Restoration of block-transform compressed images via homotopic regularized sparse reconstruction

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1. INTRODUCTION

Block-transform image compression is the most widely-adopted approach to compress images and video and is used in existing standards, including JPEG,[1] H.264[2] and HEVC.[3] It has the advantage of good compression performance and energy compacting property while being easy to implement.[4] Block-transform compression strategies divide the image into smaller blocks. These blocks are transformed into a block-transform domain, and are compressed through quantization and coding of the block-transform coefficients. Through the quantization process, higher frequency block-transform coefficients are not retained which leads to a degradation of information and the presence of coding artifacts. Images can be compressed at higher compression rates by increasing the quantization of coefficients, but this increases the presence of image artifacts in the decompressed images.

Given that the most prominent and noticeable compression artifacts are blocking artifacts, most of the attention on compressed image quality improvement has focused on deblocking. Existing deblocking algorithms typically reduce the presence of blocking artifacts using filtering in the spatial or block-transform domain. Total variation methods[5]aim to impose a smoothness constraint in the spatial domain to reduce blocking artifacts and preserve details. Rational filters[6] reduce blocking artifacts by acting like low-pass filters at block boundaries.

Block-transform domain algorithms[7] modify the block-transform coefficients to minimize blocking artifacts. Overcomplete wavelet representations[8] first decompose an image using a set of wavelets at different scales before filtering the image. A "field of experts" algorithm has been proposed,[9] using a maximum a posteriori criterion to solve the field of experts framework. Projections Onto Convex Sets algorithms iteratively project images on to different sets with smoothness of quantization constraints until convergence, at which point the blocking artifacts are minimized.[10]

The process of deblocking can also be viewed as a sparse reconstruction problem. Sparse reconstruction algorithms can be used to estimate the missing block-transform coefficients in order to reconstruct the deblocked image. These approaches have the advantage of removing other unwanted effects of quantization, through the restoration of degraded block-transform coefficients. Recent algorithms include using a dictionary approach to fill in coefficients.[11]

In this paper, we propose a novel restoration algorithm for block-transform compressed images using homotopic regularized sparse reconstruction. Similar approaches to signal reconstruction exist in medical imaging,[12] with significant improvements over total variation approaches, but to the best of our knowledge, have never been formulated for compressed image restoration.

For the sake of simplicity, the quantization process for a block-transform compression strategy based on fixed block size is described (one can easily extend this for variable block sizes). Let f be an $N_1 \times N_2$ image that is divided into blocks of $n \times n$ pixels. Then, let f_b be the b^{th} block in the image and F_b represents the block's coefficients in the block-transform domain. The quantization process is denoted as $Q(\cdot)$, let q be an $n \times n$ matrix containing the quantization coefficients, and let u be defined as a pixel location (x, y) in the block.

$$R_b = Q(F_b) \text{ where } R_b[u] = \left\lfloor \frac{F_b[u]}{q[u]} \right\rfloor \tag{1}$$

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Each block is quantized independently, resulting in the matrix R which contains all the blocks of the quantized transform coefficients R_b for the image. Because of the floor function in Equation 1, entries in R are rounded to their nearest integer value before encoding and storing the modified block-transform coefficients. This process leads to degradation of information, especially for high frequency coefficients which become zero.

To construct the stored image in the spatial domain, the inverse of Equation 1 is applied to the modified block-transform coefficients and the inverse block-transform is taken. However, the degraded set of block-transform coefficients caused blocking artifacts to appear in the constructed image. The homotopic regularized sparse reconstruction algorithm treats this inverse problem as a sparse reconstruction problem, where the original image f is reconstructed from a set of sparse observations contained in the block-transform coefficient matrix R. In the process, missing coefficients in R are estimated, which corrects the blocking artifacts.

2. METHODOLOGY

The proposed algorithm estimates the original block-transform coefficients based on the available degraded compressed coefficients using a homotopic, non-local regularization framework to better restore structural details. To reduce the loss of fine details even with significant degradation of block-transform coefficients, the non-local regularization function is integrated into the homotopic minimization framework. The homotopic minimization framework[13] and integration of the non-local regularization function[12] have been proposed for highly undersampled medical images and have improved the restoration of fine details, compared to total variation approaches. Equation 2 shows the proposed framework, where $\eta(\cdot)$ represents a homotopic, non-local regularization function with strength σ and ϵ enforces the data fidelity in the block-transform domain. The matrix ϵ is the data fidelity matrix of size $n \times n$ and each entry in ϵ is inversely proportional to its respective entry in the quantization matrix q. The regularization term suppresses blocking artifacts and the data fidelity term ensures that the reconstructed image is similar to the original signal.

$$\hat{f}_b = \arg\min_{f_b} \eta(f_b, \sigma) \tag{2}$$

$$\text{s.t. } ||R_b[u] - \hat{R}_b[u]||_2 < \epsilon[u] \; \forall \, u$$

The non-local regularization function is defined in Equation 3,[14] where u and v are pixel locations. The set Ω represents the entire set of pixels in the image and the set $\mathcal{S}_u$ represents the search region around u in the image f and $w(\cdot)$ is a weight based on the similarity of pixels around u and v.

