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Improving the quality of coded still images by post-processing

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ABSTRACT

Coding techniques, such as JPEG and MPEG, result in visibly degraded images at high compression. The coding artifacts are strongly correlated with image features and result in objectionable structured errors. Among structured errors, the reduction of the end of block effect in JPEG encoding has received recent attention, with advantage being taken of the known location of block boundaries. However, end of block errors are not apparent in subband or wavelet coded images. Even for JPEG coding, end of block errors are not perceptible for moderate compression, while other artifacts are still quite apparent and disturbing. In previous work, we have shown that the quality of images can be in general improved by analysis based processing and interpolation. In this paper, we present a new approach that addresses the reduction of the end of block errors as well as other visible artifacts that persist at high image quality. We demonstrate that a substantial improvement of image quality is possible by analysis based post-processing.

Keywords: inhomogeneous diffusion, coding artifact removal, image interpolation.

1 INTRODUCTION

The standardization of image coding methods on JPEG and MPEG limits the development of alternate approaches for improved coding performance. However, wavelet and subband coders continue to be studied extensively, for their performance or for some implementation advantages, and they are occasionally incorporated into systems. For both standard and non-standard coding techniques, one additional option that is always available is the processing of decoded images so as to reduce coding artifacts. Since at low bit rate and low quality, the image impairments due to coding are strongly structured, such as occurring only at the end of blocks, new algorithms are being developed to exploit this error structure. Since the major coding errors are introduced in the quantization process, we use the quantization equations to provide constraints on the maximum error that can be introduced in coding.

In Figure 1, we show two decoded images, where one was coded with a JPEG coder and the other was coded by a subband or wavelet based coder. The coding artifacts in these images are obvious with blocking effects apparent in the image coded by the DCT-based JPEG method and ringing artifacts apparent in the image coded by the wavelet based method. It is clear from these two examples that the coding errors are not well described as random noise, that most errors are structured, and that end of block errors are not the only image impairment.

Figure 1: Reconstructed images: (a)left: 0.244bpp by JPEG baseline DCT; (b)right: 0.2bpp by subband or wavelet coder.

2 REDUCING ERRORS ON DECODED IMAGES

Various approaches have been proposed to process the decoded image to reduce coding artifacts. A space-invariant filter[1] and space-variant filters[2,3] have been used. In these approaches, the decoded image is filtered without using prior information about the image compression process. Therefore, there is no guarantee that the resulting filtered image will approximate the original image in some sense. An image recovery approach has been proposed[4] that employs prior information about the image compression process by using the quantization transformation equation as a constraint

$$\mathbf{y} = Q[T\mathbf{z}], \tag{1}$$

where $\mathbf{z}$ is the reconstructed image, T represents the DCT transform, $Q[.]$ represents the quantization operation and $\mathbf{y}$ is the transmitted data. However, only a space-invariant low-pass filter has been considered and the reconstructed image is overly smoothed. In another approach[5] a Gibbs Huber-Markov random field image model is assumed, and the compressed image is reconstructed using a maximum a posterior probability (MAP) method. This results in a convex constrained optimization

$$\hat{z} = \mathrm{argmin}_{z \in C} \sum_{1 \leq m,n \leq N} \sum_{k,l \in N_{m,n}} p_H(z(m,n) - z(k,l)) \tag{2}$$

where M and N represent the image width and height, $N_{m,n}$ consists of the eight nearest neighbors of pixel located at (m,n), and p_H is the Huber function

$$p_H(x) = \begin{cases} x^2, & |x| \leq H \\ H^2 + 2H|x - H|, & |x| > H \end{cases} \tag{3}$$

and C is the constraint set which is given by

$$C = \{\mathbf{z} : \mathbf{y} = Q[T\mathbf{z}]\} \tag{4}$$

The Huber function $p_H(x)$ is used to allow relatively large discontinuities by reducing the importance of the discontinuity when the value of the discontinuity measure exceeds some threshold, H. The projections onto convex sets (POCS) based recovery algorithm[6,7] is used to reconstruct the compressed image. In this approach, a convex set is proposed to specifically deal with the blocking effects. Therefore, this approach only works well for blocking effect removal. Furthermore, the reconstructed image still exhibits blocking effect.[6] When a perceptually based weight[8] is included to define the block boundary continuity constraint sets, a better reconstructed image can be obtained. However, this approach requires heavy computational effort.[7]

3 CONSTRAINED INHOMOGENEOUS DIFFUSION

In this section, we describe a constrained inhomogeneous diffusion based approach to image improvement. In this approach, the reconstruction is based on both the received data and on prior knowledge that complements the available data. In our approach, inhomogeneous diffusion is employed to remove the coding artifacts. Unlike the pass filtering, which results in the smoothing of edges,[4] inhomogeneous diffusion can reduce coding artifacts and, at the same time, maintain the discontinuities of the original image.

