Compression Artifacts Removal Using an Adaptive POCS Algorithm and Explicit Region Modeling

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Abstract: An effective compression artifacts removal algorithm is proposed based on thin-plate spline interpolation and the theory of projections onto convex sets (POCS). The thin-plate spline model is used to model the luminance in the flat regions of the image. Adaptive projections are used to suppress the compression artifacts in the spatially active image regions. The algorithm includes block mapping, prediction of the spatial distribution of the quantization error and estimation of the visibility of the compression artifacts. Information obtained from the transform domain is used in the thin-plate interpolation phase. The adaptive projections use information from both the spatial and transform domains. Experiments performed with JPEG-compressed images demonstrate the effectiveness of the proposed algorithm in suppressing the compression artifacts, along with its ability for preserving the image sharpness.

Key words: Image compression, compression artifacts, POCS.

INTRODUCTION

DCT-based compression schemes are widely used in standardized image and video compression. DCT-based image compression has proven itself to be very efficient and to be able to provide very good visual quality of the decompressed image at high bit-rates. At low bit-rates, however, the visual quality of the decompressed image is significantly degraded as a result of visible artifacts introduced by the quantization process. Blocking artifacts, which appear as artificial block boundaries, and ringing artifacts, which appear as artificial edges in the vicinity of real edges, are the two major types of artifacts. An ideal compression artifacts reduction algorithm should be able to remove the visible compression artifacts while preserving the original image content.

Significant efforts have been made to solve the problem of compression artifacts reduction in block DCT-coded images. The most frequently used approach has been to utilize some appropriate post-processing technique. Post-processing techniques based on statistical models are often used because of their ability to incorporate the statistical knowledge about the uncompressed image and the image degradations [Robertson & al., 2001] [Robertson & al., 2005]. A major disadvantage of these techniques is over-smoothing of the restored image due to inaccurate image and/or noise modeling. Deterministic regularization methods have also been used. They are suitable for incorporating the deterministic a priori knowledge about the original image. Constrained least squares (CLS) are among the most popular deterministic regularization techniques [Lee & al., 2000] [Kim & al., 2003].

In order to achieve both fast (possibly real-time) and effective deblocking, different filtering techniques have also been developed [Tai & al., 2005] [Kong & al., 2004]. In [Liu & al., 2002] modeling of blocking artifacts as two-dimensional (2-D) step functions was proposed, which works well for blocks having all AC
coefficients equal to zero. Unfortunately, for blocks having non-zero AC coefficients, it can result in over-compensation of the blocking effect in some pixels and under-compensation in others, which manifests as a very annoying visual artifact.

Post-processing techniques based on the theory of projections onto convex sets (POCS) have drawn much attention because of their flexibility in utilizing the known constraints of the restored image [Yang & al., 1997] [Zou & al., 2005]. Such techniques have proven to be quite effective in suppressing the coding artifacts and in increasing the perceptual quality, but have a major drawback in their high computational complexity. Recently, a POCS-algorithm for blocking artifacts suppression has been proposed based on explicit modeling of image regions using a spatially adaptive thin-plate spline [Liew & al., 2005]. Its effectiveness has been demonstrated for graphic images with smooth areas. The algorithm, although effective for graphic images, has several drawbacks when applied to real-world images. To preserve the sharpness of the real edges within the block, the gradient method is used for edge detection and the edge pixels are retained as data points. Retaining different numbers of data points in thin-plate spline modeling in adjacent blocks often results in the introduction of an additional blocking effect and a mosaic pattern effect. The application of the POCS algorithm could also result in extensive blurring of the image. In order to solve this problem quantization constraints are used, but this approach sometimes results in the preservation of the compression artifacts.

We present an effective compression artifacts removal algorithm based on a combination of the thin-plate spline modeling of the smooth regions of the image and the theory of projections onto convex sets. The first part of the algorithm uses the DCT coefficients of the compressed image, available at the decoder, to map flat blocks into flat regions and to perform thin-plate spline modeling of the luminance of the mapped flat regions of the image. The second part of the algorithm uses adaptive projections in the spatial domain to remove the compression artifacts in the spatially active regions of the image. The projections are adapted to the local characteristics of the image and to the spatial distribution of the quantization error predicted using the DCT coefficients of the compressed image.

