INTER-BLOCK CONSISTENT SOFT DECODING OF JPEG IMAGES WITH SPARSITY AND GRAPH-SIGNAL SMOOTHNESS PRIORS

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ABSTRACT

Given the prevalence of JPEG compressed images on the Internet, image reconstruction from the compressed format remains an important and practical problem. Instead of simply reconstructing a pixel block from the centers of assigned DCT coefficient quantization bins (hard decoding), we propose to jointly reconstruct a neighborhood group of pixel patches using two image priors while satisfying the quantization bin constraints. First, we assume that a pixel patch can be approximated as a sparse linear combination of atoms from an offline-learned over-complete dictionary. Second, we assume that a patch, when interpreted as a graph-signal, is smooth with respect to an appropriately defined graph that captures the estimated structure of the target image. Finally, neighboring patches in the optimization have sufficient overlaps and are forced to be consistent, so that blocking artifacts typical in JPEG decoded images are avoided. To find the optimal group of patches, we formulate a constrained optimization problem and propose a fast alternating algorithm to find locally optimal solutions. Experimental results show that our proposed algorithm outperforms state-of-the-art soft decoding algorithms by up to 1.47dB in PSNR.

***Index Terms*—** image decoding, sparse signal representation, graph signal processing

1. INTRODUCTION

In the age of big data, millions of images are captured and viewed on social networks and photo-sharing sites daily[1]. The most prevalent compression format for these images remains JPEG (Joint Photographics Expert Group): a lossy image compression standard whose first and most commonly deployed version was finalized more than two decades ago. JPEG is a block-based transform coding scheme, where an image is first divided into non-overlapping 8×8 pixel blocks, transformed via discrete cosine transform (DCT) to coefficients, then quantized and entropy coded. When the quantization is coarse, the reconstructed image quality can be poor.

More precisely, given encoded quantization bin indices of different DCT coefficients in a pixel block, a typical decoding method—called *hard decoding* in the sequel—chooses the bin centers as reconstructed coefficients and performs inverse DCT to recover the block's pixels. It is thus inevitable that the reconstruction quality worsens when the sizes of the quantization bins increase. Instead of hard decoding, one can instead take a *soft decoding* approach: each DCT coefficient is only constrained to be within the indexed quantization bin, and the reconstruction value is chosen with the aid of pre-determined signal priors and optimization [1, 2, 3]. As an example, assuming vertical and horizontal discontinuities along block boundaries are coding artifacts, [3] performed *projection on convex sets* (POCS) between a space spanned by bandlimited vertical and horizontal frequencies and a space with DCT coefficients within the confine of indexed quantization bins. There are two problems, however. First, projection onto low-frequency subspace means high-frequency details in the original image would be eliminated, resulting in an overly smoothed signal. Second, because patches are optimized individually, inter-patch consistency is not guaranteed.

In this paper, we propose a new soft decoding approach where a neighborhood group of overlapping pixel patches are optimized jointly. We employ two priors with different characteristics to aid in signal reconstruction. First, we assume a *sparse signal representation* prior, where a pixel patch can be approximated as a sparse linear combination of atoms chosen from an over-complete dictionary trained offline from a large set of natural images. It has been previously shown [4] that sparsity prior can restore high-frequency details (*textural* content) in an inverse imaging setting.

Second, we assume a *graph-signal smoothness* prior, where a pixel patch—when interpreted as a graph-signal—is smooth with respect to an appropriately defined graph that captures the estimated structure of the target image. Recent works have shown [5, 6, 7] that the graph-signal smoothness prior can restore sharp discontinuities (image *structure*) in an image *if* an appropriate underlying graph can be chosen. The combination of these two priors can thus *both* recover high frequencies in areas rich in textural content (*e.g.* wood grain on a bookshelf), *and* restore discontinuities in areas with distinct structure (*e.g.* foreground / background boundaries). *To be best of our knowledge, we are the first in the literature to design a soft decoding scheme to recover explicitly both texture and structure in JPEG compressed images.*

Finally, neighboring patches in the optimization have sufficient overlaps and are forced to be consistent, so that typical blocking artifacts in JPEG decoded images are avoided. To find the optimal group of patches, we formulate a constrained optimization problem and propose a fast alternating algorithm to find locally optimal solutions. Experimental results show that our proposed algorithm outperforms state-of-the-art soft decoding algorithm by up to 1.47dB in PSNR.

