

An amended Joint Super-Resolution and Deblocking for a Compressed Images

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Abstract- Super-resolution imaging (SR) is a class of techniques that improve the resolution of an imaging system. A highly compressed image is typically not only of low resolution, but also undergoes from compression artifacts. In this paper, we suggest a learning-based framework to accomplish joint single-image SR and deblocking for a highly-compressed image. We say that individually performing deblocking and SR (i.e., deblocking followed by SR, or SR followed by deblocking) on a highly compressed image usually cannot achieve a satisfactory visual quality. In our method, we suggest to learn image sparse representations for modeling the relationship between low and high-resolution image patches in terms of the learned dictionaries for image patches with and without blocking artifacts, respectively.

Index Terms- Image super-resolution, sparse representation, dictionary learning, self-learning, image decomposition

I. INTRODUCTION

Super-resolution (SR) techniques estimate a high resolution (HR) image from one or more low resolution (LR) images, and has applications in surveillance, forensics, medical imaging, satellite imaging, and consumer photography. In multimedia systems, for example, transmission bandwidth for videos may be reduced by sending an LR video, if the display equipment can produce a super-resolved HR video. Although SR may not be a replacement for a higher native resolution based on upgraded hardware, it can be a much cheaper alternative for small zoom factors as evident from pervasive availability of “digital zoom” in consumer cameras and software. SR frameworks can also be adapted for other image enhancement tasks such as denoising and deblurring. There has been a great demand for improving the perceptual quality of images in terms of the spatial resolution enhancement of an image, also known as image super-resolution (SR). The goal of image SR is to recover a high-resolution (HR) image from one or multiple low-

resolution (LR) input images, which is essentially an ill-posed inverse problem [2]. There are mainly two categories of approaches for image SR: (i) traditional approaches and (ii) exemplar/learning-based approaches. In the traditional approaches, one sub-category is reconstruction-based schemes, where a set of LR images of the same scene are aligned with sub-pixel accuracy to generate a HR image [3]. Such kind of approaches mainly rely on multi-frame alignment, which is usually time-consuming and inaccurate, and cannot be used for single-image SR since it requires multiple input LR images. The other sub-category is frame interpolation [4], which has been shown to generate overly smooth images with ringing and jaggy artifacts. The exemplar/learning-based methods [5]–[14] hallucinate the high frequency details of a LR image based on the co-occurrence prior between LR and HR image patches in a training set, which has proven to provide much finer details compared to the traditional approaches. More specifically, for a LR input, exemplar-based methods [5]–[8] search for similar image patches from a pre-collected training LR image dataset or the same image itself based on self-examples, and use their corresponding HR versions to produce the final SR output. Nevertheless, the fine details reconstructed by such exemplar-based methods, though looking visually similar, cannot be guaranteed to provide the true missing HR details. Hence, the performance of this approach highly relies on the similarity between the training set and test set or the self-similarity in the image itself.

It should be noted that most research works on pure SR usually simulate the production of an input LR image as two degradation steps. For example, in [9], [10], it is assumed that an observed LR image is a blurred and down-sampled version of its HR version. In addition, the work proposed in [11] considers a more general image restoration problem, where an observed LR image is a blurred and down-sampled

version of its HR version with additional additive noise. Moreover, the context-aware approach in [12] was proposed for LR images with Gaussian noise of known standard deviation. However, the image artifacts (e.g., additive Gaussian noise or blurring effect) considered in these works are significantly different from blocking artifact considered in this paper.

II. RELATED WORKS

Works related to JPEG compression, photo matting, and image super-resolution are discussed. Since every of those represent well-studied regions on their very own, best relevant and representative works are mentioned. JPEG compression The Joint Photographic Experts Group (JPEG) compression general evolved over many years ago is the most extensively followed image compression technique to date. Because JPEG is lossy, the uncompressed image includes mistakes that are inside the form of frequency domain ringing and blocking artifacts which can be together referred to as compression artifacts. For natural images it's far often difficult to perceptually see these mistakes even for images with medium compression features around 57. While the compressed image can be perceptually acceptable, the resulting compression artifacts are widely known to adversely have an effect on low-degree image processing exercises.

There are several put up-processing strategies (e.g. [1, 2, 6]) aimed at lowering JPEG artifacts. These procedures target low-first-class compressed images and perform numerous styles of filtering to lessen blocking off and ringing artifacts. While such strategies can enhance the visual excellent of the input image, they have a tendency to easy out high frequency info. As proven in our effects, we achieve better outcomes than deblocking carried out either as pre-processing to the input image or as put up-processing to the alpha matte. Image matting Image matting approaches (for a quality level see) can be kind of classified into two categories: affinity-primarily based techniques and sampling-primarily based methods. Affinity-based totally techniques (e.g. [12, 11, 3]) predicted alpha values for the unknown area by way of propagating the recognised alpha values in accordance with the pixel affinities. Affinity-based techniques propagate alpha values nicely in uncompressed and maximum-exceptional JPEG images (e.g. quality level 12).

