IMAGE DEBLOCKING USING GROUP-BASED SPARSE REPRESENTATION AND QUANTIZATION CONSTRAINT PRIOR

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ABSTRACT

To alleviate the conflict between bit reduction and quality preservation, deblocking as a post-processing strategy is an attractive and promising solution without changing existing codec. In this paper, in order to reduce blocking artifacts and obtain high-quality image, image deblocking is formulated as an optimization problem via maximum a posteriori framework, and a novel algorithm for image deblocking using group-based sparse representation (GSR) and quantization constraint (QC) prior is proposed. GSR prior is utilized to simultaneously enforce the intrinsic local sparsity and the nonlocal self-similarity of natural images, while QC prior is explicitly incorporated to ensure a more reliable and robust estimation. A new split Bregman iteration based method with adaptively adjusted regularization parameter is developed to solve the proposed optimization problem for image deblocking. The parameter-adaptive advantage enables the whole algorithm more attractive and practical. Experiments manifest that the proposed image deblocking algorithm improves current state-of-the-art results by a large margin in both PSNR and visual perception.

Index Terms— Image deblocking, sparse representation, blocking artifact reduction, quantization constraint

1. INTRODUCTION

Recent years have witnessed the rapid developments of social network and mobile internet, and image and video have been becoming the main carrier of multimedia. For image and video compression, block-based transform coding has been widely adopted in various current coding standards, such as JPEG [1], H.264/AVC [2], and H.265/HEVC [3], due to its regularity and simplicity for hardware implementation. Among all the transform kernels, block discrete cosine transform (BDCT) is the most popular one owing to its good energy compaction and de-correlation properties. However, due to independent and coarse quantization of discrete cosine transform (DCT) coefficients in each block, BDCT coding technique usually results in visually annoying blocking artifacts in coded images and videos, especially at low bitrates, which greatly prevents further bit reduction.

The procedure to effectively remove the blocking artifacts and obtain visually acceptable quality for BDCT coded images and videos is referred to as image/video deblocking, which has attracted great interest of researchers [4]–[14]. This paper mainly focuses on image deblocking for JPEG-coded images. In order to alleviate the conflict between bit reduction and image quality preservation while maintaining standard compliant, image deblocking as a post-processing technique becomes an attractive and promising solution due to its advantage of requiring no change of existing codec. Remarkably reducing blocking artifacts is able to increase compression ratios for a particular image quality, or improve image quality with respect to a specific bit rate of compression.

In recent years, researchers have developed a number of post-processing methods for image deblocking, which can be generally divided into two categories [4] [5]: image enhancement based deblocking methods and image restoration based deblocking methods. The basic idea of image enhancement based deblocking methods is to consider deblocking as an image enhancement process, and to conduct filtering in spatial and frequency domain to smooth visible artifacts. For image restoration based deblocking methods, deblocking is usually formulated as an ill-posed image inverse problem by exploiting some image prior knowledge and observed data at the decoder. Total variation [6], block-based sparse representation [7] [8] [9], Markov random field (MRF) [10] [11] were utilized as image prior models to seek the MAP estimation of the original image. Typically, Sun and Cham modeled the quantization distortion as Gaussian noise, and used FoE as image prior to construct image deblocking optimization problem [12]. By clustering similar blocks, low-rank approximation models were also utilized for image deblocking [13]. Recently, Zhang et al. proposed a deblocking algorithm with image block similarity prior model, and to reduce compression artifacts by the overlapped block transform coefficient

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estimation from non-local blocks [14].

The purpose of this paper is to make better use of image prior and quantization constraint (QC) prior simultaneously, and to remove blocking artifacts, achieving higher quality for BDCT coded images. Inspired by the success of group-based sparse representation (GSR) image prior model in image inpainting, image deblurring and image compressive sensing recovery [15], we exploit GSR prior for image deblocking problem, which enforces the intrinsic local sparsity and the nonlocal self-similarity of natural images at the same time. Quantization constraint (QC) prior is formulated an indication function. Under the Gaussian distribution of quantization noise, a novel algorithm for image deblocking using GSR prior and QC prior is proposed based on maximum a posteriori (MAP) framework. Moreover, a new split Bregman iteration based method adaptively adjusted regularization parameter is developed to solve the proposed optimization problem for image deblocking, with QC working at each iteration to ensure a more reliable and robust estimation. It is worth emphasizing that the proposed image deblocking algorithm GSRQC is parameter-adaptive, which enables the whole algorithm more effective and attractive. Extensive experiments manifest that the proposed image deblocking algorithm outperforms current state-of-the-art algorithms in both PSNR and visual perception, and greatly improve current existing image deblocking results.

