Data-driven Sparsity-based Restoration of JPEG-compressed Images in Dual Transform-Pixel Domain

Xianming Liu[1*], Xiaolin Wu[2], Jiantao Zhou[3], Debin Zhao[1]
[1]School of Computer Science and Technology, Harbin Institute of Technology, China
[2]Department of ECE, McMaster University, Canada
[3]Department of CIS, Faculty of Science and Technology, University of Macau
*xmliu.hit@gmail.com

Abstract

Arguably the most common cause of image degradation is compression. This papers presents a novel approach to restoring JPEG-compressed images. The main innovation is in the approach of exploiting residual redundancies of JPEG code streams and sparsity properties of latent images. The restoration is a sparse coding process carried out jointly in the DCT and pixel domains. The prowess of the proposed approach is directly restoring DCT coefficients of the latent image to prevent the spreading of quantization errors into the pixel domain, and at the same time using on-line machine-learnt local spatial features to regulate the solution of the underlying inverse problem. Experimental results are encouraging and show the promise of the new approach in significantly improving the quality of DCT-coded images.

1. Introduction

One of significant advances in the fields of computer vision and image processing is sparsity-based visual signal analysis and processing. In particular, sparsity-based image restoration has been proven highly successful for a wide range of applications, such as denoising, deblurring, interpolation, color demosaicking, etc., as reported in a large number of research papers [30, 11, 19, 29, 12, 21, 22]. In comparison relatively few papers were devoted to sparsity-based restoration of compressed images [13, 15, 5, 18], despite the fact that the most common cause of image degradation in practice is compression.

In image compression products and systems, by far the most commonly used compression technique is that of discrete cosine transform (DCT), which is adopted in popular compression standards JPEG [27], MPEG [1], H.264/AVC [28] and HEVC [25]. Motivated by the practical importance this research focuses on the restoration of DCT-coded images.

Apparently, following the tradition of assuming degradations to be signal independent in image restoration literature, existing works on restoring compressed images model compression noises to be signal independent. Examples are uniform noises in the DCT domain [24], white Gaussian noises (WGN) in spatial domain [23] [20], or generalized Gaussian noises [33]. Unfortunately, compression-induced degradations, mostly in the form of quantization noises, are far from being white and signal-independent as taken for granted in papers on other image restoration tasks [26, 9, 6, 11, 21]. Current inaccurate modeling of compression degradations limits the restoration performance.

In this work we do away with any preassumption on compression noises and aim to repair signal-dependent degradations via a novel data-driven approach. The new restoration approach performs a joint sparse coding in both DCT domain and pixel domain. As natural images are statistically non-stationary with spatially varying sparse representations, sparse coding is performed on individual DCT patches, one at a time, so that the restoration can adapt to local statistics. For each restoration patch two dictionaries of PCA bases are learnt in the DCT and pixel domains respectively, using sample sets of approximately matched quantized DCT code blocks. The two learnt dictionaries are used to generate two locally adaptive sparse representations that jointly determine the restored image patch. Fig. 1 depicts the architecture of the proposed image restoration system, in which the degraded input is the decompressed (hard-decoded) image and the restored output is called soft-decoded image. In the compression literature, the task of repairing hard-decoded results is commonly referred to as soft decoding.

The premise of soft decoding is that practical image compression methods, such as popular international standards JPEG, JPEG 2000 [2], H.264/AVC, HEVC etc., are not information theoretically optimal. Therefore, the resulting compression code streams still have residual redundan-

