REDUCTION OF CODING ARTIFACTS IN TRANSFORM IMAGE CODING BY USING LOCAL STATISTICS OF TRANSFORM COEFFICIENTS

Steven S. O. Choy and Yuk-Hee Chan

Department of Electronic Engineering
The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong

ABSTRACT

This paper proposes a new approach to reduce coding artifacts in transform image coding. We approach the problem in an estimation cf each transform coefficient from the quantized data by using its local mean and variance. The proposed method can reduce much coding artifacts of low bit-rate coded images, and at the same time guarantee that the resulting images satisfies the quantization error constraint.

1. INTRODUCTION

Block transform-based image coding offers a good trade-off between bit rate and subjective image quality, and hence is the most widely used technique in image compression. Unfortunately, noise caused by the coarse quantization of transform coefficients is noticeable in a form of visible block boundaries when the compression ratio is sufficiently high. Various techniques had been proposed to remove blocking artifacts of low bit-rate coded images. In order to make encoder efficient, most of them involves post-processing at the decoding side, rather than approaching the problem from the encoding side. For instance, in [1-2], blocking artifacts in compressed images are concealed with low-pass filtering (LPF) techniques. With this approach, subjectively blocking-artifacts-free image can be achieved without burden the computation too much at the decoder. However, it produces smeared edges and the resulting transform coefficients may spread beyond their original quantization interval. In [3-6], the image reconstruction is viewed as an ill-posed recovery problem. Specifically, the approaches proposed in [3-4] are based on the theory of *projections onto convex sets* (POCS) while in [5-6] a stochastic image model is first assumed and *maximum a posteriori* (MAP) estimation is then applied to reconstruct the image. Although methods based on image recovery approach can reconstruct a good quality image in terms of both objective PSNR and subjective judgment, they are intrinsically iterative and hence take time to converge to their solutions.

Without taking the channel error into account, the quantization error is the sole error source in transform based coding scheme. The quantization error is introduced in transform domain, although it manifests itself as undesirable artifacts in spatial domain. Hence, tackling the coding artifacts problem in transform domain is more appropriate and should be more efficient than in spatial domain. Classical methods for reducing coding artifacts devote their efforts to spatial domain processing of the encoded image based on some *a priori* knowledge about the image, and they cannot perform the reconstruction efficiently. In this paper, we propose to deal with the problem as a noise reduction in transform domain. We formulate a weighted-least-squares estimation of the transform coefficients from their quantized version, and the computation of the estimate involves only local statistics of the quantized coefficients. The proposed algorithm is non-iterative and the required computation is not much heavier than those of simple low-pass filtering methods. The proposed method reduces the coding artifacts and confines the resulting transform coefficients to their original quantization intervals simultaneously by means of weighting values that are devised on the local statistics of the transform coefficients, as well as the *a priori* quantizer information.

2. FORMULATION

Throughout this paper a digital $N\times N$ image, as well as its corresponding transform, is treated as an $N^2\times 1$ vector in the space R^{N^2} by lexicographic ordering. Block transform is then a $N^2\times N^2$ matrix which carries out linear transformation from R^{N^2} to R^{N^2}. The lossy effects of the block transform-based compression can be modeled by $Y = Q[Tx]$, where x is the original image, T

This work was supported by the PolyU Research Grant: Project account 340.813.A3.420.

0-7803-3583-X/97 $10.00 ©1997 IEEE

is the transform matrix, Y is the encoded data and $Q[\bullet]$ represents the quantization process. The encoded image with blocking artifacts is given by $y = T^{-1}Q[Tx]$, where T^{-1} is the inverse transform. If uniform scalar quantizers are used, Y can be decomposed as

$$Y = X + n, \tag{1}$$

where X is the transform of x and n is the additive zero-mean noise introduced by the quantizers.