The remainder of this paper is organized as follows. The background of JPEG compression and some notations are given in Section 2. Section 3 elaborates the proposed image deblocking framework. Experimental results are reported in Section 4. In Section 5, we conclude this paper.

2. BACKGROUND

The mathematical formulation is given below. In this paper, the boldface uppercase letters denote matrices, e.g. $\mathbf{X}$, and $\mathbf{X}_{[i,j]}$ is defined as the $(i,j)^{th}$ entry of matrix $\mathbf{X}$. The boldface lowercase letters denote column vectors, e.g. $\mathbf{x}$, and $\mathbf{x}_{[k]}$ is defined as the k^{th} entry of vector $\mathbf{x}$. Italics denotes scalars. $\|\mathbf{x}\|_0$ counts the nonzero elements in $\mathbf{x}$, and $\|\mathbf{x}\|_F$ denotes the Frobenius norm of $\mathbf{X}$. Suppose we have an image $\mathbf{X}$ of size $N \times N$. Then its vector representation is $\mathbf{x}$, and $\mathbf{x}_{[i*(n-1)+j]}$ stands for the pixel with the coordinates in the vertical and the horizontal directions being i and j in image $\mathbf{X}$, respectively.

Here, to formulate the JPEG compression, let us define a block DCT $N \times N$ matrix operator $\mathcal{A}$, which can transform each non-overlapped 8×8 block of the input image to its frequency domain. Similarly, the matrix operator $\mathcal{A}^{-1}$ represents the inverse process. The quantization matrix of size 8×8 is denoted by $\mathbf{M}^q$, determined by the quality factor q in the range [1 100]. Let $\mathbf{y}$ be the observed JPEG-coded image which is directly decompressed from the JPEG compressed bit-stream by JPEG decoder. Denote

$$\widehat{\mathbf{x}} = \mathcal{A}\mathbf{x};\ \widehat{\mathbf{y}} = \mathcal{A}\mathbf{y}, \tag{1}$$

which stand for the frequency images of $\mathbf{x}$ and $\mathbf{y}$, respectively.

Then, according to the process of JPEG compression described above, we have

$$\widehat{\mathbf{y}}_{[k*(n-1)+l]} = round\left(\frac{\widehat{\mathbf{x}}_{[k*(n-1)+l]}}{\mathbf{M}_{[k,l]}}\right) * \mathbf{M}_{[k,l]}, \tag{2}$$

where $1 \le k, l \le N$, $round(\cdot)$ is to round towards the nearest integer, $\mathbf{M}$ is a matrix of size $N \times N$ with $\mathbf{M}_{[k,l]} = \mathbf{M}^q_{[\bar{k},\bar{l}]}$, and $\bar{k} = mod(k, 8); \bar{l} = mod(l, 8)$.

The purpose of image deblocking is to take advantage of the information in JPEG compressed bit-stream, such as $\mathbf{y}$ and $\mathbf{M}^q$, to suppress blocking artifacts and obtain high-quality reconstruction image.

3. PROPOSED IMAGE DEBLOCKING FRAMEWORK

In this paper, we cast image deblocking as an image inverse problem, and formulate the proposed algorithm through maximum a posteriori (MAP) framework.