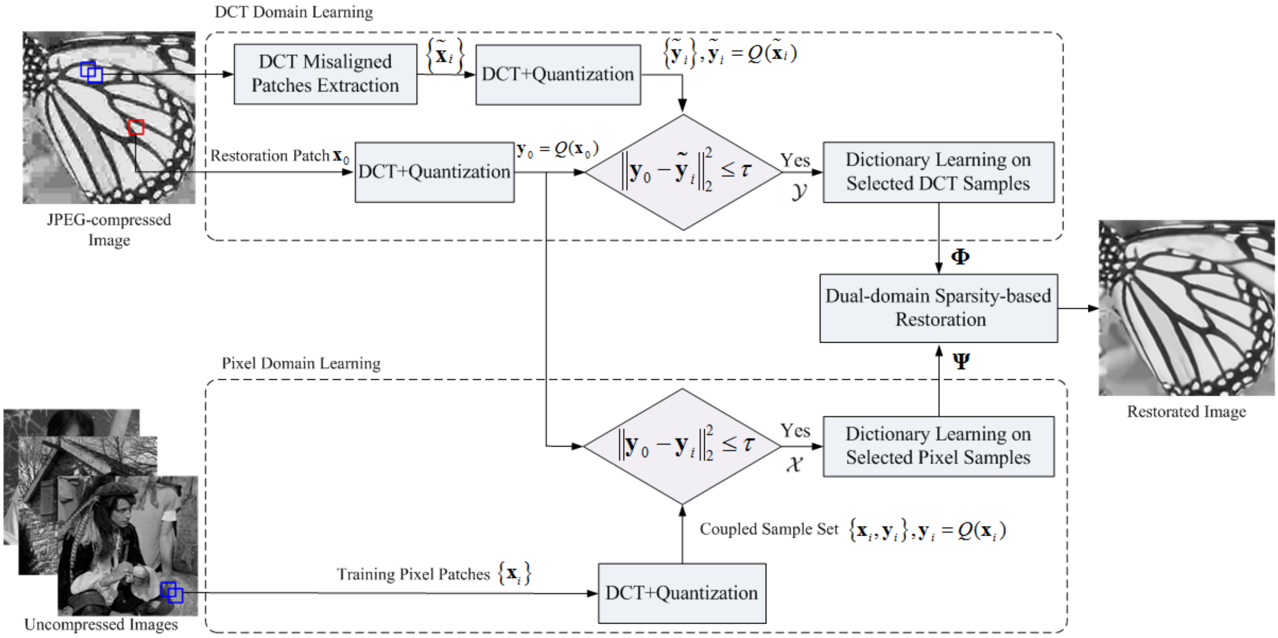


Figure 1. Block diagram of the proposed data-driven soft decoding system in dual transform-pixel domain.

cies; it is possible, at least theoretically, to improve the reconstruction by reestimating the original signal by exploiting the knowledge ignored or underused by the encoder. In particular, in the ubiquitous local DCT block-based coding framework, correlations exist between different code blocks, because natural images have similar local structures due to self-similarity but the code block size is not large enough to capture the underlying statistical redundancy. These inter-block correlations, which are not exploited by the encoder, can be used by the decoder to increase the reconstruction fidelity without receiving any extra bits.

Up to now all existing soft decoding techniques work either in the pixel domain [4, 32, 31, 34, 8] or in the DCT domain [7, 17, 16, 14]. But the restoration in either domain has its own drawbacks. As the pixel domain restoration works with hard-decoded image, the inverse DCT is required; this will propagate an isolated quantization error, which is originally confined to a DCT coefficient, to all pixels of the corresponding DCT block. To make the matter worse, an aggressively quantized DCT coefficient can produce structured errors in the pixel-domain that correlate to the latent signal, complicating the restoration task. On the other hand, the pure DCT-domain restoration is severely restricted by the fact that the compression process set most of high frequency coefficients to zero, making the recovery of edges and fine textures impossible. In the proposed dual domain soft decoding, the advantages and disadvantages of the pixel-domain and DCT-domain restorations are made to complement one the other. The design motive, which is also a main contribution of this work, is to exploit residual redundancies (e.g., inter-DCT-block correlations) in the DCT domain without spreading errors into the pixel domain, and at the same time recover high frequency information with machine learning driven by a large training set. A uniqueness of our machine learning method for soft decoding is in its feature selection: the quantized DCT code block rather than the (or some attributes of) corresponding hard-decoded pixel patch is used as the feature vector. Directly associating the DCT code block to the underlying latent image block isolates the degradation cause at its root and hence simplifies the learning task. Also, the soft decoding performance is further boosted by incorporating the known boundaries of quantizer cells, which is a strong piece of available side information in the DCT code stream, into the new sparsity-based restoration scheme.

The rest of the paper is organized as follows. Section II details the proposed technique of sparse coding in the DCT domain; here the main novelty is the collecting and clustering of a sample set created by performing forward DCT of overlapped pixel patches in the hard-decoded image. By breaking free from the rigid DCT code block tessellation the proposed sparse coding process can fully benefit from the self-similarities of the latent image and remove the blocking compression artifacts. In Section IV we extend sparse coding from the DCT domain to the dual DCT-pixel domain and finally cast the dual sparse coding-based restoration of compressed images as a mixed ℓ_1-ℓ_2 minimization problem. The highlight of this section is the new data-driven learning method for repairing distorted high-frequency image features. Section V reports experimental results, and Section

VI concludes the paper.