$$\eta(f_b, \sigma) = \sum_{u \in \Omega} \sum_{v \in \mathcal{S}_u} w(u, v, \sigma) \left(f_b[u] - f_b[v]\right)^2 \tag{3}$$

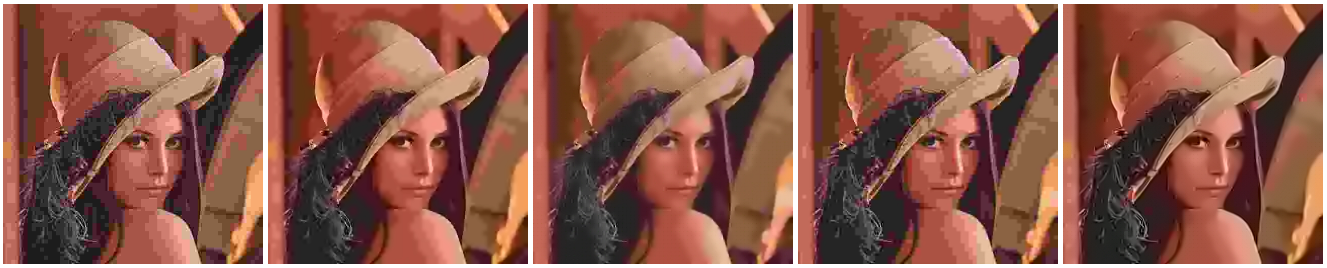
The weight function used in this implementation is defined in Equation 4, where Z is a normalizing constant so that $\sum_v w(u, v, \sigma) = 1$. $\mathcal{N}_u$ and $\mathcal{N}_v$ are neighbourhoods around u and v respectively.

$$w(u, v, \sigma) = \frac{1}{Z} e^{\frac{-||f_b[\mathcal{N}_u] - f_b[\mathcal{N}_v]||^2}{\sigma^2}} \tag{4}$$

3. EVALUATION

Preliminary results are shown below using fifteen images from the USC-SIPI image database.[15] They are all compressed using the discrete cosine transform and the standard JPEG quantization matrix[1] with a quantization scaling factors of $QF = 10$ (avg bits per pixel= 0.0268). The compressed images are processed using the proposed algorithm and with three other state-of-art algorithms, including a DCT domain-based algorithm,[7] a wavelet domain-based algorithm[8] and a field of experts algorithm.[9] These algorithms are state-of-art and the field of experts algorithm[9] has been shown to produce better resulting images than Projection Onto Convex Sets algorithms. The processed images are compared visually and quantitatively. The averages of four metrics are used to compare images: peak signal-to-noise ratio (PSNR),[16] structural similarity (SSIM),[17] generalized block-edge impairment metric (GBIM),[18] and PSNR including blocking effects (PSNR-B).[19] These metrics are presented in Table 1. The proposed algorithm has the lowest GBIM indicating that it is the most successful at deblocking the images. For the other metrics, the proposed algorithms performs comparably.

Processed images of Lena (one of the fifteen) are shown in Figure 1. Observing these images visually, the proposed algorithm is able to reconstruct smooth colour gradients while able to maintain image structure. We believe that given these results on Lena, this algorithm is worth further exploration and presentation.



(a) Uncorrected (28.36 / 0.791 / 8.00 / 25.88)

(b) DCT-domain (28.47 / 0.845 / 3.03 / 27.51)

(c) Wavelet-domain (28.94 / 0.834 / 1.69 / 28.78)

(d) Field of experts (28.53 / 0.816 / 2.83 / 27.32)

(e) Proposed (28.51 / 0.855 / 1.49 / 28.18)

Figure 1: Corrected images of Lena compressed with $QF = 10$ (bits per pixel = 0.207). The (PSNR/SSIM/GBIM/PSNR-B) values are provided beneath each image.

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Table 1: Image quality metrics averaged across 15 test images

Method	$QF = 10$ (Average $bpp = 0.268$)							
	PSNR (dB)		SSIM		GBIM†		PSNR-B (dB)	
	μ	σ	μ	σ	μ	σ	μ	σ
Uncorrected	28.41	1.42	0.818	0.049	6.78	1.246	25.86	1.612
DCT-domain	27.54	1.305	**0.850**	0.052	2.97	0.361	26.71	1.632
Wavelet-domain	**28.69**	1.514	0.847	0.054	1.70	0.087	**28.61**	1.503
Field of experts	28.26	1.351	0.832	0.051	2.99	0.292	26.95	1.607
Proposed	27.23	1.433	0.845	0.053	**1.61**	0.184	26.93	1.598

† A lower GBIM indicates fewer blocking artifacts in the corrected image.

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