filtering can degrade the sharpness of the original image. While the HVS indicates the image from the overlap method is better than that from the modified overlap method, the discontinuity of the overlap method is larger than that of the modified overlap methods. Fig. 7 shows the discontinuities of various algorithms for LENA. The discontinuity of the reconstructed image depends on that of the original image. In this respect, we can say that the image has good quality as the discontinuity converges to that of the original image. In Fig. 7, the discontinuity of the original image is 85007 (flat line). In this respect, the globally optimum filter shows the best quality and the LOT shows the second.

4 Conclusions

In this paper, we have tested several algorithms for reducing the blocking effect. We have also have derived an optimal filter for reducing the blocking effect, assuming that we have an information of the input spectrum. The resulting post-filter is similar to the Wiener filter. If we use an estimation technique for the input spectrum, the performance of the Wiener filter may be degraded. In this paper, we have proposed a new criterion for comparing the degree of blocking effect reduction. In comparisons with this new criterion, our optimal filter shows the best result.

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