2. Sparsity-based Restoration of DCT Coefficients

As outlined in the introduction, we advocate to restore DCT coefficients of the latent image, i.e., suppressing quantization noises directly in the DCT domain rather than denoising in the pixel domain after inverse DCT. This confines the quantization errors to individual DCT coefficients instead of propagating them over a wide area of pixels.

2.1. Adaptive DCT Dictionary Learning

We divide the hard decoded JPEG image $\mathbf{I}$ into a set of overlapped patches $\{\widetilde{\mathbf{x}}_i\}$ of size 8×8, and perform transformation and quantization on these blocks to get the corresponding DCT patches $\{\widetilde{\mathbf{y}}_i\}$; the resulting DCT blocks constitute the online training data set. Here we emphasize that the said training pixel patches $\{\widetilde{\mathbf{x}}_i\}$ be extracted in arbitrary positions that misalign with the DCT code block boundaries of the JPEG standard. This is an important detail to destroy artificial structures of JPEG compression method and remove much of the notorious DCT blocking artifacts.

To build the sparsity dictionary for restoring the current DCT patch $\mathbf{y}_0$, we select from the training set $\{\widetilde{\mathbf{y}}_i\}$ a set of sample patches

$$\mathcal{Y} = \{\widetilde{\mathbf{y}}_i \,\big|\, ||\widetilde{\mathbf{y}}_i - \mathbf{y}_0||_2^2 \leq \tau\}, \tag{1}$$

where τ is a threshold. We stack the vectors of collected patches into a matrix denoted by $\mathbf{Y}$. Then, we learn an adaptive sub-dictionary $\mathbf{\Phi}$ that is most relevant to $\mathbf{Y}$ by applying *principal component analysis* (PCA) on $\mathbf{Y}$. PCA generates the dictionary $\mathbf{\Phi}$ whose atoms are the eigenvectors of the covariance matrix of $\mathbf{Y}$. In this way, we construct one sub-dictionary per DCT patch separately.

2.2. Restoration in Transform Domain

After getting the dictionary, the sparse representation vector $\boldsymbol{\alpha}$ of the current restorated DCT patch $\mathbf{y}_0$ can be obtained by:

$$\boldsymbol{\alpha}^* = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y}_0 - \mathbf{\Phi}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1. \tag{2}$$

In addition to the sparsity image prior, the DCT image code stream contains strong pieces of side information on the original image that should be exploited to improve restoration performance. For each coding DCT coefficient $\mathbf{y}_0(u, v)$, u and v being the indices of the corresponding 2D subband in DCT domain, we know its quantization interval $(q_{u,v}^L, q_{u,v}^U)$, i.e.,

$$q_{u,v}^L \leq \mathbf{y}_0(u, v) \leq q_{u,v}^U. \tag{3}$$

These inequalities can be incorporated into (2) to further confine the solution space and improve the restoration performance. Finally, we formulate our problem of soft decoding in transform domain as the following constrained convex optimization problem:

$$\begin{aligned} &\arg\min_{\boldsymbol{\alpha}} \|\mathbf{y}_0 - \mathbf{\Phi}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1, \\ &\text{s.t.,} \quad \mathbf{q}^L \preceq \mathbf{\Phi}\boldsymbol{\alpha} \preceq \mathbf{q}^U, \end{aligned} \tag{4}$$

where $\preceq$ denotes the operation of element-wise comparison, $\mathbf{q}^L$ and $\mathbf{q}^U$ are vectors containing bound values of the quantization interval.

3. Sparsity-based Restoration in Dual Transform-Pixel Domain

The restoration in the DCT domain only cannot fully recover the high-frequency features that are discarded or distorted by JPEG quantization of DCT coefficients. This weakness can be mitigated by machine learning that allows incorporation of high-frequency priors of uncompressed images in restoring JPEG-compressed images.

3.1. Adaptive Pixel Dictionary Learning

The learning uses a training set of uncompressed images and extracts from the set coupled patches in pixel and DCT domains. Specifically, 8×8 pixel blocks $\{\mathbf{x}_i\}$ drawn from the training images are DCT transformed and quantized as in JPEG compression, generating corresponding quantized DCT coefficient blocks $\{\mathbf{y}_i\}$. This creates a sample set of paired pixel and DCT patches $\{\mathbf{x}_i, \mathbf{y}_i\}$.