2. RELATED WORK

There exist many JPEG image soft decoding methods in the literature [2]-[8], following the assumption that natural images are smooth in some pre-defined notions. Bredies *et al.* [9] proposed a variational model for JPEG decompression, which is based on the minimization of the total variation (TV) given available compressed JPEG data. Zhai *et al.* [10] utilized the assumption that natural images are local smooth, and proposed a block-shift filtering-based algorithm. How-

[1]It is estimated that 300 million photos are uploaded to Facebook a day.

ever, over-smoothing is unavoidable in many cases, which we avoid by using an image-dependent graph-signal smoothness prior.

Some works focused on the reduction of compression artifacts in the transform domain. Lee *et al.* [11] proposed to reduce artifacts by first low-pass filtering the decoded image and then predicting the image by a linear regression model in transform domain. Foi *et al.* [12] utilized a point-wise shape-adaptive DCT for denoising. Zhang *et al.* [13] proposed to restore compressed image by using the non-local self-similarity of DCT coefficients. In contrast, we avoid blocking artifacts by jointly and efficiently optimizing a neighborhood group of patches that overlap, and enforcing inter-patch consistency.

There also are sparsity-based compressed image restoration algorithms, such as [14, 8, 15]. Farinella *et al.* [14] employed the Structure Sparse Coding Model Selection (SSMS) to reduce blocking artifacts. Jung *et al.* [8] proposed a deblocking method based on sparse representation using a dictionary learned from a set of training images by K-SVD. In [15], Chang *et al.* proposed to learn the dictionary from the input compressed image, and use total variation regularization for decompressed images. In contrast, we combine a sparsity prior with a graph-signal smoothness prior, which can recover *both* high-frequency texture *and* structure defined by discontinuities in an image.

3. PROBLEM FORMULATION

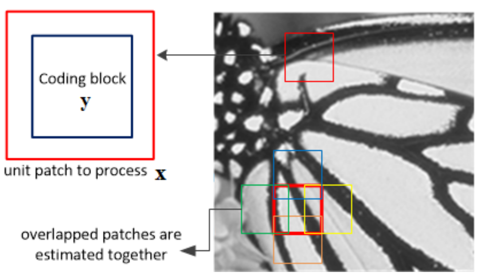

Fig. 1. A patch being optimized encloses a smaller code block. Overlapped patches in a local neighborhood are optimized jointly.

3.1. Overview

JPEG images are coded as non-overlapping 8×8 blocks independently via transform coding. More precisely, each 8×8 pixel block $\mathbf{y}$ is transformed via DCT to 64 transform coefficients $\mathbf{Y} = \mathbf{T}\,\mathbf{y}$. The i-th coefficient Y_i is quantized using quantization parameter (QP) Q_i—assigned a quantization index $q_i \in \mathbb{I}$ (called *q-index* in the sequel) as:

$$q_i = \texttt{round}\,(Y_i/Q_i)\,. \tag{1}$$

Thus, at the decoder, having received only q-index q_i there exists an uncertainty when recovering Y_i, in particular:

$$q_i Q_i \leq Y_i < (q_i + 1) Q_i. \tag{2}$$

To help resolve the uncertainty (2) in each DCT coefficient Y_i, we employ two signal priors in the reconstructed image. First, we assume that a pixel patch $\mathbf{x}$ enclosing a coded DCT block $\mathbf{y}$, as shown in Fig. 1, can be approximated as a sparse linear combination of dictionary atoms—*sparse signal representation prior* [4]. Second, we assume that the same patch $\mathbf{x}$ is smooth with respect to a defined graph $\mathcal{G}$—*graph-signal smoothness prior* [16]. Finally, we enforce consistency among adjacent patches with overlaps. We discuss these points in order.

3.2. Sparse Signal Representation Prior

Research in image statistics [4] shows that an image patch of dimension N, $\mathbf{x} \in \mathbb{R}^N$, can be well approximated by a sparse linear

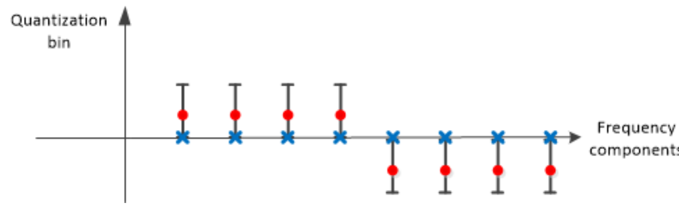

Fig. 2. Illustration of over-smoothing effect of TV. TV will choose the values indicated by $\times$, while MMSE will choose values indicated by red points.

combination of atoms from an appropriately chosen over-complete dictionary of size D, $\mathbf{\Phi} \in \mathbb{R}^{N \times D}$, $D \gg N$, *i.e.*,

$$\mathbf{x} = \mathbf{\Phi}\boldsymbol{\alpha} + \varepsilon, \tag{3}$$

where $\varepsilon \in \mathbb{R}^N$ is a small perturbation term.

