Learning-Based Image Restoration for Compressed Image through Neighboring Embedding

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Abstract. In this paper, we propose a novel learning-based image restoration scheme for compressed images by suppressing compression artifacts and recovering high frequency components with the priors learned from a training set of natural images. Specifically, Deblocking is performed to alleviate the blocking artifacts. Moreover, consistency of the primitives is enhanced by estimating the high frequency components, which are simply truncated during quantization. Furthermore, with the assumption that small image patches in the enhanced and real high frequency images form manifolds with similar local geometry in the corresponding image feature spaces, a neighboring embedding-based mapping strategy is utilized to reconstruct the target high frequency components. And experimental results have demonstrated that the proposed scheme can reproduce higher-quality images in terms of visual quality and PSNR, especially the regions relating to the contours.

Keywords: Image restoration, Compression artifacts, Primitive, Neighboring Embedding.

1 Introduction

Block-based discrete cosine transform (BDCT) coding has prevailed in the mainstream image and video compression standards, which aims at reducing the inter-pixel statistical redundancy. However, for sake of achieving higher compression ratio, BDCT together with the coarse quantization gives rise to the discontinuity of intensities between adjacent blocks which is named as blocking artifacts, and truncates the high frequency (HF) DCT coefficients, which results in ringing artifacts around the contours. Therefore, the visual quality is unsatisfactory and image restoration for compression artifacts reduction is demanded.

In order to alleviate the blocking artifacts, many postprocessing schemes have been proposed. In [1], a filter is applied along the block boundaries for processing pixel-by-pixel to reduce the blocking artifacts. However, it always leads to overblurring. Also,

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Wang et al. proposed a fast edge-preserved postprocessing scheme [2], which decomposed DCT coefficients into low frequency (LF) and HF subband. Blocking artifacts are reduced by smoothing LF components and discarding invalid HF coefficients, while ringing artifacts are suppressed by simple bilateral filtering. However, the traditional postprocessing techniques could not recover the HF components, which have been discarded during the quantization step of compression.

Recently, learning-based image restoration schemes have been brought forward to reconstruct a high-quality image by introducing the learned HF information from pre-designed codebooks into the degraded low-quality image. In [3], Sheppard et al. introduced nonlinear interpolative vector quantization (NLIVQ) into image restoration. Based on NLIVQ, a blind image restoration algorithm [4] is proposed by estimating the HF information of a given blurred image from its LF information based on the designed multiple codebooks. Also, Liaw et al. proposed restoring the images based on classified vector quantization (CVQ) [5], which employs a codebook to transform the compressed image into a set of indices, and decodes the indices to restore the image based upon a corresponding different codebook. Actually, all of these existed learning-based restoration schemes share the same assumption as image super-resolution [6], which is that the degraded LF image patch can be employed as the index to find the proper HF image patch in the learnt codebooks. However, it is an ill-posed problem. Since the degraded image patch is of low-dimension, whereas HF image patch is of high-dimension, one degraded LF patch can be mapped to more than one HF patches.

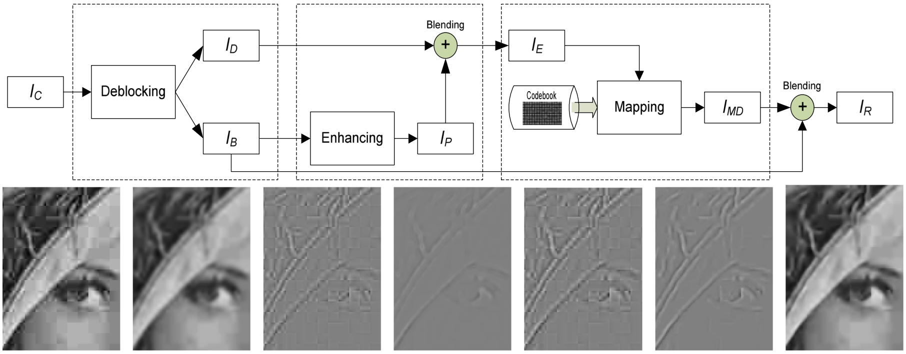
In this paper, inspired by recent progresses on image hallucination [7] [8], a novel learning-based image restoration scheme is proposed. Firstly, blocking artifacts are alleviated with a simple filtering. Differential image is obtained by subtracting the deblocked image from the input one. Secondly, the differential image is enhanced to preserve its local consistency along the contours. Thirdly, the manifold learning method called locally linear embedding (LLE) [9] is utilized to model the relationship between the existent HF patches in the learnt codebook and the enhanced ones. Finally, the resulting restored image is obtained by blending the target HF component inferred by LLE into the deblocked image.

The rest of the paper is organized as follows. In Section 2, a brief description of our proposed image restoration scheme is introduced. And some key technologies of the proposed scheme are described in Section 3. The experimental results are demonstrated in Section 4. Finally, Section 5 concludes the paper.