The paper is organized as follows. Section 2 describes the proposed algorithm. Experimental results illustrating the proposed scheme are presented in Section 3. Conclusions are given in Section 4.

1. Compression Artifacts Removal Using Adaptive Projections

1.1. Thin-plate Projections

Thin-plate spline modeling of the luminance is used in the flat regions of the image. The image luminance of all pixels in the flat region is interpolated using a smooth function, analogous to a thin metal plate which minimizes the total bending energy given by (1) [Liew & al., 2005].

\[
E = \int \int_{\mathbb{R}^2} \left( \frac{\partial^2 f}{\partial x^2} \right)^2 + 2 \left( \frac{\partial^2 f}{\partial x \partial y} \right)^2 + \left( \frac{\partial^2 f}{\partial y^2} \right)^2 \, dx \, dy 
\] (1)

The process of thin-plate spline modeling consists of two parts. The first part maps the totally flat regions in the image, and the second part applies the thin-plate spline model to the pixels of every mapped region. The mapping is performed in the DCT domain. An 8×8 pixel block is defined as totally flat if all its AC-DCT coefficients are zero (the only non-zero coefficient being the DC-DCT coefficient). The flat regions consist of the pixels of all flat blocks that are 8-connected. The smallest regions consist of only two blocks. The mapping for the decompressed 512×512 Lena image (Figure 3a) is shown in Figure 1. The totally flat regions are depicted in white.

![Figure 1. Map of the totally flat regions in the image.](image_url)
\[ f(x, y) = \sum_{i=1}^{m} a_i K_i(x, y) + a_{m+1} + a_{m+2} x + a_{m+3} y \] 
\[ (2) \]

where

\[ K_i(x, y) = r_i^{-2}(x, y) \cdot \log r_i^{-2}(x, y) \] 
\[ (3) \]

\[ r_i(x, y) = \sqrt{(x-x_i)^2 + (y-y_i)^2} \] 
\[ (4) \]

and \((x_i, y_i)\) are the \(x\) and \(y\) coordinates of \(m\) landmark points located at the centers of the flat blocks belonging to the particular flat region. The spline coefficients \(a_i\) are calculated from the values of the luminance at the landmark points.

Replacing the image luminance function with the thin-plate surface function completely removes the thin-plate surface function completely removes the blocking artifacts in the flat regions of the image.

1.2 POCS Background and Adopted Notation

We use a lexicographical representation of an image in which an \(MN \times N\) image \(f\) is represented by a \(MN \times 1\) vector in the Euclidean space \(R^{MN}\) by lexicographically ordering its pixels in rows. Let \(C_1, C_2, \ldots, C_m\) be \(m\) closed convex sets in \(R^{MN}\), such that \(C_0 = \bigcap_{i=1}^{m} C_i\) is nonempty, and let \(P_i (i = 1, 2, \ldots, m)\) be the projector onto \(C_i\), i.e.,

\[ \| \tilde{f} - P_i \tilde{f} \| = \min_{f \in C_i} \| f - \tilde{f} \|, \] 
\[ (5) \]

where \(\tilde{f} \in R^{MN}\).

Let \(T_i\) be a relaxed projector given by \(T_i = I + \lambda_i (P_i - I)\), \(0 < \lambda_i < 2\). For any initial point \(f_0 \in R^{MN}\), the sequence

\[ f_{n+1} = T_m T_{m-1} \ldots T_i f_n, \quad n = 0, 1, 2, \ldots, \] 
\[ (6) \]

converges to a point \(f^+ \in C_0\) [Liew & al., 2005].

1.3 Adaptive Smoothness Constraints

In the proposed scheme adaptive smoothness constraints are defined in both the horizontal and vertical directions. What follows is a discussion of the smoothness constraints in the horizontal direction. The vertical direction smoothness constraints are defined in a similar way. We define an adaptive smoothness constraint set \(C^H_{AS}\), containing images smoothed in the horizontal direction, as:

\[ C^H_{AS} = \{ \tilde{f} : |\tilde{f}_i + \tilde{f}_{i+1}| \leq \varepsilon_i, \quad i = 1, 2, \ldots, MN - 1, \text{ and } i \neq Nk (k = 1, 2, \ldots, M - 1) \}. \] 
\[ (7) \]