Constructing a good dictionary $\mathbf{\Phi}$ is critical to the above sparse model. Similarly done in [17], we learn a dictionary as follows. We first collect training patches from many clean natural images, then classify them into clusters with similar geometric structures via a K-means clustering method. Finally, for a given cluster i with n_i image patches, we compute a sub-dictionary $\mathbf{\Phi}_i$ by first stacking the vectors of patches into a matrix $\mathbf{P}_i$, and then performing *principal component analysis* (PCA) on $\mathbf{P}_i$: atoms in $\mathbf{\Phi}_i$ are the eigenvectors of the covariance matrix of $\mathbf{P}_i$.

As shown in Fig. 1, let $\mathbf{x} \in \mathbb{R}^N$ be a larger patch enclosing a smaller DCT block $\mathbf{y} \in \mathbb{R}^M$, *i.e.*, $\mathbf{y} = \mathbf{M}\mathbf{x}$, where binary matrix $\mathbf{M} \in \{0,1\}^{M \times N}$ extracts pixels in $\mathbf{x}$ corresponding to the smaller coded block $\mathbf{y}$. Using the sparsity prior, we can formulate the soft decoding problem for a single patch $\mathbf{x}$ as follows:

$$\min_{\{\mathbf{x},\boldsymbol{\alpha}\}} \|\mathbf{x} - \mathbf{\Phi}\boldsymbol{\alpha}\|_2^2 + \lambda_1 \|\boldsymbol{\alpha}\|_1, \tag{4}$$

where each DCT coefficient Y_i in $\mathbf{Y} = \mathbf{TMx}$ must satisfy the i-th q-bin constraint in (2). λ_1 is a parameter trading off the importance of the fidelity term with the sparsity prior.

3.3. Graph-Signal Smoothness Prior

Note that both quantities in the fidelity term in (4)—target signal $\mathbf{x}$ and sparse code $\boldsymbol{\alpha}$—are unknown variables. When quantization is coarse, QPs Q_i are large and q-bins are wide, and any sparse solution to (4) within the large q-bins is equally good. Thus, more prior information is required to further regularize the problem.

Given the observation that natural images tend to be smooth, one can use the popular total-variation (TV) prior [18] for regularization. However, employing TV for our soft decoding problem would encourage the smoothest signal possible within the q-bin constraints, potentially resulting in over-smoothing. As an illustrative example, consider the q-bins for AC frequencies of a 1D 8-sample signal in Fig. 2. Regardless of the q-bin sizes, TV norm would promote coefficient reconstructions closest to the zero q-bin boundaries, resulting in an almost DC signal. Assuming that each DCT coefficient takes on a Laplacian probability distribution (common in the image / video coding literature [19]), the TV-reconstructed DC signal can be arbitrarily far from the minimum mean square error (MMSE) solution closer to the q-bin centers as the q-bin sizes increase.

Instead, we propose to employ a graph-signal smoothness prior for appropriate smoothing, similarly done in [20, 6, 7, 21] for image interpolation, denoising and bit-depth enhancement. The key to an effective graph-based regularizer is to capture the estimated structure of the target image patch as edge weights in a graph $\mathcal{G}$. Assuming a 4-connected graph $\mathcal{G}$ for a given pixel patch, edge weight $W_{i,j}$ between two neighboring pixels x_i and x_j is conventionally computed using a Gaussian kernel:

$$W_{i,j} = \exp\left\{-\|x_i - x_j\|_2^2/\sigma^2\right\}. \tag{5}$$

$W_{i,j} = 0$ if x_i and x_j are not connected.

