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

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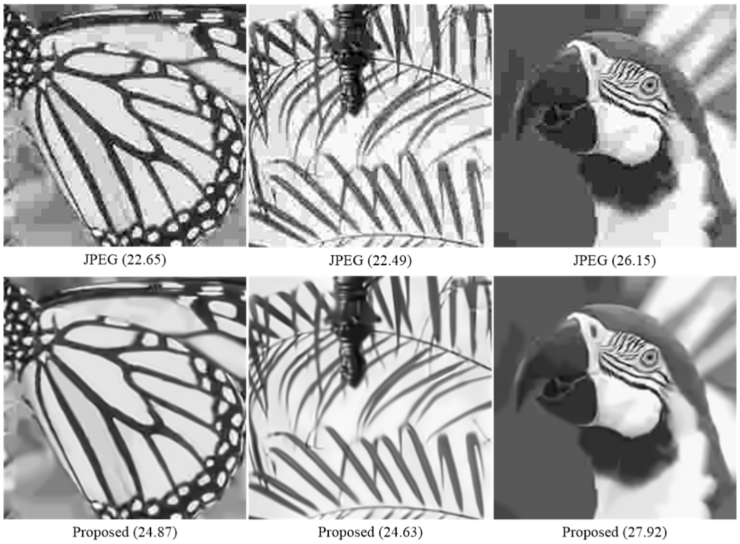

Figure 1: Comparison of JPEG-compressed images and the restored images by the proposed method in visual quality. PSNR values (in dB) are also given.

Arguably the most common cause of image degradation is compression. Sensor noises and low spatial resolution are much lesser problems nowadays because modern digital cameras, even mass-marketed ones, offer sufficiently high spatial/spectral resolutions and high signal-to-noise ratio (SNR) to meet the image quality requirements of most users. But compression is and will continue to be indispensable in almost all visual communication and computing systems, as the the sheer volume of image data can easily overwhelm the communication bandwidth and in-device storage. However, so far the sparsity-based image restoration approaches are seemingly not as effective on combating compression artifacts as on other types of degradations. Relatively few papers were devoted to sparsity-based restoration of compressed images.

The relative lack of success in sparsity-based restoration of compressed images is largely due to the fact that the compression noises are much more difficult to model than other degradation sources, e.g., motion blur and sensor noises. The non-linearity of quantization operations in image compression systems makes quantization noises *signal dependent*, far from being white and independent, as commonly assumed by works on other image restoration problems [1]. Following the tradition of assuming degradations to be signal independent, most existing works on restoration of compressed images modeled quantization noises as signal independent ones, e.g., uniform noises in DCT domain, white Gaussian noises (WGN) in spatial domain, or generalized Gaussian noises. 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.

Up to now all existing techniques for restoring compressed image work either in the pixel domain [2] or in the DCT domain [3]. But the restoration in either domain has its own drawbacks. As the pixel domain restoration works with JPEG-compressed 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 approach, 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 compressed image restoration is in its feature selection: the quantized DCT code block rather than the (or some attributes of) corresponding JPEG-compressed 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 restoration 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.

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 $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ 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. Finally, given the two online learnt dictionaries $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ in transform and pixel domain, we jointly search for two sparse code vectors $\boldsymbol{\alpha}$ and β in the dual domain that best explain the observed DCT patch $\mathbf{y}_0$:

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

where $\mathbf{T}^{-1}$ is the inverse discrete cosine transform; $\preceq$ denotes the operation of element-wise comparison; $\mathbf{q}^L$ and $\mathbf{q}^U$ are vectors containing bound values of the quantization interval. Joint restoration in the DCT and pixel domain allows the two sparse representations $\boldsymbol{\alpha}$ in dictionary $\boldsymbol{\Phi}$ and β in dictionary $\boldsymbol{\Psi}$ to cross validate each other, enhancing the quality of soft decoded image patches.

Experimental results are encouraging and show the promise of the new approach in significantly improving the quality of DCT-coded images. Please refer to Fig. 1 for the subjective comparison of JPEG-compressed images and the restored images by the proposed method.

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This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.