For transform coding, since the original image satisfies the quantization transformation equation (1), it is reasonable that this be used as a constraint in the inhomogeneous diffusion process. The idea is that within the constraint set: $C = \{\mathbf{z} : \mathbf{y} = Q[T\mathbf{z}]\}$, an inhomogeneously smoothed image is sought as the final reconstructed image. That means that the transform coefficients for processed images have to remain within the same quantization range as for unprocessed images. Here T represents the transformation which is a block DCT transformation in JPEG coding and a wavelet transformation in subband or wavelet coding. Q represents the specific quantization procedure used in the coding process.

Inhomogeneous diffusion was first proposed by Perona and Malik[9] for scale space analysis and edge detection and is based on the partial differential equation

$$\frac{\partial f(x,y,t)}{\partial t} = \nabla \cdot (c(||\nabla f(x,y,t)||)\nabla f(x,y,t)), \tag{5}$$

where $\nabla\cdot$ is the divergence operator, ∇ the gradient and $f(x,y,t)$ represents the inhomogeneously diffused image at time t. The diffusion coefficient $c(||\nabla f(x,y,t)||) \in [0,1]$ is required to be a decreasing function of the magnitude of local gradient such that (5) diffuses more in regions of small gradients and less around edges where the gradients are large. Two functions, Gaussian and Cauchy have been proposed[9]

$$c(||\nabla f(x,y,t)||) = \exp\left(-\frac{(\nabla f(x,y,t))^2}{k^2}\right) \tag{6}$$

$$c(||\nabla f(x,y,t)||) = \frac{1}{1+(\nabla f(x,y,t))^2/k^2} \tag{7}$$

However, these inhomogeneous diffusions have been shown to be ill-posed processes in the sense that images close to each other are likely to diverge during the diffusion process.[10,11] A well-posed inhomogeneous diffusion has been introduced by El-Fallah and Ford[12,13] and later further studied and expanded to constrained inhomogeneous diffusion for image interpolation and for coding artifact removal by Chen and Ford.[14] The diffusion coefficient in this work was chosen to be:

$$c(||\nabla f(x,y,t)||) = \frac{1}{\sqrt{1+(\nabla f(x,y,t))^2}} \tag{8}$$

The well-posedness of this inhomogeneous diffusion has been explained from two different points of view, and its desirable properties have also been described.[14,13]

For coding artifact removal, the following constrained inhomogeneous diffusion is applied.

$$\frac{\partial f(x,y,t)}{\partial t} = \nabla \cdot (c(||\nabla f(x,y,t)||)\nabla f(x,y,t)) \tag{9}$$

$$y = Q[Tf(x,y,t)] \tag{10}$$

$$f(x,y,0) = T^{-1}y \tag{11}$$

using the diffusion coefficient $c(||\nabla f(x,y,t)||)$ of (8). Here y is the image decoded from either a JPEG coder or a wavelet coder. The initial step $f(x,y,0)$ in the iterative diffusion is chosen to be the decoded image y.

4 IMPLEMENTATION AND EVALUATION

An iterative approach is used to implement the constrained diffusion algorithm. Each iteration includes two steps: inhomogeneous diffusion smoothing and constraint space mapping. The inhomogeneous diffusion step is implemented as follows. First, the first order derivatives in the x and y directions are approximated on a 3×3 window in a manner similar to that of the Sobel operator.

$$\begin{aligned} f_x(i,j) &= 0.5(f(i+1,j) - f(i-1,j)) \\ &\quad +0.25(f(i+1,j+1) - f(i-1,j+1)) \\ &\quad +0.25(f(i+1,j-1) - f(i-1,j-1)) \end{aligned} \tag{12}$$

$$\begin{aligned} f_y(i,j) &= 0.5(f(i,j+1) - f(i,j-1)) \\ &\quad +0.25(f(i+1,j+1) - f(i+1,j-1)) \\ &\quad +0.25(f(i-1,j+1) - f(i-1,j-1)) \end{aligned} \tag{13}$$

This approximation is chosen because of its symmetric structure and good response to diagonal features. By substituting $f(i,j,n+1) - f(i,j,n)$ to the left side of (9) and the approximate differentiations of (12) and (13) into the right side of (9), we get

$$f(i,j,n+1) = f(i,j,n) + g(i,j,n) \tag{14}$$

Here $g(i,j,n)$ can be shown to have eight terms:

$$g(i,j,n) = \sum_{k=1}^{8} g_k(i,j,n) \tag{15}$$

with

$$g_1(i,j,n) = \frac{-f_x(i-1,j-1,n) - f_y(i-1,j-1,n)}{8\sqrt{1 + f_x^2(i-1,j-1,n) + f_y^2(i-1,j-1,n)}} \tag{16}$$