2 The Proposed Image Restoration Scheme

The framework of our proposed image restoration scheme is illustrated in Figure 1, which consists of three steps. The left dash-line box is proposed ***Deblocking*** step; the middle is the proposed ***Enhancing*** step; and the right is the corresponding ***Mapping*** step.

In the ***Deblocking*** step, the deblocked image I_B is obtained by convolving the input compressed image I_C with a pre-designed deblocking filter:



(a) I_C (b) I_B (c) I_D (d) I_P (e) I_E (f) I_{MD} (g) I_R

Fig. 1. The proposed image restoration framework: (a) the input compressed image I_C ; (b) deblocked image I_B ; (c) differential image I_D ; (d) predictive HF image I_P ; (e) enhanced differential image I_E ; (f) mapped HF image I_{MD} by our scheme; (g) resulting restored image I_R

$$I_B = I_C * f \tag{1}$$

where "*" is the convolution operator, and f is the deblocking filter. Subtracting I_B from I_C , differential image I_D is generated. And compared with I_C , blocking artifacts have been alleviated, however little detailed HF information exists in I_B , whereas I_D comprises some detailed HF information as well as the compression artifacts.

In the ***Enhancing*** step, local consistency of enhanced differential image I_E is preserved by blending the predictive HF image I_P into I_D . It can be viewed as an image enhancement process, which can be defined as:

$$\begin{aligned} I_E &= I_D + I_P \\ &= I_D + \lambda \cdot I_O \end{aligned} \tag{2}$$

where λ is a scaling factor, and I_O is the output of a suitable enhancing filter. Since each blended HF image patch in I_E is not as realistic as the one in the learnt codebook, the subjective quality of the image is unsatisfactory when I_E is combined with I_B . Consequently, a mapping strategy is put forward to replace the enhanced HF patch with the existent one in the learnt codebook.

Besides the compression artifacts suppression, the key problem is to reproduce the detailed HF information, which is removed from compression as well as the previous ***Deblocking*** step. Therefore, in the ***Mapping*** step, a neighboring embedding algorithm is employed to model the relationship between the enhanced and existent HF patches as well as the neighboring HF patches. Mapped HF image I_{MD} is obtained by maximizing posterior probability $p(H \mid I_E)$, with $p(H)$ as the learnt priors:

$$\begin{aligned} I_E &= \arg\max\left(p(H \mid I_E)\right) \\ &= \arg\max\left(\prod_i \gamma\left(H^i, I_E^i\right)\prod_{(i,j)}\varphi\left(H^i, H^j\right)\right) \end{aligned} \tag{3}$$

where $\gamma\left(H^i, I_E^i\right)$ indicates the mapping accuracy from the enhanced image patches to the existent ones in the learnt codebook, and $\varphi\left(H^i, H^j\right)$ denotes the compatibility between neighboring patches in the mapped image I_{MD}.

In the end, by blending the mapped HF image I_{MD} into the deblocked image I_B, the resulting restored image I_R is constructed.

3 Key Technologies of Proposed Scheme

3.1 Learnt Primitives

What we learn as the image restoration priors are the image primitives. They are the elements that describe intensity variations in images and their local geometries in Marr's vision [10]. The primitives in the learnt codebook are extracted along the contours. On one hand they not only contain intensity information but also indicate the geometric edge information. On the other hand, high contrast intensity changes of primitive parts in the image are sensitive to humans [10], because strong stimuli are generated in the visual field by the primitives. And the Receiver Operating Characteristics (ROC) curve [7] has demonstrated that primitives are more representative and lower-dimensional than non-primitives, which are more reasonable for further ***Mapping***.

3.2 The Proposed Enhancement

Our proposed enhancement algorithm is inspired by recent progresses in image and resolution enhancement [11] [12]. However, unlike other enhancement schemes, which employ Laplacian image pyramids for enhancing image, the single deblocked image is utilized for predicting the HF component.

Similar to [12], control function [13] is employed to depict local activities of I_B and generate the predicting HF component I_P. Accordingly, Equation (2) can be modified as:

$$I_E = I_D + \lambda \cdot C \cdot I_{HB} \tag{4}$$

where C is the control function which is calculated from I_B, and I_{HB} is the HF component of I_B as output of the enhancing filter. Therefore, selected detailed information which relates to the contour regions is enhanced, whereas other regions remain unaffected, which can be observed in Figure 1 (d). By combining I_P together with I_D, enhanced HF image I_E is constructed with local compatibilities between primitives preserved, which greatly resembles the HF information of the original image.

3.3 Neighboring Embedding-Based Mapping

In the ***Mapping*** step, the replacement of enhanced HF primitive should take both the mapping accuracy and compatibility of neighboring patches into consideration. In our proposed restoration scheme, due to the assumption that manifolds of small image primitives in the enhanced and real HF images both bear similar local geometry in the two image feature space, local linear embedding (LLE) [9] algorithm is utilized to denote the mapping accuracy γ from the existent primitive to the enhanced one. Its key idea is that neighboring characteristics of each data point could be depicted by linear parameters which could be utilized to reconstruct the data point from its neighbors. Detailed algorithm of LLE is described in Figure 2. As to the compatibility function φ, some techniques are utilized to evaluate the compatibility, such as Sum Squared Difference (SSD) of overlapped region between adjacent HF primitives. However, in our scheme a simple method is employed to enforce local compatibility and smoothness constraints between adjacent primitives by averaging the pixel values in overlapped regions.