In (7), the threshold \(\varepsilon_i\) is computed based on the local activity in the \(3 \times 3\) neighborhood of the considered pixel \(f_i\), as follows:

\[ \varepsilon_i = \frac{1}{2} \left( \phi(A_L) + \phi(A_R) \right) \cdot \varepsilon_i^0, \] 
\[ (8) \]

where \(\varepsilon_i^0\) is the median of the intensity differences in the horizontal direction in the considered \(3 \times 3\) neighborhood. \(A_L\) and \(A_R\) are the block activity indices of two adjacent blocks sharing the vertical boundary that is closest to the considered pixel location. \(\phi(A)\) is defined as:

\[ \phi(A) = \frac{1}{1 + \gamma_A \sqrt{A}} \] 
\[ (9) \]

where \(A\) is the block activity index and \(\gamma_A\) is an empirically determined coefficient. The block activity index \(A\) is determined, for an \(8 \times 8\) block, using perceptually weighted DCT coefficients, as given by:

\[ A = \sum_{u=0}^{7} \sum_{v=0}^{7} B \cdot (u, v) - \bar{B} \cdot (0, 0) \] 
\[ (10) \]

and \(\bar{B}\) is estimated as:

\[ \bar{B} (u, v) = H (u, v) B (u, v) \] 
\[ (11) \]

where \(H\) is a weighting function estimated according to [Ngan & al., 1989] and \(B\) is the matrix of block DCT coefficients.

1.4 Artifacts Removal Algorithm

The relaxed projection \(\tilde{f}\) of \(\tilde{f}\) onto \(C^H_{AS}\) is obtained using \(\tilde{f} = T^H_{AS} \tilde{f}\) and the kth pixel of \(\tilde{f}\) is given by:

\[ \tilde{f}_k = \left\{ \begin{array}{ll} \hat{f}_i - \lambda_i (1 - \alpha_i) (\hat{f}_i - \hat{f}_{i+1}), & \text{if } k = i \\
\hat{f}_{i+1} + \lambda_i (1 - \alpha_i) (\hat{f}_i - \hat{f}_{i+1}), & \text{if } k = i + 1 \\
\tilde{f}_k, & \text{otherwise} \end{array} \right. \] 
\[ (12) \]

where \(\alpha_i = 0.5 (\varepsilon_i / |\hat{f}_i - \hat{f}_{i+1}| + 1)\), and \(\lambda_i \in (0, 2)\) is a relaxation coefficient. In order to avoid the introduction of new artifacts, we pose the constraint \(\lambda_i \in (0, 1]\). The possibility to use an adaptive relaxation coefficient is very attractive since it gives the opportunity to take into consideration the visibility and/or the statistics of the compression artifacts. We
calculate $\lambda_i$ as $\lambda_i = \lambda_{A(i)} \lambda_{B(i)}$, where $\lambda_{A(i)}$ depends on the block activity index, and $\lambda_{B(i)}$ depends on the position of the pixel location inside the block.

To compute $\lambda_{A(i)}$, we use

$$\lambda_{A(i)}(A_L, A_R) = \frac{1}{2} \left( \frac{1}{1 + \gamma_A \sqrt{A_L}} + \frac{1}{1 + \gamma_R \sqrt{A_R}} \right) \quad (13)$$

where $A_L$ and $A_R$ are the block activity indices on both sides of the vertical boundary closest to the pixel-location $i$, and $\gamma$ is an empirically determined coefficient.

$\lambda_{B(i)}$ is important for retaining the image sharpness and depends on the pixel location inside the block. In [Robertson & al., 2005], the authors have shown that the quantization error is not spatially invariant and that it is higher for pixels near block boundaries, especially at block corners. Our experiments confirm this conclusion and show that blocks having a larger number of non-zero DCT coefficients have higher error differences between border pixels and pixels in the interior of the block. Hence, we use a simple scheme to calculate $\lambda_{B(i)}$, as illustrated in Figure 2, which shows block regions with different $\lambda_{B(i)}$ values ($A^l$, $A^r$, and $B^l$). At the corner pixel locations $\lambda_{B(i)} = 1$.