In order to restore a pixel patch $\mathbf{x}_0$ that is coded by JPEG into DCT block $\mathbf{y}_0$, a dictionary can be constructed using the training data in set $\{\mathbf{x}_i, \mathbf{y}_i\}$. Similarly to dictionary learning in the DCT domain, we collect a set of pixel patches $\mathbf{x}_i$ that have their DCT representations sufficiently close to $\mathbf{y}_0$:

$$\mathcal{X} = \{\mathbf{x}_i | \|\mathbf{y}_i - \mathbf{y}_0\|_2^2 \leq \tau\}, \tag{5}$$

and perform PCA on $\mathcal{X}$. The resulting PCA basis vectors constitute the dictionary $\mathbf{\Psi}$ that gives the input patch $\mathbf{x}$ a sparse representation $\boldsymbol{\beta}^*$, namely,

$$\boldsymbol{\beta}^* = \arg\min_{\boldsymbol{\beta}} \|\mathbf{x}_0 - \mathbf{\Psi}\boldsymbol{\beta}\|_2^2 + \lambda\|\boldsymbol{\beta}\|_1. \tag{6}$$

3.2. Restoration in Dual Domain

Given the two online learnt dictionaries $\mathbf{\Phi}$ and $\mathbf{\Psi}$ in transform and pixel domain, we jointly search for two sparse code vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ that best explain the observed

Figure 2. Six test images

DCT patch $\mathbf{y}_0$ in the dual domain:

$$\begin{aligned}&\underset{\{\boldsymbol{\alpha},\boldsymbol{\beta}\}}{\arg\min}\left\{\begin{array}{l}\|\mathbf{y}_0-\boldsymbol{\Phi}\boldsymbol{\alpha}\|_2^2+\lambda_1\|\boldsymbol{\alpha}\|_1\\+\lambda_2\left\|\mathbf{T}^{-1}\boldsymbol{\Phi}\boldsymbol{\alpha}-\boldsymbol{\Psi}\boldsymbol{\beta}\right\|_2^2+\lambda_3\|\boldsymbol{\beta}\|_1\end{array}\right\},\\&\text{s.t.,}\quad \mathbf{q}^L\preceq\boldsymbol{\Phi}\boldsymbol{\alpha}\preceq\mathbf{q}^U,\end{aligned} \tag{7}$$

where $\mathbf{T}^{-1}$ is the inverse discrete cosine transform; λ_1, λ_2 and λ_3 are Lagrange multipliers. Joint restoration in the DCT and pixel domain allows the two sparse representations $\boldsymbol{\alpha}$ in dictionary $\boldsymbol{\Phi}$ and $\boldsymbol{\beta}$ in dictionary $\boldsymbol{\Psi}$ to cross validate each other, enhancing the quality of soft decoded image patches. Note that the sparsity dictionaries $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ are made adaptive to each input patch $\mathbf{y}_0$ via the on-line learning described above.

Defining $\widehat{\mathbf{y}}_0 = [\mathbf{y}_0\ \mathbf{0}]^T$, $\boldsymbol{\theta} = [\boldsymbol{\alpha}\ \boldsymbol{\beta}]^T$, and $\mathbf{D} = \begin{bmatrix}\boldsymbol{\Phi} & \mathbf{0}\\ -\sqrt{\lambda_2}\mathbf{T}^{-1}\boldsymbol{\Phi} & \sqrt{\lambda_2}\boldsymbol{\Psi}\end{bmatrix}$, the above objective function can be simplified as follows:

$$\begin{aligned}&\underset{\boldsymbol{\theta}}{\arg\min}\ \|\widehat{\mathbf{y}}_0-\mathbf{D}\boldsymbol{\theta}\|_2^2+\lambda\|\boldsymbol{\theta}\|_1,\\&\text{s.t.,}\quad [\mathbf{q}^L\ \mathbf{0}]^T\preceq\mathbf{D}\boldsymbol{\theta}\preceq[\mathbf{q}^U\ \mathbf{0}]^T,\end{aligned} \tag{8}$$

where for simplicity we set $\lambda = \lambda_1 = \lambda_3$. This is a mixed ℓ_1-ℓ_2 minimization problem, which can be effectively solved by the iterative shrinkage algorithm [10] with the inequality as constraint for each iteration. Upon solving (8) and obtaining the optimal sparse coding vectors $\{\boldsymbol{\beta}_i^*\}$ for all DCT patches to be restorated, the whole image can be reconstructed by averaging all of the reconstructed patches:

$$\widehat{\mathbf{I}}=\left(\sum_{i=1}^{N}\mathbf{R}_i^T\mathbf{R}_i\right)^{-1}\left(\sum_{i=1}^{N}\mathbf{R}_i^T\boldsymbol{\Psi}_i\boldsymbol{\beta}_i^*\right). \tag{9}$$

where N is the number of all sampled patches, $\mathbf{R}_i$ is the matrix extracting patch $\mathbf{y}_i$ from $\mathbf{I}$ at location i, $\boldsymbol{\Psi}_i$ is the corresponding dictionary in pixel domain of $\mathbf{y}_i$.

4. Experimental Results

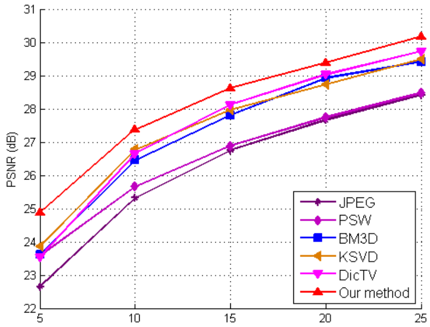
In this section, experimental results are presented to demonstrate the superior performance of the proposed dual-domain joint estimation approach for restoring JPEG-compressed images.

The new approach is compared with: 1) the PSW algorithm [32], which is a state-of-the-art soft decoding method for JPEG-compressed images; 2) the well-known denoising algorithm BM3D [9], because the restoration of compressed images can be viewed as a denoising problem, in which the noises are quantization errors; 3) two sparsity-based restoration methods: KSVD [3] and DicTV [5]. KSVD is a well-known sparse coding framework. Most existing sparsity-based compressed image restoration algorithms, such as [13, 15], are based on the general framework of KSVD. DicTV is a very recent sparsity-based compressed image restoration algorithm. The reported comparison group includes six widely used test images in the literature of image compression, which are presented in Fig. 2. For the uncompressed training set used to get the pixel-domain dictionary, we randomly select five images from the Kodak Lossless True Color Image Suite[1]. Certainly, the training set does not have any overlap with the test set.

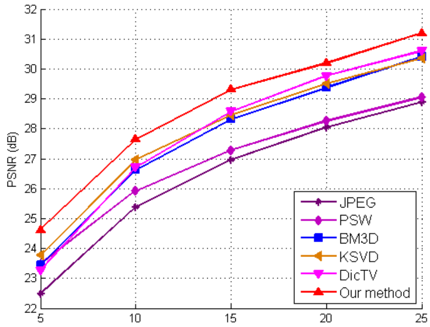
Fig. 3 plots the PSNR curves of the compared algorithms on the six test images, which are coded by JPEG compression standard with five quality factors (QF): 5, 10, 15, 20 and 25, respectively. Quality factors, which range from 1 to 100, are indexes of a set of quantization matrixes. The large QF values, the less quantization noises. The PSNR curves clearly show that the proposed technique achieves the best restoration performance for all test images on all quality factors. Compared with the PSW algorithm, the new technique enjoys a PSNR gain up to 2.18dB. Note BM3D needs the knowledge of the variance of noises, and in experiments, we feed BM3D the true values of quantization error variances (which are trained using offline samples), although in practice this may not always be possible. In this regard, the results of BM3D shown in Fig. 3 should only be treated as a performance upper bound. Even so, the new technique method outperforms BM3D and achieves PSNR gains up to 1.32dB. The new technique also makes similar performance gains over other sparse coding based methods.

In addition to its superior performance in objective fidelity metric, the new JPEG restoration technique also appears to obtain better perceptual quality of the restored images. The reader is invited to examine and compare the restored JPEG images by different methods in Fig. 4, Fig. 5, Fig. 6