$$g_2(i,j,n) = \frac{-f_x(i-1,j,n)}{4\sqrt{1 + f_x^2(i-1,j,n) + f_y^2(i-1,j,n)}} \tag{17}$$

$$g_3(i,j,n) = \frac{-f_x(i-1,j+1,n) + f_y(i-1,j+1,n)}{8\sqrt{1 + f_x^2(i-1,j+1,n) + f_y^2(i-1,j+1,n)}} \tag{18}$$

$$g_4(i,j,n) = \frac{-f_y(i,j-1,n)}{4\sqrt{1 + f_x^2(i,j-1,n) + f_y^2(i,j-1,n)}} \tag{19}$$

$$g_5(i,j) = \frac{f_y(i,j+1,n)}{4\sqrt{1 + f_x^2(i,j+1,n) + f_y^2(i,j+1,n)}} \tag{20}$$

$$g_6(i,j,n) = \frac{f_x(i+1,j-1,n) - f_y(i+1,j-1,n)}{8\sqrt{1 + f_x^2(i+1,j-1,n) + f_y^2(i+1,j-1,n)}} \tag{21}$$

$$g_7(i,j,n) = \frac{f_x(i+1,j,n)}{4\sqrt{1 + f_x^2(i+1,j,n) + f_y^2(i+1,j,n)}} \tag{22}$$

$$g_8(i,j,n) = \frac{f_x(i+1,j+1,n) + f_y(i+1,j+1,n)}{8\sqrt{1 + f_x^2(i+1,j+1,n) + f_y^2(i+1,j+1,n)}} \tag{23}$$

We now consider the mapping onto the constraint space: $C = \{\mathbf{z} : \mathbf{y} = Q[T\mathbf{z}]\}$. We form vector $\mathbf{f}(n+1)$ by concatenating $f(i,j,n+1)$ row by row sequentially. In projecting the image $\mathbf{f}(n+1)$ onto the constraint space C, we are seeking $\mathbf{p}(n+1) \in C$ for which $||\mathbf{p}(n+1) - \mathbf{f}(n+1)||$ is a minimum. If $\mathbf{f}(n+1) \in C$, then $\mathbf{p}(n+1) = \mathbf{f}(n+1)$ and $||\mathbf{p}(n+1) - \mathbf{f}(n+1)|| = 0$. Since T is unitary, we have

$$||T\mathbf{p}(n+1) - T\mathbf{f}(n+1)|| = ||\mathbf{p}(n+1) - \mathbf{f}(n+1)|| \tag{24}$$

and the projection can be carried out in transform domain.

When Q is a uniform scalar quantization of the transform coefficients, the projection onto the constraint space is rather simple. From the quantization matrix and the original decoded image, we know into which quantization bin each transform coefficient falls. Assuming one transform coefficient should fall between l and h, then if the transform coefficient in $T\mathbf{f}(n+1)$ is in this bin, simply keep it, otherwise change its value to one of the two boundary points of the bin. That is, the projected coefficient u in $T\mathbf{p}(n+1)$ is determined by

$$u = \begin{cases} l & w < l \\ w & l \leq w < h \\ h & h \leq w \end{cases} \tag{25}$$

This will minimize $||T\mathbf{p}(n+1) - T\mathbf{f}(n+1)||$ while insuring that $y = Q[T\mathbf{p}(n+1)]$. The constraint space mapped image is obtained by performing the inverse transformation on $T\mathbf{p}(n+1)$. Now we set the new $\mathbf{f}(n+1) = \mathbf{p}(n+1)$, and continue the iterative inhomogeneous diffusion (14). Iteration on the two described steps continues until $||\mathbf{f}(n) - \mathbf{f}(n+1)||$ is less than some prescribed value.

To reduce a blocking artifact, the conduction coefficient in the inhomogeneous diffusion can be effectively designed to include information on the location of the blocking artifact. That is, instead of (8), we now define the conduction coefficient as

$$c(||\nabla f(x,y,t)||) = \begin{cases} 1 & |\nabla f(x,y,t)| \leq E \text{ and } x,y \text{ a block boundary} \\ \dfrac{1}{\sqrt{1 + (\nabla f(x,y,t))^2}} & \text{otherwise} \end{cases} \tag{26}$$

The purpose of (26) is to increase smoothing at the block boundary to decrease the blocking effects. The threshold E is used to separate the real image activities and block effects along the block boundary, since a relatively large E is likely due to the existence of real image edges or corners. The value of E is obtained by analysis of the histogram of the image local gradient.

In this way, the image activity and blocking artifact location information are automatically joined in the inhomogeneous diffusion process. Therefore, there is no need to specifically calculate the weights[7] to capture the local activities of an image in order to achieve a spatially adaptive smoothness. In our approach, while the true image discontinuities are preserved, the blocking effect discontinuities are smoothed.