For the rest of the block, the particular values, $\lambda_{A(i)}$ and $\lambda_{B(i)}$, of the $\lambda_{B(i)}$ coefficient are determined depending on the number $NC$ of non-zero DCT coefficients within the block, as follows:

$$\begin{align*}
\lambda_{A(i)} &= 1, & \lambda_{B(i)} &= 1, & \text{if } NC \leq 1, \\
\lambda_{A(i)} &= 0.9, & \lambda_{B(i)} &= 0.9, & \text{if } 2 \leq NC \leq 4, \\
\lambda_{A(i)} &= 0.8, & \lambda_{B(i)} &= 0.9, & \text{if } 5 \leq NC \leq 33, \\
\lambda_{A(i)} &= 0.1, & \lambda_{B(i)} &= 0.7, & \text{otherwise}
\end{align*} \quad (14)$$

The presented scheme is useful for protecting image details in high activity blocks against blurring, while allowing at the same time effective compression artifacts removal.

The artifacts removal procedure terminates when $\|f_n - f_{n-1}\|$ is less than a preset value or when a given number of iterations is reached.

![Figure 2. Block regions with different $\lambda_{B(i)}$ coefficients.](image)

### 2. Experimental Results

The proposed method was implemented and tested on a series of images compressed according to the JPEG standard. Figure 3 shows the results obtained for the grayscale $512 \times 512$ Lena image, compressed at 0.238 bpp. The values 0.07 and 0.26 were used for the parameters $\alpha$ of (9) and $\gamma$ of (13), respectively. Figure 3a shows the original JPEG-compressed Lena image, which contains severe compression degradation mostly due to blocking and ringing artifacts. The result obtained using the proposed algorithm is shown in Figure 3d. The blocking artifacts, which are very pronounced in the original compressed image, Figure 3a, are suppressed very effectively by the proposed scheme. The thin-plate spline modeling of the luminance in the regions containing flat blocks performs well, removing completely the blocking artifacts. The POCS algorithm effectively suppresses the blocking artifacts in the spatially active regions, allowing smooth transition of the luminance between the flat regions (modeled by the thin-plate spline model) and the active regions in the image. The ringing artifacts are, also, very efficiently suppressed, although they were not treated separately. At the same time, the resulting image (Figure 3d) has retained a high level of sharpness. The improvement in the visual quality is accompanied by an improvement in PSNR of 0.592 dB. The combination of the thin-plate spline modeling of the luminance and the POCS algorithm ensures good performance of the proposed method with images containing mostly smooth regions, as well as high-activity images. For comparison, Figures 3b and 3c show the outcome of the algorithms proposed in [Liew & al., 2005] and in [Yang & al., 1997], respectively. From Figure 3b it can be seen that the application of the algorithm in [Liew & al., 2005] results in an image containing some of the compression artifacts, as well as some newly introduced ones. The presence of compression artifacts (mostly ringing and blocking) in the output image is a result of the application of the quantization constraints. The newly introduced artifacts manifest themselves as blocking artifacts, and as a mosaic pattern effect. They are the result of the different numbers of data points used in the luminance modeling in adjacent blocks and are mostly visible in the vicinity of the edges. The artefacts are especially pronounced when the image is viewed on a CRT or TFT monitor. The improvement in PSNR is 0.176 dB.

The algorithm proposed in [Yang & al.,1997] was applied using the following parameters: $\alpha = 3$ and $\kappa = 0.51$. It can be seen that suppression of blocking artifacts is less effective and that the image is more smoothed. In addition, the algorithm in [Yang & al.,1997] generates a negative PSNR gain.

### 3. Conclusions

An effective POCS-based compression artifacts removal algorithm has been proposed. The algorithm
operates in the spatial domain, while exploiting information available in the transform domain as well. The thin-plate spline model was used to model the luminance in the flat regions of the image. Adaptive projections are used to incorporate the information about the spatial activity and the spatial distribution of the quantization error inside the blocks in the spatially active regions of the image. The experimental results confirm that the application of the thin-plate spline model completely removes the blocking artifacts in the flat regions of the image. In the spatially active regions, the adaptive projections offer effective suppression of the compression artifacts, and, at the same time, preserve the image sharpness to a high extent. The combination of the thin-plate spline modeling of the luminance and the POCS algorithm ensures good performance of the proposed method when used with mainly smooth images, as well as images reach in texture and high-activity regions.

**REFERENCES**