1. To each primitive P_E in Enhanced HF image I_E:
   (a) Find the set S_t of K nearest neighbors lying in the manifold of learnt primitives.
   (b) Calculate the weights of the K neighbors to minimize the reconstruction error.
   (c) Replace P_E with the reconstructed primitive.
2. Construct the resulting HF image by enforcing relationship and smooth constraints between adjacent reconstructed primitives obtained by *STEP* 1 (c).

Fig. 2. Algorithm of local linear embedding

Euclidean distance is utilized to describe the neighboring characteristics in *STEP* 1 (a). Based on the K nearest neighbors retrieved from the learnt codebook, *STEP* 1 (b) seeks to find the best reconstruction weights for each primitive in S_t, which could be viewed as an optimization problem aiming at minimizing the reconstruction error. And *STEP* 2 attempts to meet smooth constraints and enforce local compatibility between neighboring primitives.

4 Experimental Results

We build the learnt codebook for image restoration by extracting the primitives, which are relating to HF components, from a training set of 24 Kodak images [14]. We present each primitive in the learnt codebook by a 7×7 image patch. Details of image primitive extraction can be referred to [7]. And the total number of extracted primitives in the learnt codebook is about 60,000.

The proposed scheme is tested on various images compressed by JPEG standard [15], with bit rates ranging from 0.1bpp to 0.7bpp. In our scheme, there are three parameters which should be determined. Firstly, the deblocking process adopts Gaussian blurring operator to suppress the blocking artifacts, in which simple 5- or 3- tap Gaussian filter is employed for convolution. Secondly, as control function could perfectly depict the local activities, the scaling factor λ is set as 1 for simplicity. Thirdly during the ***Mapping*** step, since the enhanced primitives greatly resemble the original ones, the size of the nearest neighbor set K is defined as 2 for low computation in our experiments.

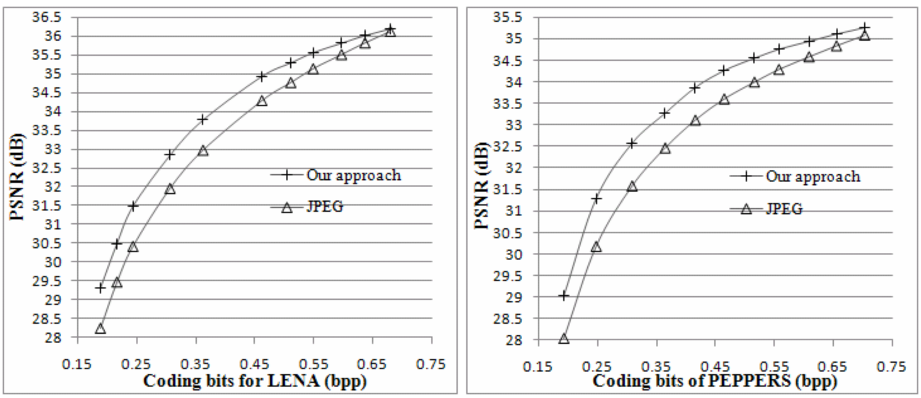


Fig. 3. Objective comparison between our restored and JPEG-coded images

The objective quality of the restored image is evaluated by the peak signal-to-noise ratio (PSNR). The higher the PSNR, the smaller is the difference between the restoration image and the original. Detailed information of PSNR is shown in Figure 3. From the results, we can see that PSNR of the restored images is significantly higher than the JPEG-coded ones. Subjective quality of the restored images is illustrated in Figure 4. Compared with JPEG-coded images, blocking artifacts are alleviated and ringing artifacts are removed with perfect HF components recovered along the contours. However, some blocking artifacts could still be observed, especially the face of LENA and the surface of PEPPERS. That is because a simple Gaussian blurring kernel is adopted to convolve with the compressed images. Recently, many successes, such as [16], have been achieved for deblocking of the compressed image. Applying these techniques, quality of restored image could be further improved.

(a)0.244bpp, PSNR=30.42dB

(b)0.244bpp, PSNR=31.47dB

(a) 0.309bpp, PSNR=31.58dB

(b)0.309bpp, PSNR=32.58dB

(a)0.291bpp, PSNR=28.13dB

(b)0.291bpp, PSNR=28.92dB

Fig. 4. Subjective quality comparison. (a) JPEG-coded image (b) the restored image by our approach.

5 Conclusions

In this paper, a novel learning-based image restoration scheme is proposed for compressed images through local neighboring embedding of learnt primitives manifold. Based on our approach, blocking artifacts are alleviated and ringing artifacts are removed, meanwhile HF components over contour regions are greatly recovered. Experimental results have shown that the restored images outperform JPEG-coded ones in terms of subjective and objection quality.

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