To be concrete, given JPEG compressed image $\mathbf{y}$, the original image $\mathbf{x}$ can be obtained by

$$\widetilde{\mathbf{x}} = arg\max_{\mathbf{x}}\ \log(p(\mathbf{y}|\mathbf{x})) + \log(p(\mathbf{x})), \tag{3}$$

where the first term represents data-fidelity, and the second term corresponds to image priors. Inspired by the success of image group-based sparse representation (GSR) prior in image inpainting, deblurring, and compressive sensing recovery [15], and motivated by the importance of quantization constraint (QC) prior in image deblocking [25] [27], we hope the prior $p(\mathbf{x})$ in Eq. (3) can characterize the above two types of priors simultaneously, and then propose to formulate $p(\mathbf{x})$ as

$$p(\mathbf{x}) = p_{GSR}(\mathbf{x}) \cdot p_{QC}(\mathbf{x}), \tag{4}$$

where $p_{GSR}(\mathbf{x})$ and $p_{QC}(\mathbf{x})$ stand for GSR prior and QC prior, respectively. Therefore, the proposed optimization problem for image deblocking through MAP is formulated as

$$\widetilde{\mathbf{x}} = arg\max_{\mathbf{x}}\ \log(p(\mathbf{y}|\mathbf{x})) + \log(p_{GSR}(\mathbf{x})) + \log(p_{QC}(\mathbf{x})). \tag{5}$$

In the following, we will provide the details about how to design each term in the proposed framework Eq. (5).

3.1. Quantization Noise Model

In the literature, the observed JPEG-coded image is usually modelled as the corrupted one by the quantization noise, i.e.

$$\mathbf{y} = \mathbf{x} + \mathbf{e}, \tag{6}$$

where $\mathbf{y}$ is the JPEG-coded image with blocking artifacts, $\mathbf{x}$ is the original image, and $\mathbf{e}$ is the quantization noise.

In this paper, we adopt Gaussian model to characterize the quantization noise $\mathbf{e}$ in Eq. (6), and exploit the approach proposed in [18] to estimate the noise variance $\sigma_{\mathbf{e}}^2$. Note that a higher compression corresponds to a larger value for the variance.

With the Gaussian quantization noise model, the first data-fidelity term in Eq. (5) thus can be formulated as

$$\log(p(\mathbf{y}|\mathbf{x})) = -\frac{1}{2\sigma_{\mathbf{e}}^2}\|\mathbf{x}-\mathbf{y}\|_2^2. \quad (7)$$

3.2. Group-based Sparse Representation Prior

GSR prior model [15] assumes that each group denoted by $\mathbf{x}_{G_k}$ can be accurately represented by a few atoms of a self-adaptive learning dictionary $\mathbf{D}_{G_k}$. Each group is represented by the form of matrix, which is in fact composed of nonlocal blocks with similar structures. Specifically, the sparse coding process of each $\mathbf{x}_{G_k}$ over $\mathbf{D}_{G_k}$ is to seek a sparse vector $\boldsymbol{\alpha}_{G_k}$ such that $\mathbf{x}_{G_k} \approx \mathbf{D}_{G_k}\boldsymbol{\alpha}_{G_k}$. Then the entire image can be sparsely represented by the set of sparse codes $\{\boldsymbol{\alpha}_{G_k}\}$ in the unit of group. Reconstructing $\mathbf{x}$ from the sparse codes $\{\boldsymbol{\alpha}_{G_k}\}$ is expressed as:

$$\mathbf{x} = \mathbf{D}_G \circ \boldsymbol{\alpha}_G \overset{\text{def}}{=} \sum_{k=1}^{n} \mathbf{R}_{G_k}^T(\mathbf{D}_{G_k}\boldsymbol{\alpha}_{G_k})./\sum_{k=1}^{n}\mathbf{R}_{G_k}^T(\mathbf{1}_{B_s\times c}), \quad (8)$$

where $\mathbf{R}_{G_k}(\cdot)$ is actually an operator that extracts the group $\mathbf{x}_{G_k}$ from $\mathbf{x}$, and its transpose, denoted by $\mathbf{R}_{G_k}^T(\cdot)$ can put back a group into the k-th position in the reconstructed image, padded with zeros elsewhere. $\mathbf{D}_G$ denotes the concatenation of all $\mathbf{D}_{G_k}$, and $\boldsymbol{\alpha}_G$ denotes the concatenation of all $\boldsymbol{\alpha}_{G_k}$.

Finally, the expression for GSR prior is formulated as

$$\log(p_{GSR}(\mathbf{x})) = -\lambda\|\boldsymbol{\alpha}_G\|_0, \quad (9)$$

which imposes the sparse codes vector $\boldsymbol{\alpha}_G$ to be sparse. Please refer to [15] for more details about GSR.