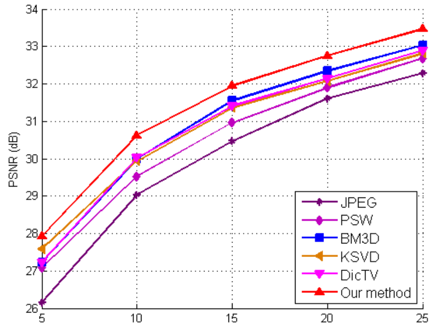
[1] http://r0k.us/graphics/kodak/



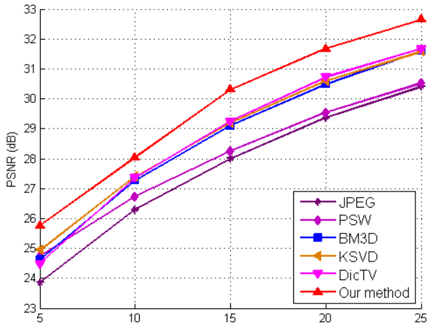
(a) Butterfly



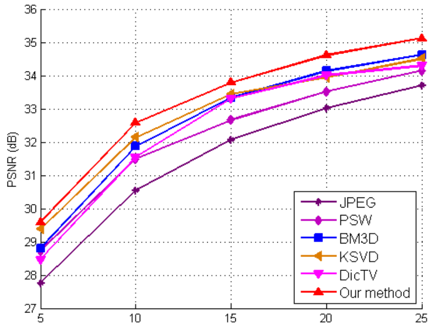
(b) Leaves



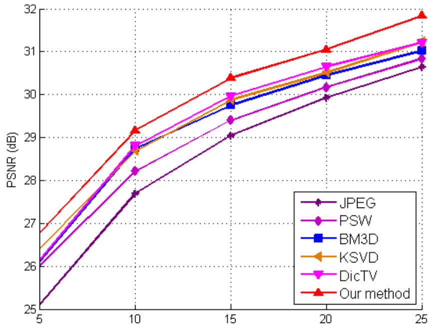
(c) Parrot



(d) Barbara



(e) House



(f) Lena

Figure 3. PSNR vs JPEG QF of different restoration methods.


JPEG (22.65)


PSW (23.58)


BM3D (23.61)


KSVD (23.86)


DicTV (23.54)


Proposed (24.87)

Figure 4. Comparison of tested methods in visual quality on *Butterfly* at QF=5. The corresponding PSNR values (in dB) are also shown.

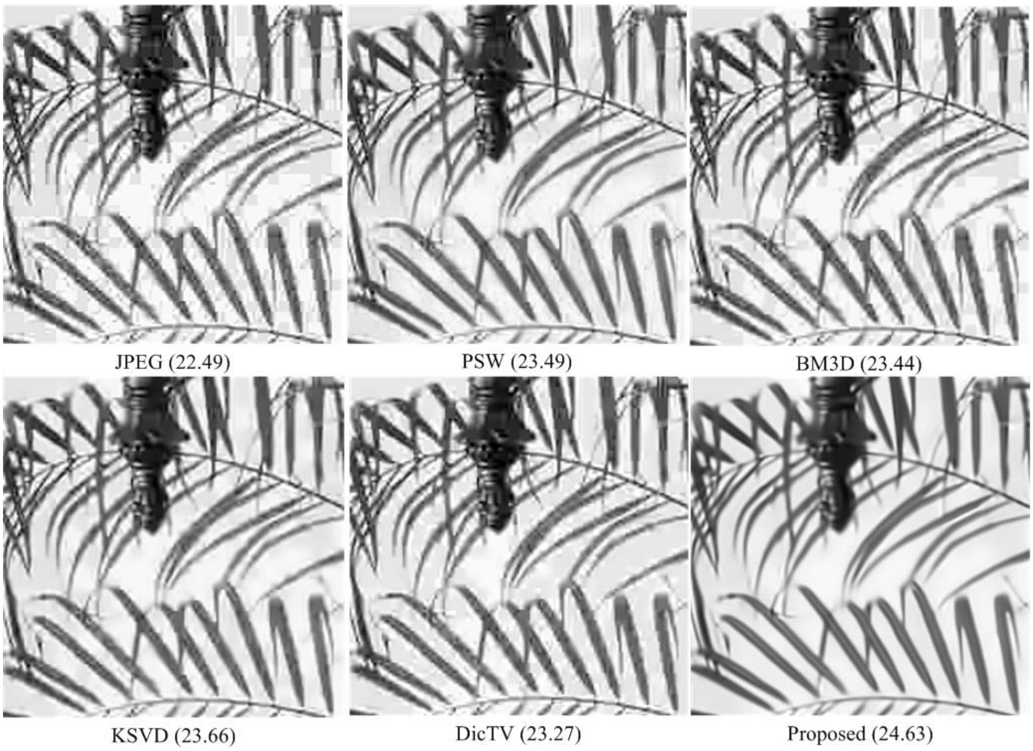


Figure 5. Comparison of tested methods in visual quality on *Leaves* at QF=5. The corresponding PSNR values (in dB) are also shown.

