CODING ARTIFACT REMOVAL WITH MULTISCALE POSTPROCESSING

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ABSTRACT

A multiscale post processing algorithm based on constrained optimization with the Huber Markov random field (HMRF) model is investigated in this research. The decoded image is enhanced from coarse to fine scales, where postprocessing at the coarse scale improves the global appearance of the image and reduces long range artifacts such as ringing while postprocessing at the fine scale keeps the sharpness of edges. The efficiency of the proposed algorithm is supported by experimental results.

Keywords: postprocessing, constraint optimization, multiscale processing, image enhancement, HMRF

1. INTRODUCTION

In image/video compression, as the coding rate becomes low, the quality of the coded image degrades and unpleasant artifacts appear. In block-based coding schemes, the most noticeable artifact is the blocking artifact appearing as discontinuities along block boundaries. For wavelet/subband coding, it is the ringing artifact appearing as ripples around sharp edges. The objective of postprocessing is to improve the subjective appearance of the decoded image after the image is decoded.

One early work in postprocessing was reported by Rosenholtz and Zakhor in [1]. They proposed a method of iterative projection onto convex sets (POCS) to reduce blocking artifacts in DCT compressed images. In addition to the transmitted coding bit stream, the *a priori* image model has to be incorporated in POCS to improve the subjective quality of the decoded image. Reeves and Eddins [2] proved that POCS provided the solution to a constrained minimization problem, where a decoded image was processed iteratively between two operations, i.e. a projection operation specified by the quantization constraint and a smoothing operation. Instead of adopting the heuristic constraint in [2], [1], Rourke and Stevenson [3] considered a statistical Huber-Markov random field (HMRF) model. Their algorithm effectively removes the blocking artifact in the DCT transformed image while retaining sharpness around boundaries. However, it is still not effective in removing the ringing artifact. The difficulty lies in the fact that the ringing artifact spreads over a wide range. The first order HMRF model adopted in [3] does not model such an artifact well. One possible improvement is to adopt a higher order HMRF model. However, since the complexity of postprocessing grows exponentially with the order of HMRF, the adoption of high order HMRF is computationally expensive.

In this research, we propose a multiscale postprocessing algorithm, in which the decoded image is enhanced from coarse to fine scales. Postprocessing at the coarse scale improves the global appearance of the image and reduces long range artifacts such as ringing while postprocessing at the fine scale keeps the sharpness of edges. The same first order HMRF model is used to characterize the long range correlation in the coarse scale and the short range correlation in the fine scale. Our another contribution is the adaptive adjustment of the continuity factor so that the intensity of smoothing is reduced in areas where the projection operation cancels the effect of smoothing.

This work is organized as follows. The theoretical foundation of constrained optimization-based postprocessing is reviewed in Section 2. The implementation details of multiscale postprocessing are described in Section 3. Experimental results are given in Section 4.

2. POSTPROCESSING BASED ON CONSTRAINED OPTIMIZATION

For simplicity, the effect of entropy coding is removed in the following discussion. That is, for quantized data coded with an entropy coder, we assume that they are

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decoded with the corresponding entropy decoder already. Let the coded bit stream, the decoded image in the transform domain, and the width of the quantization bins be denoted by $\mathbf{y}$, $\mathbf{m}$ and $\mathbf{q}$, respectively. Also, let Q and Q^{-1} denote the quantizer and the dequantizer, H and H^{-1} be the forward and backward transforms. The direct decoding can be written as:

$$\mathbf{m} = Q^{-1}[\mathbf{y}]. \tag{1}$$

Let $\mathcal{Z}$ be the set of images which generates the compressed bitstream $\mathbf{y}$. For most decoding algorithms, the dequantized value is chosen to be at the center of the quantization bin. Thus, it can be easily derived that

$$\begin{aligned} \mathcal{Z} &= \{\mathbf{z} : Q\, H[\mathbf{z}] = \mathbf{y}\} \\ &= \{\mathbf{z} :\mid Hz(x,y) - m(x,y) \mid < q(x,y)\}. \end{aligned} \tag{2}$$