3.3. Quantization Constraint Prior

According to Eq. (2), define the lower and upper bound vectors $\widehat{\mathbf{l}}$ and $\widehat{\mathbf{u}}$, i.e.,

$$\begin{aligned}\widehat{\mathbf{l}}_{[k*(n-1)+l]} &= \left(\widehat{\mathbf{y}}_{[k*(n-1)+l]} - \omega\right) * \mathbf{M}_{[k,l]};\\ \widehat{\mathbf{u}}_{[k*(n-1)+l]} &= \left(\widehat{\mathbf{y}}_{[k*(n-1)+l]} + \omega\right) * \mathbf{M}_{[k,l]}.\end{aligned} \quad (10)$$

Therefore, the frequency coefficients of the original image should satisfy $\boldsymbol{\Omega} = \{\mathbf{x}|\widehat{\mathbf{l}} \preceq \mathcal{A}\mathbf{x} \preceq \widehat{\mathbf{u}}\}$. Here $\preceq$ denotes the operator of element-wise comparison. Note that $\boldsymbol{\Omega}$ can be directly obtained from the given JPEG compressed bit-stream. The most commonly way is to apply QC to restrain the final deblocking result to improve the performance. However, this way can't fully exploit QC. In this paper, in order to incorporate QC prior into Eq. (5), we define the indicator function by $\boldsymbol{\Omega}$ as

$$\psi(\mathbf{x}) = \begin{cases} 0, & if\ \mathbf{x} \in \boldsymbol{\Omega} \\ +\infty, & if\ \mathbf{x} \notin \boldsymbol{\Omega}. \end{cases} \quad (11)$$

Then the QC prior is formulated as

$$\log(p_{QC}(\mathbf{x})) = -\psi(\mathbf{x}), \quad (12)$$

which plays an important role in the algorithm performance.

3.4. Proposed Image Deblocking Framework

Incorporating the above quantization noise model and two image priors into Eq. (5), we have the proposed image deblocking minimization problem GSRQC as follows

$$\left(\widetilde{\boldsymbol{\alpha}}_G, \widetilde{\mathbf{D}}_G\right) = arg\ \min_{\boldsymbol{\alpha}_G,\mathbf{D}_G} \frac{1}{2\sigma_{\mathbf{e}}^2}\|\mathbf{D}_G\circ\boldsymbol{\alpha}_G - \mathbf{y}\|_2^2 + \lambda\|\boldsymbol{\alpha}_G\|_0 + \psi(\mathbf{D}_G\circ\boldsymbol{\alpha}_G). \quad (13)$$

After getting $\widetilde{\boldsymbol{\alpha}}_G$ and $\widetilde{\mathbf{D}}_G$, the deblocking image is reconstructed by $\widetilde{\mathbf{x}} = \widetilde{\mathbf{D}}_G \circ \widetilde{\boldsymbol{\alpha}}_G$. Note that Eq. (13) jointly exploits the quantization model, GSR prior and QC prior within the MAP framework. Thus, it is expected that better deblocking results will be achieved.

In this paper, we adopt the framework of split Bregman iteration (SBI) [16] [17] to solve Eq. (13). Let $\mathbf{x} = \mathbf{D}_G\circ\boldsymbol{\alpha}_G$, and define $f(\mathbf{x}) = \frac{1}{2\sigma_{\mathbf{e}}^2}\|\mathbf{x}-\mathbf{y}\|_2^2$, $g(\boldsymbol{\alpha}_G) = \lambda\|\boldsymbol{\alpha}_G\|_0 + \psi(\mathbf{D}_G\circ\boldsymbol{\alpha}_G)$, then the minimization problem Eq. (13) is equivalently transformed into three iterative steps:

$$\mathbf{x}^{(t+1)} = arg\ \min_{\mathbf{x}} \frac{1}{2\sigma_{\mathbf{e}}^2}\|\mathbf{x}-\mathbf{y}\|_2^2 + \frac{1}{2\beta^{(t)}}\left\|\mathbf{x} - \mathbf{D}_G^{(t)}\circ\boldsymbol{\alpha}_G^{(t)} - \mathbf{b}^{(t)}\right\|_2^2, \quad (14)$$