The problem here is to estimate X from Y and the available information of the quantizers. Suppose the *a priori* mean of X is $\bar{X}$. One very reasonable estimation of X, by taking Y into account, is the weighted-least-squares estimation [7], which is formulated as finding the X that minimizes the functional

$$J = (X - \bar{X})^t M(X - \bar{X}) + (Y - X)^t R(Y - X), \tag{2}$$

where M and R are weighting matrices. We denote this estimate as $\hat{X}$ and it is given explicitly as

$$\hat{X} = \bar{X} + W(Y - \bar{X}), \tag{3}$$

with $W = (M + R)^{-1}R$. Here, $(M + R)$ is assumed invertible. Note that W can be rewritten as $W = M^{-1}(R^{-1} + M^{-1})^{-1}$, provided that M^{-1} and R^{-1} exist.

To ensure that the method would be practical with light computational cost, it is desirable to chose both M and R to be diagonal. In this case, we have

$$\hat{X}_i = \bar{X}_i + w_i(Y_i - \bar{X}_i), \tag{4}$$

where w_i is the i-th diagonal element of W, and $[\cdot]_i$ represents the i-th element of a vector. It can be derived that w_i's that minimize the mean-square error of $\hat{X}$ are given as

$$w_i = \frac{\sigma_{X_i}^2}{\sigma_{X_i}^2 + \sigma_{n_i}^2}, \tag{5}$$

where $\sigma_{X_i}^2$ and $\sigma_{n_i}^2$ are the variance of X_i and n_i respectively. It is worthwhile noticing that the above choice of w_i is identical to choosing the i-th diagonal elements of M and R to be the reciprocal of the variance of X_i and n_i, respectively.

The computation of $\hat{X}$ requires the *a priori* mean and variance of X_i, as well as the quantization-error variance of X_i. By assuming that the quantization error n_i has a uniform probability density function, the quantization-error variance is given as

$$\sigma_{n_i}^2 = \frac{1}{12}q_i^2, \tag{6}$$

where q_i is the known step size of the corresponding quantizer applied to X_i. Both the mean and variance of X_i can be estimated from Y_i. Since n_i is assumed zero-mean and uncorrelated with X_i, from (1) it can be derived that

$$\bar{X}_i = \bar{Y}_i \tag{7}$$

and

$$\sigma_{X_i}^2 = \sigma_{Y_i}^2 - \sigma_{n_i}^2, \tag{8}$$

where $\bar{Y}_i$ and $\sigma_{Y_i}^2$ are the mean and variance of Y_i respectively. (Note that in practice $\sigma_{X_i}^2$ is determined as $\max\{0, \sigma_{Y_i}^2 - \sigma_{n_i}^2\}$ to guarantee its positive nature.) As an approximation in practical realization, the mean and variance of Y_i are computed as the 'local' mean and variance of Y_i. Our idea on local statistics of transform coefficients is illustrated in the following. Let $y^{<m,n>}$ denote y that is shifted in image domain by (m, n). Its transform, $Ty^{<m,n>}$, is then denoted as $Y^{<m,n>}$. The local mean $\bar{Y}_i$ and the local variance $\sigma_{Y_i}^2$ are defined by

$$\bar{Y}_i = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} Y_i^{<m,n>} \tag{9}$$

$$\sigma_{Y_i}^2 = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} \left[Y_i^{<m,n>} - \bar{Y}_i\right]^2, \tag{10}$$

where $(2L + 1)^2$ is the extent of the analysis window.

The definition of w_i in (5) can be rewritten as $w_i = \Sigma_i/(\Sigma_i + 1)$, where $\Sigma_i = \sigma_{X_i}^2/\sigma_{n_i}^2$, which is the signal-variance to noise-variance ratio. Moreover, (4) can be rewritten as $\hat{X}_i = (1 - w_i)\bar{X}_i + w_i Y_i$. In view of these, a physical interpretation of the estimate is that $\hat{X}_i$ will be biased towards Y_i when Σ_i is relatively large and towards $\bar{X}_i$ when Σ_i is relatively small. However, in order to guarantee that $\hat{X}_i$ satisfies the quantization constraint, i.e.