Since the receipt of bitstream $\mathbf{y}$ indicates that the original image is an element of $\mathcal{Z}$, we call $\mathcal{Z}$ the coding constraint. The postprocessing technique can be formulated as a constrained optimization problem:

$$\hat{\mathbf{z}} = \arg\min_{\mathbf{z}\in\mathcal{Z}}\{U(\mathbf{z})\}, \quad \text{with } U(\mathbf{z}) = -\log Pr(\mathbf{z}). \tag{3}$$

In words, under the constraint $\mathcal{Z}$, we maximize the *a priori* probability of image $\mathbf{z}$ associated with a quality measure $U(\mathbf{z})$. The smaller the value $U(\mathbf{z})$, the smoother the image with a potentially better subjective quality. The model in use for $U(\mathbf{z})$ is the Huber Markov random field (HMRF) [4], which has been successfully to model both smooth regions and discontinuities in an image. Since the probability distribution function of the Markov random field can be explicitly written as the Gibbs function, one can derive the *a priori* probability of image $\mathbf{z}$ as

$$Pr(\mathbf{z}) = \frac{1}{A}\exp\left\{-\sum_{c\in\mathcal{C}} V_c(\mathbf{z})\right\}. \tag{4}$$

Comparing (3) and (4), we have

$$U(\mathbf{z}) = \sum_{c\in\mathcal{C}} V_c(\mathbf{z}), \tag{5}$$

where c is a pair of two neighboring pixels, $\mathcal{C}$ is the set of all such pixel pairs, and $V_c(\cdot)$ is a local potential function of the form

$$V_c(\mathbf{z}) = \rho(\mathbf{d}_\mathbf{c}^\mathbf{t}\mathbf{z}, T_c) = \rho(x_1 - x_2, T_c), \;\; x_1, x_2 \in c, \tag{6}$$

$$\rho(u, T_c) = \begin{cases} u^2, & \mid u \mid \le T_c, \\ T_c^2 + 2T_c(\mid u \mid - T_c), & \mid u \mid > T_c, \end{cases} \tag{7}$$

and where d_c is the differential operator and T_c is the continuity factor of the pixel pair. Since $\rho(\cdot)$ is known as the Huber minimax function, this statistical model is called the Huber-Markov random field (HMRF) model.

3. MULTISCALE POSTPROCESSING ALGORITHM

In this section, we describe a multiscale postprocessing algorithm to solve the above constrained optimization problem. The algorithm has been successfully used to remove the ringing artifact in wavelet coded images and the blocking and ringing artifacts in DCT coded images. Due to the space limit, we will focus on the application of this algorithm to wavelet coded images below.

Step 1: Dequantization

The coded bitstream is dequantized, and the output data include the dequantized wavelet coefficient $\mathbf{m}$ and the quantization bin width $\mathbf{q}$.

Step 2: Multiscale postprocessing

The algorithm is a top-down process, which proceeds from the coarsest scale $s = d$ to the finest scale $s = 1$. At each scale, it solves the constrained optimization

$$\hat{\mathbf{z}}_s = \arg\min_{\mathbf{z}_s\in\mathcal{Z}_s} U(\mathbf{z}_s). \tag{8}$$

The initial value $\mathbf{z}_s^{(0)}$ at scale s is derived from the final result obtained at scale $s+1$. That is,

$$\mathbf{z}_s^{(0)} = \begin{cases} \hat{\mathbf{z}}_{s+1}, & \text{for scale s+1 and above,} \\ \mathbf{m}_s, & \text{for scale s.} \end{cases} \tag{9}$$

The continuity factor T_c is initialized at a value of 16 for all pixel pairs.

Step 3: Smoothing with the steepest descent search

Given the postprocessing result $\mathbf{z}_s^{(k)}$ at the kth iteration, we use the steepest descent algorithm to find the estimate $\mathbf{z}_s^{(k+1)}$ at the $(k+1)$th iteration. The gradient is calculated as

$$\mathbf{g}_s^{(k)} = \nabla U(\mathbf{z}_s^{(k)}) = \sum_{c\in\mathcal{C}_s} \rho'(\mathbf{d}_\mathbf{c}^\mathbf{t}\mathbf{z}^{(k)}, T_c)\mathbf{d}_\mathbf{c}^\mathbf{t}, \tag{10}$$