$$\left(\boldsymbol{\alpha}_G^{(t+1)}, \mathbf{D}_G^{(t+1)}\right) = arg\ \min_{\boldsymbol{\alpha}_G,\mathbf{D}_G} \frac{1}{2\beta^{(t)}}\left\|\mathbf{x}^{(t+1)} - \mathbf{D}_G\circ\boldsymbol{\alpha}_G - \mathbf{b}^{(t)}\right\|_2^2 + \lambda\|\boldsymbol{\alpha}_G\|_0 + \psi(\mathbf{D}_G\circ\boldsymbol{\alpha}_G), \quad (15)$$

$$\mathbf{b}^{(t+1)} = \mathbf{b}^{(t)} - \left(\mathbf{x}^{(t+1)} - \mathbf{D}_G^{(t+1)}\circ\boldsymbol{\alpha}_G^{(t+1)}\right). \quad (16)$$

Following the similar procedures of [15], each above separated sub-problem can acquire an efficient solution. It is worth emphasizing that, different from previous works [16] [17] [15], we propose to utilize the implicit physical meaning of the parameter $\beta^{(t)}$ to determine it adaptively. Define $\mathbf{s}^{(t)} = \mathbf{x} - \mathbf{D}_G^{(t)}\circ\boldsymbol{\alpha}_G^{(t)} - \mathbf{b}^{(t)}$, and assume $\mathbf{s}^{(t)}$ also obeys a Gaussian distribution. It is straightforward to suppose that $\beta^{(t)}$ is proportional to the variance of $\mathbf{s}^{(t)}$. Hence, we express $\beta^{(t)}$ as

$$\beta^{(t)} = \rho\cdot\left(\sigma_{\mathbf{s}}^{(t)}\right)^2. \quad (17)$$

Here ρ denotes a scaling factor. Then the estimation problem of $\beta^{(t)}$ is changed to the estimation problem of $\sigma_{\mathbf{s}}^{(t)}$. To this end, we use the suggestion in [19] as

$$\sigma_{\mathbf{s}}^{(t)} = \delta\sqrt{\sigma_{\mathbf{e}}^2 - \left\|\mathbf{D}_G^{(t)}\circ\boldsymbol{\alpha}_G^{(t)} + \mathbf{b}^{(t)} - \mathbf{y}\right\|_2^2}, \quad (18)$$

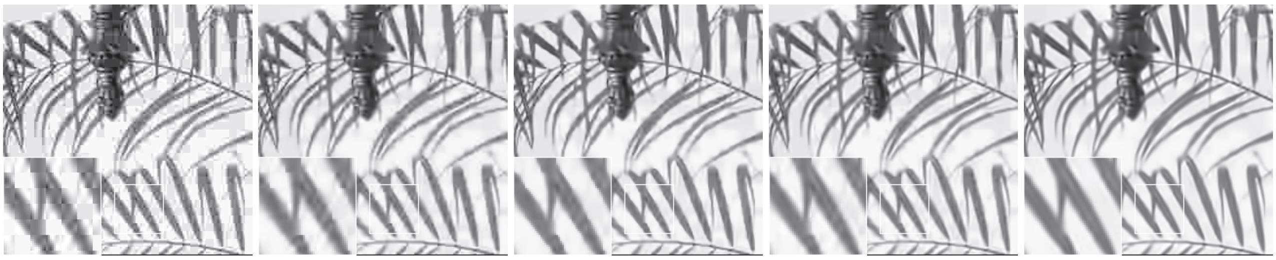

Fig. 1. Visual quality comparison of image deblocking for *Leaves* in the case of QF=5. From left to right: JPEG compressed image (PSNR=22.49dB; SSIM=0.7775), the deblocking results by Sun's [12] (PSNR=23.47dB; SSIM=0.8382), Foi's [18] (PSNR=24.28dB; S-SIM=0.8653), Zhang's [14] (PSNR=24.13dB; SSIM=0.8548), and the proposed GSRQC (PSNR=25.11dB; SSIM=0.8865).