and Fig. 7. When QF is 5, the quantization noise is severe, the JPEG-compressed images have very poor subjective quality. The images reproduced by PSW and BM3D suffer from highly visible noises that accompany edges and textures. KSVD and DicTV can suppress most of blocking artifacts, but there are still noticeable artifacts along edges. This is because, in KSVD and DicTV, patches are encoded independently. Therefore, similar patches sometimes admit very different estimates due to the potential instability of sparse decompositions, which can result in noticeable reconstruction artifacts. The proposed dual domain restoration approach can effectively mitigate this problem. The images restored by our method are much cleaner, in which the structures and sharpness of edges and textures are well preserved. The proposed method can also remove DCT blocking artifacts in smooth areas completely, and is largely free of the staircase and ringing artifacts along edges.

5. Conclusion

A novel data-driven sparsity-based approach is proposed for the restoration of JPEG-compressed images in the dual DCT-pixel domain. The main technical contribution of this work is the combined use of dual dictionaries learnt respectively using samples drawn from the hard-decoded JPEG input image and samples drawn from uncompressed training images; both dictionaries adapt to the pixel patch being restored. Experimental results demonstrate the efficacy of the proposed JPEG restoration approach. The reported research findings reveal so-far under-utilized potential of improving DCT-compressed images and videos via sophisticated post-processing after decompression.

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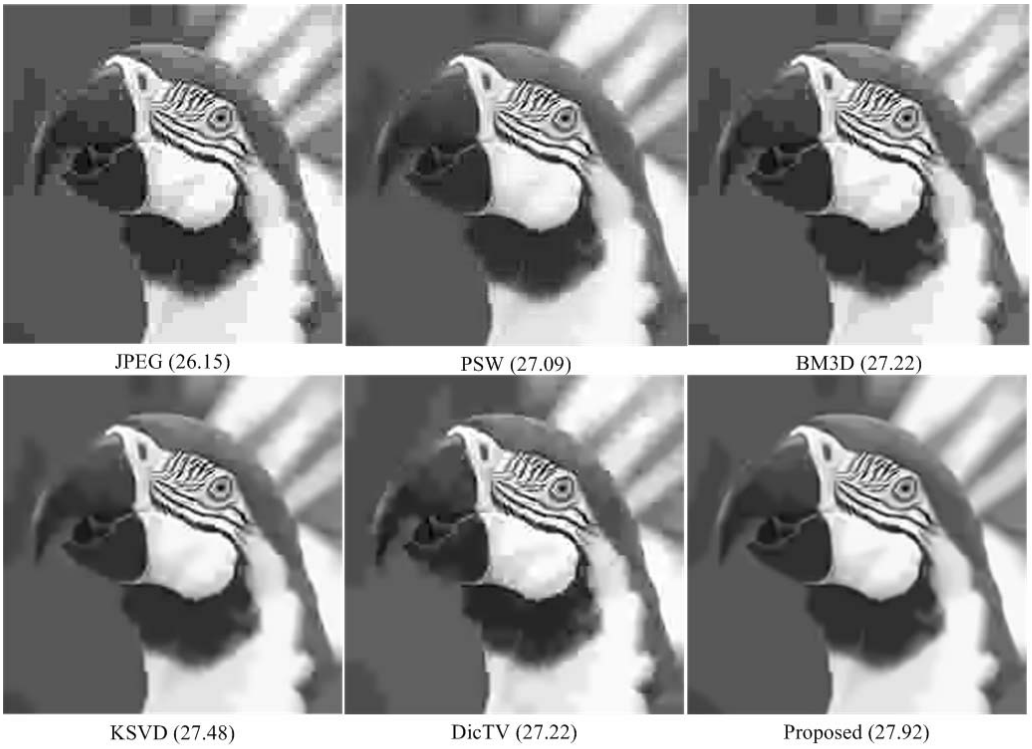

Figure 6. Comparison of tested methods in visual quality on *Parrot* at QF=5. The corresponding PSNR values (in dB) are also shown.

Figure 7. Comparison of tested methods in visual quality on *Barbara* at QF=5. The corresponding PSNR values (in dB) are also shown.

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