Given edge weights $W_{i,j}$, one can define an *adjacency matrix* $\mathbf{A}$ where $A_{i,j} = W_{i,j}$, and a diagonal *degree matrix* $\mathbf{D}$ where $D_{i,i} = \sum_j A_{i,j}$. A *combinatorial* or *unnormalized graph Laplacian* $\mathbf{L}$ is defined as: $\mathbf{L} = \mathbf{D} - \mathbf{A}$. Given $\mathbf{L}$, one can describe the squared variations of the signal $\mathbf{x}$ with respect to the graph $\mathcal{G}$ using the *graph Laplacian regularizer* $\mathbf{x}^T\mathbf{L}\mathbf{x}$ [22, 23]:

$$\mathbf{x}^T\mathbf{L}\mathbf{x} = \frac{1}{2}\sum\nolimits_{i,j}(x_i - x_j)^2\, W_{i,j}. \tag{6}$$

(6) states that the graph Laplacian regularizer is small if the signal variation at connected pair (x_i, x_j) is small, *or* the modulating edge weight $W_{i,j}$ is small. Thus, if a discontinuity is expected at pixel pair (x_i, x_j), one can pre-set a small edge weight $W_{i,j}$ in graph $\mathcal{G}$, so that employing the graph Laplacian regularizer as smoothness prior for optimization will not result in over-smoothing at this pair.

With both sparsity and graph-signal smoothness priors, we can write the objective function for a patch $\mathbf{x}$ as follows:

$$\min_{\{\mathbf{x},\boldsymbol{\alpha}\}} \|\mathbf{x} - \boldsymbol{\Phi}\boldsymbol{\alpha}\|_2^2 + \lambda_1\|\boldsymbol{\alpha}\|_1 + \lambda_2\mathbf{x}^T\mathbf{L}\mathbf{x} \tag{7}$$

where λ_2 is another parameter that values the importance of the graph-signal smoothness term relative to the others.

Given $\mathbf{x}$ is an unknown variable in (7), we need a good initial estimation of $\mathbf{x}$ so that edge weights computed using (5) can capture the underlying image structure. (7) will then be solved iteratively, where the edge weights used to define Laplacian $\mathbf{L}$ will be updated using the obtained solution $\mathbf{x}$ in the previous iteration. In this paper, given q-bin constraints we compute a *minimum mean square error* (MMSE) solution $\mathbf{x}^o$ as the initial estimate of $\mathbf{x}$. More precisely, each MMSE coefficient Y_i^o is computed as:

$$Y_i^o = \arg\min_{Y_i^o} \int_{q_iQ_i}^{(q_i+1)Q_i} (Y_i^o - Y_i)^2\, Pr(Y_i)\, dY_i, \tag{8}$$

where we assume that the pdf $Pr(Y_i)$ of coefficient Y_i is a Laplacian distribution with parameter μ. By taking the derivative of (8) with respect to Y_i^o and setting it to zero, we obtain a closed-form solution:

$$Y_i^o = \frac{(q_iQ_i + \mu)\, e^{\left\{-\frac{q_iQ_i}{\mu}\right\}} - ((q_i+1)Q_i + \mu)\, e^{\left\{-\frac{(q_i+1)Q_i}{\mu}\right\}}}{e^{\left\{-\frac{q_iQ_i}{\mu}\right\}} - e^{\left\{-\frac{(q_i+1)Q_i}{\mu}\right\}}}. \tag{9}$$

The initial estimation $\mathbf{x}^o$ can be finally obtained by performing inverse transformation on the estimated DCT coefficients $\{Y_i^o\}$.

3.4. Inter-Patch Consistency

Since by design neighboring patches $\{\mathbf{x}_i\}$ have overlaps, the pixel values in an overlapping region from two patches should be as similar as possible. For each patch $\mathbf{x}_i$ at location i, there are four neighboring patches $\mathcal{N}(i)$ that it overlaps. Define $\mathbf{R}_{i,j}$ to be the matrix that extracts $\mathbf{x}_i$'s overlapping pixels with neighboring patch $\mathbf{x}_j$. To enforce inter-patch consistency we can write:

$$\sum\nolimits_{j=\mathcal{N}(i)} \|\mathbf{R}_{i,j}\mathbf{x}_i - \mathbf{R}_{j,i}\mathbf{x}_j\|_2^2 \le \tau, \tag{10}$$

where τ is a threshold that determines how strictly inter-patch consistency should be enforced.