Table 1. PSNR (Unit: dB) and SSIM Results of All Image Deblocking Algorithms

Test image	*Barbara*	*Butterfly*	*Camera.*	*House.*	*Leaves*	Average
Size	256×256	256×256	256×256	256×256	256×256	**PSNR SSIM**
QF = 5						
JPEG Decoded	23.86	22.58	24.45	27.77	22.49	24.23
	0.6563	0.7378	0.7283	0.7733	0.7775	0.7346
Sun's [12]	24.78	23.83	25.25	29.09	23.47	25.29
	0.7103	0.8234	0.7693	0.8117	0.8382	0.7906
Foi's [18]	25.00	24.69	25.53	29.30	24.28	25.76
	0.7124	0.8474	0.7694	0.8144	0.8653	0.8018
Zhang's [14]	25.23	24.20	25.39	29.24	24.13	25.64
	0.7132	0.8313	0.7672	0.8141	0.8548	0.7961
Proposed GSRQC	**25.91**	**25.23**	**25.86**	**30.27**	**25.11**	**26.48**
	0.7453	**0.8630**	**0.7882**	**0.8285**	**0.8865**	**0.8223**
QF = 10						
JPEG Decoded	26.29	25.24	26.47	30.56	25.40	26.79
	0.7901	0.8235	0.7965	0.8183	0.8609	0.8179
Sun's [12]	27.10	26.52	27.26	32.00	26.60	27.90
	0.8208	0.8874	0.8363	0.8507	0.9140	0.8618
Foi's [18]	27.36	27.25	27.48	32.09	27.30	28.30
	0.8300	0.9016	0.8339	0.8494	0.9284	0.8687
Zhang's [14]	27.77	26.83	27.45	32.11	27.26	28.28
	0.8288	0.8923	0.8329	0.8513	0.9212	0.8653
Proposed GSRQC	**28.46**	**27.63**	**27.68**	**32.93**	**28.06**	**28.95**
	0.8543	**0.9104**	**0.8405**	**0.8604**	**0.9379**	**0.8807**

which has been widely used for Gaussian noise variance estimation. δ is a scaling factor to control the variance estimation. The adaptivity of $\beta^{(t)}$ enables the whole algorithm parameter-adaptive, and enables the whole algorithm adaptively adjusted for different QFs and different images, making the proposed framework more attractive and practical.

4. EXPERIMENTAL RESULTS

In this section, experimental results are conducted to verify the performance of the proposed GSRQC for image deblocking. Due to the limit of space, only parts of the experimental results are reported in this paper. Our Matlab code and more visual results can be found at the website [1].

[1] http://idm.pku.edu.cn/staff/zhangjian/deblocking/

The proposed GSRQC is compared with three state-of-the-art image deblocking algorithms: Sun's [12], Foi's [18], and Zhang's [14], whose results are generated by the original authors softwares in their websites. The PSNR and SSIM comparisons for four test images in the cases of QF=5 and QF=10 are provided in Table 1, with the best results highlighted in bold. From Table 1, it is obvious to observe that the proposed GSRQC achieves the highest PSNR and FSIM among the four comparative algorithms, greatly improving the current existing image deblocking quality. Concretely, in the case of QF=5, GSRQC achieves (1.19 dB, 0.72 dB, 0.84 dB) gain in PSNR and (0.0317, 0.0205, 0.0262) gain in SSIM over Sun's [12], Foi's [18] and Zhang's [14] on average; in the case of QF=10, it achieves (1.05 dB, 0.65 dB, 0.67 dB) gain in PSNR and (0.0189, 0.0120, 0.0154) gain in SSIM over Sun's [12], Foi's [18] and Zhang's [14] on average. Fig. 1 presents the deblocking results for *Leaves* in the case of QF=5, which clearly shows the proposed GSRQC not only reduces most of the blocking artifacts significantly, but also provides better reconstruction on both edges and textures than other competing methods.

5. CONCLUSION

In this paper, in order to reduce blocking artifacts and obtain high-quality image, a novel image deblocking algorithm is proposed by utilizing group-based sparse representation (GSR) prior and quantization constraint (QC) prior simultaneously under maximum a posteriori framework. To make the proposed optimization problem tractable, a new split Bregman iteration based method with adaptively adjusted regularization parameter is developed. This parameter-adaptive advantage enables the whole algorithm more attractive and practical. It is worth emphasizing that the proposed algorithm GSRQC outperforms current state-of-the-art algorithms in both PSNR and visual perception, and greatly improves existing image deblocking results, which enables bit reduction while preserving visually acceptable image quality.

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