where $\rho'(\cdot)$ is the first derivatives of the Huber function. Thus, the image is updated according to

$$\mathbf{w}_s^{(k)} = \mathbf{z}_s^k - \alpha_s^{(k)}\mathbf{g}_s^{(k)}, \tag{11}$$

where $\alpha_s^{(k)}$ is the stepsize calculated via

$$\alpha_s^{(k)} = \frac{\nabla U^t \cdot \nabla U}{\nabla U^t \cdot \Delta U \cdot \nabla U} \tag{12}$$

$$= \frac{(\mathbf{g}_s^{(k)})^t \mathbf{g}_s^{(k)}}{(\mathbf{g}_s^{(k)})^t (\sum_{c \in C_s} \rho''(\mathbf{d}_c^t \mathbf{z}_s^{(k)}) \mathbf{d}_c \mathbf{d}_c^t) \mathbf{g}_s^{(k)}}.$$

Step 4: Projection

Since the updated image may fall outside of the coding constraint set $\mathcal{Z}_s$, $\mathbf{w}_s^{(k)}$ should be projected back to $\mathcal{Z}_s$ via

$$\mathbf{z}_s^{(k+1)} = \mathcal{P}_{\mathcal{Z}_s}\left(\mathbf{w}_s^{(k)}\right). \quad (13)$$

Step 5: Adjustment of continuity factor T_c

Before the next smoothing operation, we adjust the continuity factor T_c adaptively. For each pair of pixels $x_1, x_2 \in c$, we check the difference in their pixel values before the steepest descent smoothing $x_1^A - x_2^A$, after the steepest descent smoothing $x_1^B - x_2^B$, and after the projection $x_1^C - x_2^C$. The continuity factor T_c is reduced by half if both of the following conditions are satisfied:

$$| x_1^A - x_2^A | > 0.7 | x_1^B - x_2^B | \quad (14)$$

$$\text{and} \quad | x_1^C - x_2^C | > 0.7 | x_1^B - x_2^B |, \quad (15)$$

The rationale of the above rule is that if the edge over the pixel pair c is at first smoothed by the steepest descent algorithm (14) and then pulled back by the projection operation (15), we conclude that continuity factor T_c is too strong and should be reduced.

Step 6: Iterative postprocessing

We iterate Steps 3-5 until the decrease in the image quality measure $U(\mathbf{z}_s)$ is smaller than a certain threshold. Then, we proceed to the the next finer scale and repeat Steps 2-5. The postprocessing is terminated until we obtain the optimal decoded image $\hat{\mathbf{z}}$ which minimizes the image quality measure $U(\mathbf{z})$ at scale 1.

4. EXPERIMENTAL RESULTS

We tested the proposed postprocessing algorithm on the Lena image of size 512 × 512 with both wavelet and DCT coders. Results are shown in Fig. 1. For clarity, only the central region of size 256 × 256 is shown. The wavelet coder used was a modified layered zero coder (LZC) [5]. The DCT coder was the standard baseline JPEG coder developed by the independent JPEG group. The original image and the wavelet coded image are shown in Fig. 1 (a) and (b), respectively. At such a low bit rate, the decoded image suffers from severe ringing artifacts around the hat, eye, and cheek of Lena. We applied a single scale HMRF based postprocessing algorithm proposed by Rourke [3] and the result is given in Fig. 1(c). Although the image looks better than the directly decoded result, there are still long range ringing artifacts appearing as large shadows and lights. For example, the ringing in the hat, eye and cheek areas of Lena is still not completely removed. This is due to the fact that the single-scale HMRF can only model the short range distortion. It fails to catch the long range ringing artifact caused by the tail of the wavelet filters and the truncation of wavelet coefficients at coarse scales. The result of multiscale postprocessing is shown in Fig. 1(d). The subjective appearance of the image is much better with almost all ringing artifact removed while the sharp edges at the hat, cheek and eyes are retained. The JPEG coded Lena and its postprocessing result are also shown in Fig. 1(e) and Fig. 1(f), respectively. We see that the proposed technique also effectively removes the blocking and ringing artifacts in the DCT coded image.