The proposed recovery algorithm was evaluated by applying it to the 512×512 Lena image compressed with a DCT-based JPEG coder and with a wavelet coder, with decoded images shown in Figure 1.

For blocking effect removal, the upper bound E in (26) has to be determined. From observations, we found that there are two peaks in the histogram of the gradient image with the one of zero corresponding and the other due to the blocking effects. Therefore, E was estimated from the blocky image in Figure 1(a) by: calculating the histogram of the gradient along block boundaries and setting the bound E to the gradient value associated with the peak of the histogram other than 0.

The images recovered by using our algorithm are shown in Figure 2. For comparison purposes, we show results in Figure 3 from other algorithms. Figure 3(a) shows the results from the Zakhor's algorithm,[4] which smoothes the image excessively around edges. In Figure 3(b), we show the reconstructed image using the POCS based approach,[6] where some blockiness can still be seen in the reconstructed image.

Figure 2: Reconstructed images by proposed approach: (a)left: for JPEG baseline DCT decoded image; (b)right: for wavelet decoded image

Figure 3: Reconstructed images: (a)Left: Zakhor's method; (b)Right: POCS method

5 IMPROVEMENT OF IMAGE QUALITY BY INTERPOLATION

At high quality, substantial loss of quality in the color images is due to the sub-sampling of the chrominance. The NTSC standards which affect the choice of representation and sampling parameters treats lower chrominance bandwidth as perceptually acceptable. This premise is only approximately correct, and often the image quality will be degraded by color bleeding along luminance contours. We use constrained inhomogeneous diffusion to perform chrominance interpolation. We show in Figure 4(a) the chrominance component U interpolated by factor 4 by 4 pixel replication. In Figure 4(b), we show the result of performing constrained inhomogeneous diffusion based interpolation. This second approach is aimed at avoiding color leakage across high contrast luminance edges. The results from color images show clear advantages of the constrained inhomogeneous diffusion based approach.

6 DISCUSSION AND CONCLUSIONS

In this paper, we have described a constrained inhomogeneous diffusion based approach for removing coding artifacts. Experiments demonstrate that our approach works well for removing both the blocking effects due to DCT based coding and the ringing artifacts that occur in wavelet coding. Comparison with other approaches shows the advantages of the proposed method. We have also presented a method of improving color image quality by interpolation of chrominance components using the constrained inhomogeneous diffusion based approach. For color image processing, further study needs to be carried out on a vector constrained inhomogeneous diffusion. That is, using the gradient information from luminance component as well the chrominance components to obtain a better interpolated result for the chrominance.

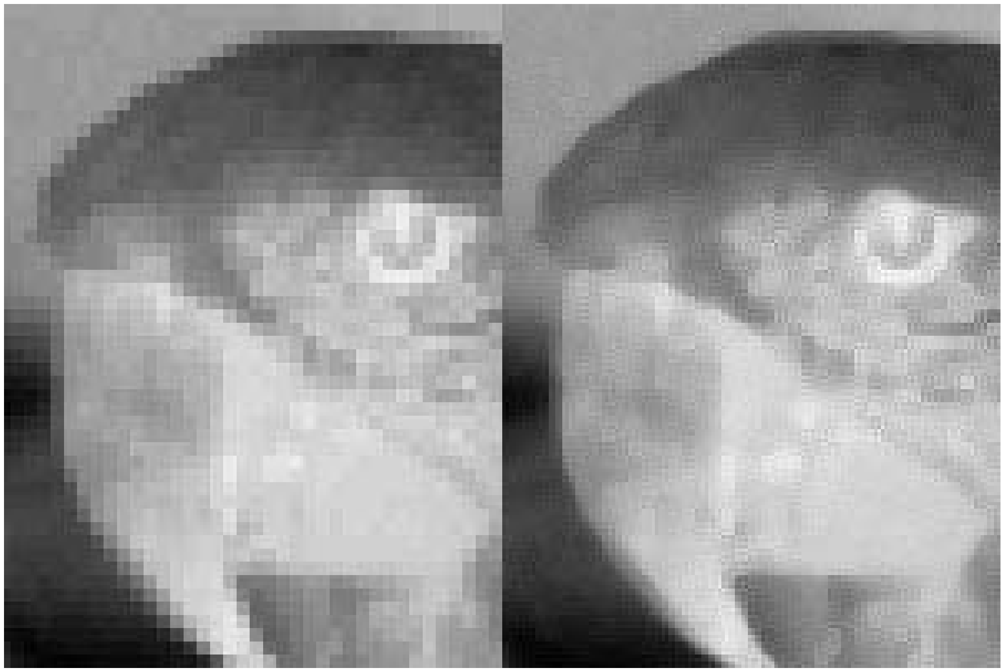

Figure 4: Interpolated U component: (a)left: by pixel replication; (b)right: by constrained inhomogeneous diffusion

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