4. OPTIMIZATION

We can now write the joint optimization for neighborhood group of patches $\{\mathbf{x}_i\}$ as follows. We assume that the same QP Q_k is used for quantization of coefficient k of all code blocks. Given patch $\mathbf{x}_i$, the k-th DCT coefficient of the enclosed code block $\mathbf{y}_i = \mathbf{M}\mathbf{x}_i$ is computed as $\mathbf{1}(k)^T\mathbf{T}\mathbf{M}\mathbf{x}_i$, where $\mathbf{1}(k)$ is a zero vector except for the k-th entry, which is 1. The corresponding encoded q-bin index is $q_{k,i}$. The optimization problem is:

$$\begin{aligned} &\arg\min_{\{\mathbf{x}_i,\boldsymbol{\alpha}_i\}} \sum\nolimits_i \|\mathbf{x}_i - \boldsymbol{\Phi}\boldsymbol{\alpha}_i\|_2^2 + \lambda_1\|\boldsymbol{\alpha}_i\|_1 + \lambda_2\mathbf{x}_i^T\mathbf{L}_i\mathbf{x}_i \\ &\text{s.t.,}\quad q_{k,i}Q_k \le \mathbf{1}(k)^T\mathbf{T}\mathbf{M}\mathbf{x}_i < (q_{k,i}+1)Q_k, \quad \forall k \\ &\qquad \sum\nolimits_{j\in\mathcal{N}(i)} \|\mathbf{R}_{i,j}\mathbf{x}_i - \mathbf{R}_{j,i}\mathbf{x}_j\|_2^2 \le \tau \qquad \forall i. \end{aligned} \tag{11}$$

We propose to employ an alternating procedure to optimize $\{\mathbf{x}_i\}$ and $\{\boldsymbol{\alpha}_i\}$ iteratively. Each iteration of the optimization procedure is described as follows:

1) Fix $\mathbf{x}_i$ and estimate $\boldsymbol{\alpha}_i$:

Estimate $\mathbf{x}_i$ initially as described in Section 3.3, The optimization problem becomes a standard sparse coding:

$${\boldsymbol{\alpha}_i}^* = \arg\min_{\boldsymbol{\alpha}_i} \sum\nolimits_i \|\mathbf{x}_i - \boldsymbol{\Phi}\boldsymbol{\alpha}_i\|_2^2 + \lambda_1\|\boldsymbol{\alpha}_i\|_1, \tag{12}$$

which can be efficiently solved by a fast ℓ_1-minimization algorithm called Augmented Largrangian Methods (ALM) [24].

2) Fix $\boldsymbol{\alpha}_i$ and estimate $\mathbf{x}_i$:

Denoting $\mathbf{b}_i = \boldsymbol{\Phi}_i\boldsymbol{\alpha}_i^*$, the objective function can be simplified to:

$$\min_{\{\mathbf{x}_i\}} \sum_i \|\mathbf{x}_i - \mathbf{b}_i\|_2^2 + \lambda_2\mathbf{x}_i^T\mathbf{L}\mathbf{x}_i + \lambda_3 \sum_{j\in\mathcal{N}(i)} \|\mathbf{R}_{i,j}\mathbf{x}_i - \mathbf{R}_{j,i}\mathbf{x}_i\|_2^2 \tag{13}$$

Because the second-order derivative of $\mathcal{J}$ with respect to $\mathbf{x}_i$ is a positive definite matrix, the objective function in (13) is convex [25], and thus admits a closed form solution.

3) Quantization Bin Constraints:

To satisfy the q-bin constraints, we simply clip each k-th coefficient outside the q-bin to within the q-bin boundaries.

After each iteration, edge weights in the graph Laplacian $\mathbf{L}_i$ are updated via (5) using the outputted solution $\mathbf{x}_i$ in the previous iteration. The algorithm terminates when both $\{\mathbf{x}_i\}$ and $\{\boldsymbol{\alpha}_i\}$ converge.

5. EXPERIMENTATION

In this section, experimental results are presented to demonstrate the superior performance of our proposed soft decoding approach for restoring compressed images. For the training set, five images are randomly selected from Kodak Lossless True Color Image Suite, which do not include any of the test images.

The new approach is compared with: 1) The ANCE algorithm [13], which is a state-of-the-art compressed image restoration method. 2) Two sparsity-based restoration methods: KSVD [26] and DicTV [15]. KSVD is a well-known sparse coding framework. Most existing sparsity-based compressed image restoration algorithms, such as [14, 8], are based on the general framework of KSVD. KSVD for compressed image restoration can be regarded as the benchmark algorithm that only utilizes the sparisty prior and quantization bin constraint. DicTV is a very recent sparsity-based compressed image restoration algorithm, which exploits both sparsity and TV priors. The source codes are all kindly provided by their authors. For thoroughness of our comparison study, we select five widely used images in the literature as test images. The images are all sized of 256×256.