5. ACKNOWLEDGMENT

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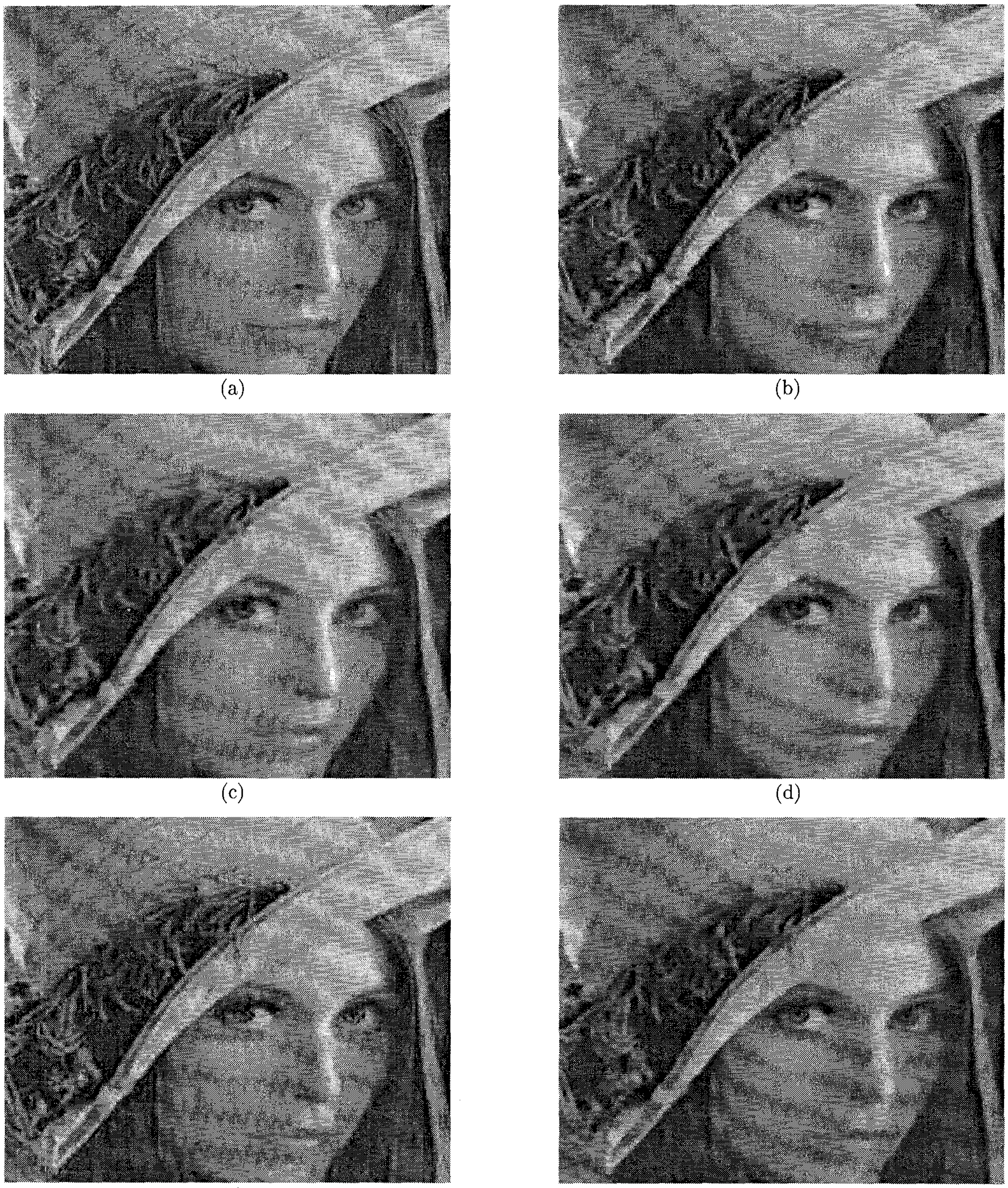

(a) (b) (c) (d) (e) (f)

Figure 1: Experimental results of the Lena image: (a) the Original (shown center region of size 256×256), (b) LZC coded Lena at 0.125bpp, (c) LZC with single scale postprocessing, (d) LZC with multiscale postprocessing, (e) JPEG coded Lena at 0.307bpp, (f) JPEG with multiscale postprocessing.