$$|Y_i - \hat{X}_i| < \frac{q_i}{2}, \tag{11}$$

there should be one more bound for w_i. By substituting (4) into this quantization constraint, we have

$$w_i > 1 - \frac{q_i}{2|Y_i - \bar{Y}_i|}. \tag{12}$$

Therefore, in order to obtain an $\hat{X}$ that satisfies the quantization constraint, w_i is given by

$$w_i = \max\left\{\frac{\sigma_{X_i}^2}{\sigma_{X_i}^2 + \sigma_{n_i}^2}, 1 - \frac{q_i}{2|Y_i - \bar{Y}_i|}\right\}. \tag{13}$$

Finally, we remark that the computation of both $\bar{Y}_i$ and $\sigma_{Y_i}^2$ can be implemented by some sort of fast algorithms. In fact, it is clear that $\bar{Y}_i = [T\bar{y}]_i$, where $\bar{y}$ is the local mean of image y, and we had found empirically in our simulation that $|[T\sigma_y^2]_i|$, where σ_y^2 denotes the local variance of y, can well approximate $\sigma_{Y_i}^2$.

Table 1: PSNR IMPROVEMENTS OF THE IMAGES RECONSTRUCTED BY THE IMPLEMENTED ALGORITHMS.

JPEG Encoded Image	bpp	PSNR	PSNR Improvement			
			LPF [1]	POCS [4]	WLS	WLS*
Baboon	0.449	21.244	-0.026	0.085	0.190	0.126
Cameraman	0.315	26.442	-0.288	0.119	0.405	0.251
Peppers	0.323	27.686	0.374	0.361	0.655	0.556
House	0.244	30.512	0.404	0.432	0.767	0.720
Lenna	0.318	27.879	0.447	0.389	0.734	0.597
Girl	0.231	30.502	0.633	0.486	0.822	0.747
Germany	0.238	29.287	0.487	0.357	0.645	0.618
Couple	0.233	30.597	0.433	0.479	0.649	0.521
Sailboat	0.374	25.693	0.222	0.287	0.491	0.399
Tiffany	0.232	29.328	0.477	0.398	0.715	0.674
Face	0.282	30.171	0.922	0.680	1.073	1.051
Hat	0.352	29.399	1.164	0.779	1.394	1.353

3. PERFORMANCE EVALUATION

Experiments were carried out to evaluate the performance of the proposed method and compare it to other approaches. In order to show its robustness, we used a number of *de facto* standard 256 gray-level test images of size 256×256 each. At first the test images were encoded with the block DCT based JPEG compression algorithm. All of them were encoded with the same quantization table as used in [3-4]. The LPF algorithm [1], the POCS algorithm [4] and the proposed algorithm, denoted WLS, were used to reconstruct the encoded data. As we have remarked before, $\sigma^2_{Y_i}$ can be well approximated by $|[T\sigma_y^2]_i|$. This approximated version of WLS, denoted WLS*, was also implemented for comparative studies. Images reconstructed with these algorithms were then compared with each other. Table 1 shows their PSNR improvement, with respect to the JPEG-encoded image. It is found that the proposed method outperforms other methods in terms of objective PSNR improvement. It is also shown by the experimental results that the proposed method can provide reconstructed images of subjectively better quality. An example is shown in Figures 1-4: Figure 1 shows a magnified portion of the JPEG-encoded 'Lenna' at 0.318 bpp. Figures 2, 3 and 4 show the same magnified portion of the reconstructed 'Lenna' after the application of the LPF, POCS and WLS algorithms, respectively.

4. CONCLUSIONS

In this paper, we have proposed a new technique to reduce coding artifacts in block-transform compressed images. The proposed method is based on the weight-least-squares estimation of the transform coefficients from the encoded data and the available information on the quantizers used. The proposed method can reconstruct an objectively and subjectively better image, and at the same time can assure that the reconstructed image satisfies the quantization error constraint. Finally, the proposed method is non-iterative and thus allows real-time applications. Though in this paper only uniform quantizer is considered, it can be easily generalized to the case with non-uniform quantizer.

5. ACKNOWLEDGMENT

The authors would like to thank Mr. S. W. Hong for his assistance in preparing part of the simulation result.

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Figure 1: JPEG encoded 'Lenna'.

Figure 2: LPF processed 'Lenna'.

Figure 3: POCS processed 'Lenna'.

Figure 4: WLS processed 'Lenna'.

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