Table 1. Objective quality comparison with respect to PSNR (in dB) at QF = 5, QF = 15 and QF = 25

Images	QF = 5					QF = 15					QF = 25				
	JPEG	KSVD	ANCE	DicTV	Ours	JPEG	KSVD	ANCE	DicTV	Ours	JPEG	KSVD	ANCE	DicTV	Ours
Butterfly	22.65	23.96	24.31	23.54	**24.72**	26.75	27.97	28.26	28.13	**28.44**	28.41	29.49	29.84	29.73	**30.57**
Barbara	23.85	24.93	25.17	24.49	**25.46**	28.01	29.19	29.79	29.25	**30.72**	30.41	31.57	32.23	31.67	**33.05**
Boat	25.23	26.64	26.62	26.31	**26.84**	29.72	30.71	30.97	30.54	**31.24**	31.63	32.32	32.90	32.31	**33.11**
Leaves	22.49	23.76	24.13	23.27	**24.65**	26.96	28.46	28.91	28.58	**29.16**	28.89	30.36	30.83	30.61	**31.63**
Bike	21.72	22.56	22.81	22.28	**22.87**	25.42	26.15	26.53	26.25	**26.62**	27.19	27.88	28.46	28.01	**28.69**
Average	23.18	24.37	24.87	24.09	**24.91**	27.37	28.49	28.89	28.55	**29.24**	29.31	30.32	30.85	30.46	**31.41**

JPEG (22.65,0.7571) KSVD (23.86,0.8417) ANCE (24.31,0.8532) DicTV (23.54,0.8228) Proposed (24.72,0.8621)

Fig. 3. Comparison of tested methods in visual quality on *Butterfly* at QF=5. PSNR and SSIM values are also given.

JPEG (22.49,0.7775) KSVD (23.66,0.8481) ANCE (24.18,0.8551) DicTV (23.27,0.8245) Proposed (24.65,0.8642)

Fig. 4. Comparison of tested methods in visual quality on *Leaves* at QF=5. PSNR and SSIM values are also given.

Table 1 tabulates the PSNR results of the above algorithms for eight test images, which are coded by a JPEG coder with quality factors (QF) 5, 15 and 25. Larger QF value means smaller quantization bins. Our proposed algorithm has the best objective performance for all test images and over all three QFs. Compared with the ANCE algorithm, our proposed method greatly improves the reconstruction quality. The average PSNR gains is up to 0.46dB. Our method also works better than state-of-the-art sparse coding based methods. Compared with KSVD, our method can achieve PSNR gain up to 1.53dB (*Barbara* when QF = 15). DicTV is also specially designed for recovering compressed images. Compared with DicTV, our method is better for all test images, and the highest average gain is 0.86dB, and can achieve PSNR gain up to 1.47dB for some test image (*Butterfly* when QF = 15).

In addition to its superior performance in objective fidelity metric, our soft decoding algorithm also achieves better perceptual quality of the restored images. Fig. 3 and Fig. 4 illustrate the perceptual quality comparison. When QF is 5, the quantization noise is severe, and the JPEG-compressed images have very poor subjective quality. The images reproduced by KSVD suffer from highly visible noises. ANCE can suppress most of blocking artifacts, but there are still noticeable artifacts along edges. In results produced by DicTV, there are still strong blocking artifact. This is because, in DicTV, the dictionary is learnt from the JPEG image. When quantization is heavy, the structure noise is also learnt as atoms of dictionary. Therefore, it will enhance but not suppress the quantization noise through subsequent sparse coding based restoration. The images restored by our method are much cleaner, in which the structures and sharpness of edges and textures are well preserved. Our proposed method can also remove DCT blocking artifacts in smooth areas completely, and is largely free of the staircase and ringing artifacts along edges. Due to space limitation, here we only show the subjective comparisons for low QF, as the superiority can be better visually reflected in these cases. Our method also achieves better subjective quality for medium to high QFs as well.

6. CONCLUSION

In this paper, a novel soft decoding approach for the restoration of JPEG-compressed images is proposed. The main technical contribution is the combined use of two image priors while satisfying the quantization bin constraints. First, a pixel patch is approximated as a sparse linear combination of atoms from a learned over-complete dictionary. Second, a patch is assumed to be smooth with respect to an appropriately defined graph that captures the structure of the target signal. Experimental results demonstrate that our method achieves better objective and subjective restoration quality compared to state-of-the-art soft decoding algorithms.

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