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Joint denoising and decompression using CNN regularization

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Abstract

Wavelet compression schemes (such as JPEG2000) lead to very specific visual artifacts due to the quantization of noisy wavelet coefficients. They have highly spatially-correlated structure that makes it difficult to be removed with standard denoising algorithms. In this work, we propose a joint denoising and decompression method that combines a data-fitting term which takes into account the quantization process and an implicit prior contained in a state-of-the-art denoising CNN.

1. Introduction

Transform coding image compression consists of applying a linear invertible transform that sparsifies the data (like block-wise DCT for JPEG compression or a Wavelet Transform in JPEG2000) followed by a quantization of the transformed coefficients which are finally compressed by a lossless encoder. This family of compression schemes may achieve very high compression ratios but may lose some details in the quantization step. This lossy quantization is also responsible for well-known artifacts that may appear in the compressed image in the form of texture loss or Gibbs effects near edges. Many solutions have been proposed in the literature to remove some of these artifacts: many of them are variational and involve the minimization of the total variation (to minimize ringing) among all images that would lead to the observed quantized image [6, 3, 15].

However little attention has been paid in previous works to the fact that the image to be compressed may contain noise, and that noise may interact in subtle ways with the compressor, producing new kinds of artifacts that we call outliers (see figure 1). Those artifacts cannot be removed by the previously cited works which only aim at removing compression artifacts but not noise or its complex interactions with the compressor. However such artifacts are particularly annoying in the case of wavelet-based compressors like JPEG2000 and the CCSDS recommendation [8], which are extensively used to compress digital cinema and high-resolution remote sensing images. More recently, joint denoising and decompression procedures have been considered to remove both artifacts due to the compressor and its interaction with noise. Such methods use either TV regularization or patch-based Gaussian models in combination with relaxed versions of the quantization constraint, in order to take the effects of noise into account [7, 12, 13]. However the TV based approaches could only reliably remove isolated outliers in relatively constant areas, and patch-based approaches could only marginally improve the performance of standard denoising techniques like non-local Bayes [10].

In this work we propose a novel method for joint denoising and decompression. Our method uses a probabilistic data-fitting term similar to [13] coupled with a CNN based regularization which more closely captures natural image statistics than previously proposed patch-based methods. The proposed method is detailed in Section 3 after a short modeling of our joint denoising and decompression problem in Section 2. The rest of the paper includes the numerical implementation details (Section 4) and our experimental results (Section 5).

2. Modeling Noisy Compressed Coefficients

We assume that our image u is corrupted by additive white Gaussian noise $n_u \sim N(0, \sigma^2 I)$. The first step of the CCSDS compression applies a wavelet transform W to the noisy image. Hence the corresponding wavelet coe-
quantized coefficients $w$ in Figure 1. If there was no noise we would obtain the
understand why this occurs consider the situation depicted
recovered from the compressed image. From these values
algorithm to optimize the rate/distortion trade-off, and can be

The values of $m(k)$ are chosen by the compression algo-
use, however, the CDF 9/7 biorthogonal wavelet transform [5], but even in that case $WW^T \simeq I$ is a good ap-
next section we propose a Bayesian approach
to estimate the original image $u$ from its noisy, quantized
observation. The datafit term will be formulated in the
waveslet domain; this is the natural choice since quantiza-

3. Proposed restoration method
3.1. Motivation via MAP estimation

The Maximum A Posteriori (MAP) estimation of the non-
degraded image $u$ knowing its degraded version $u_{qn}$ is
stated as

$$
\hat{u} = \arg \max_u p(u | u_{qn}) = \arg \max_u p(u_{qn} | u) p(u)
$$

(1)

$$
= \arg \min_u -\log(p(u_{qn} | u)) - \log(p(u)),
$$

(2)

where $\hat{u}$ is the MAP estimator of $u$. Finding $\hat{u}$ amounts to
solve the optimization problem

$$
\hat{u} = \arg \min_u D(u) + \lambda R(u),
$$

(3)

where $D(u)$ is a data-fitting term that depends on the forward operator and the noise model, $R$ is the regularization
($-\log(prior))$ to be used in the restoration, and $\lambda > 0$ is the strength of the regularization.

3.2. Data fitting

Let $w = Wu$ the coefficients of the original (unknown) image, and $w_{qn} = W u_{qn}$ the wavelet coefficients of
the corrupted image. As stated before, the quantization intervals of each of these coefficients can be retrieved as
$[a(k), b(k)] = Q^{-1}(w_{qn}(k)) = \mathcal{Q}^{-1}(w_{qn}(k))$. Using this
notation, and given that the noise in the wavelet domain is $N(0,\sigma^2 I)$ (Section 2), the conditional probability of the
quantized coefficients given the original ones is

$$
p(w_{qn} | w = \omega) = \prod_k p(w_{qn}(k) | w(k) = \omega(k))
\prod_k p(\mathcal{Q}(w(k)) + n_k = \omega_k(n))
\prod_k p(\omega(k) + n_k \in [a(k), b(k)])
\prod_k p \left( \frac{n_k}{\sigma} \in \left[ \frac{a(k) - \omega(k)}{\sigma}, \frac{b(k) - \omega(k)}{\sigma} \right] \right).
$$

(7)
In the following we consider the log-likelihood function

$$D(\omega) = -\log p(w_m|w = \omega)$$

where $$\phi$$ is the normal cumulative distribution function. This data term in the wavelet domain carefully takes into account the quantization process of the coefficients. Although this term is not quadratic as in most inverse problems, at least it is convex and we have an analytic expression for its gradient and its Hessian matrix [17].

3.3. Minimization with ADMM

Finally, problem (3) can be written as

$$\min_{w, u} D(w) + \lambda R(u) \quad \text{s.a. } W^{-1}w = u$$

where $$W^{-1}$$ is the inverse wavelet transform (synthesis). The ADMM algorithm [4] becomes (subscripts indicate the iteration number):

$$\begin{cases}
    w_{k+1} = \arg\min_w D(w) + \frac{\rho}{2} \|W^{-1}w - u_k + \frac{1}{\rho} y_k\|^2 \\
u_{k+1} = \arg\min_u \lambda R(u) + \frac{\rho}{2} \|W^{-1}w_{k+1} - u + \frac{1}{\rho} y_k\|^2 \\
y_{k+1} = y_k + \rho(W^{-1}w_{k+1} - u_{k+1}).
\end{cases}$$

(10)

3.4. Regularizing by denoising

The second subproblem can be rewritten as

$$u_{k+1} = \arg\min_x \frac{1}{2(\lambda/\rho)} \|W^{-1}w_{k+1} + \frac{1}{\rho} y_k - u\|^2 + R(u).$$

In terms of MAP estimation, this step can be seen as a Gaussian denoising of $$W^{-1}w_{k+1} + \frac{1}{\rho} y_k$$ with noise variance $$\sigma^2_G = \lambda/\rho$$. The solution can be computed using a good denoiser $$G$$ as the proximal operator of an implicit prior $$R(u)$$ [11]:

$$u_{k+1} = \mathcal{G}(W^{-1}w_{k+1} + \frac{1}{\rho} y_k), \quad \sigma^2_G = \lambda/\rho).$$

4. Numerical implementation

For the first subproblem in (10), let $$v = -u_k + \frac{1}{\rho} y_k$$, then define $$F(w) := D(w) + \frac{\rho}{2} \|W^{-1}w + v\|^2$$. The first and second derivatives of $$F(w)$$ are given by

$$\nabla F(w) = \nabla D(w) + \rho W^{-T}(W^{-1}w + v)$$

$$\nabla^2 F(w) = \nabla^2 D(w) + \rho W^{-T}W^{-1}.$$
Table 1: Results. For PSNR and SSIM, higher is better. For NLP, lower is better.

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR</th>
<th>SSIM</th>
<th>NLP</th>
</tr>
</thead>
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<tr>
<td>Corrupted</td>
<td>35.92</td>
<td>0.8320</td>
<td>5.28</td>
</tr>
<tr>
<td>WNLB</td>
<td>36.67</td>
<td>0.8537</td>
<td>30.70</td>
</tr>
<tr>
<td>[16]</td>
<td>39.59</td>
<td>0.9169</td>
<td>6.39</td>
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<tr>
<td>Ours</td>
<td>39.52</td>
<td>0.9241</td>
<td>2.95</td>
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References