However, these strategies fail to effectively propagate the alpha values throughout block artifacts whilst an image is compressed. Sampling-primarily based techniques (e.g. [4, 7, 8]) estimate alpha mattes by means of sampling the foreground and historical past coloration. For each image with an unassigned alpha value, these procedures locate the most possible pair of the foreground and the background pixels around it and clear up the matting compositing equation with the sampled color pairs. As with affinity-based totally strategies, pattern-based techniques are adversely laid low with the ringing artifacts and quantization across extraordinary blocks. For each tactics, obtaining mattes with specified shape is hard due to the blurring impact introduced via the DCT quantization.

Learning-primarily based super-resolution in which the work is closely associated to mastering-based totally image super-resolution (SR) strategies (for a quality level). These processes use a schooling-set to analyze the relationship among high resolution image patches and their corresponding downsampled (i.e. Low-resolution) image patches [9]. These learning-based tremendous decision strategies may be carried out to first to decorate a JPEG image. However, we observed that those have a tendency to provide smoothed outcomes. This is often due to the fact those strategies first follow a smoothing to the input image to reduce ringing and blocking artifacts (e.g. As finished in Kwon et al. [9]) which could eliminate excessive-frequency statistics earlier than the matting is carried out. Moreover, these procedures target natural images. Our work, however, directly operates on alpha mattes instead of pixel intensity. Since matte boundaries are more complicated than natural image obstacles (e.g. Basically sharp limitations), we find it important to learn special dictionary for unique boundary systems. As a end result, our methods requires an extra step to select the best dictionary to apply in a local way.

To achieve joint SR and deblocking, we proposed in the preliminary conference version [13] of this paper a self-learning-based SR framework to achieve joint SR and blocking artifact removal for a single LR image. The proposed method self-learns from the input image itself the sparse representations for modeling the relationship between LR and HR image patches based on the dictionaries learned from image

patches with and without blocking artifacts, respectively.

III. PROPOSED WORK

In this section, we first explain the proposed framework for self-learning-based SR. Fig. 1 depicts the proposed framework for self-learning-based joint SR and deblocking for enhancing a downsampled and highly compressed image. Our method is to formulate the image enhancement problem as an MCA-based image decomposition problem via sparse representation. As illustrated in Fig. 1, an input LR image I with blocking artifacts [Fig. 1(a)] and its downsampled version I^d [Fig. 1(b)] are first roughly decomposed into their corresponding low-frequency (LF) parts, I_{LF} and I_{LF}^d , and high-frequency (HF) parts, I_{HF} and I_{HF}^d , respectively, via a filter.

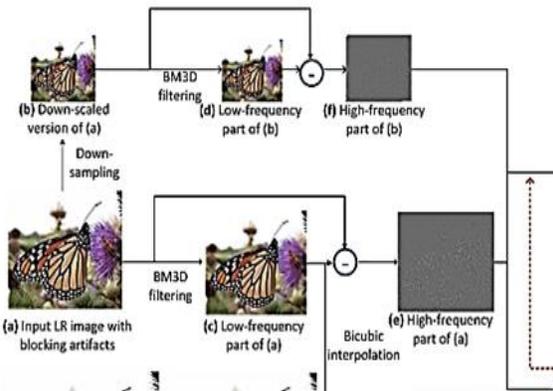


Fig. 1. Flowchart of the proposed self-learning-based super-resolution framework for a highly compressed image.

A. Preprocessing and Problem Formulation:

Without the need of pre-collecting enormous additional training patches for SR (e.g., in [9], [10], collection of additional training patches is required), the proposed method intends to extract training patches from an input LR image itself. Moreover, to achieve joint SR and deblocking, we convert the problem into the high-frequency domain of the input image and conduct the following preprocessing tasks.

Based on the two sets of training samples, we propose to learn two sets of dictionaries, respectively, for SR of non-blocking patches and joint SR and deblocking of blocking patches

B. Dictionary Learning for Single Image SR:

Based on the extracted HR/LR training patch pairs without blocking artifacts ($\{x^N, y^N\}$) from I_{HF}

itself, we intend to learn a couple of dictionaries (D^{HR}_N and D^{LR}_N) to model the relationships between HR and LR image patches.

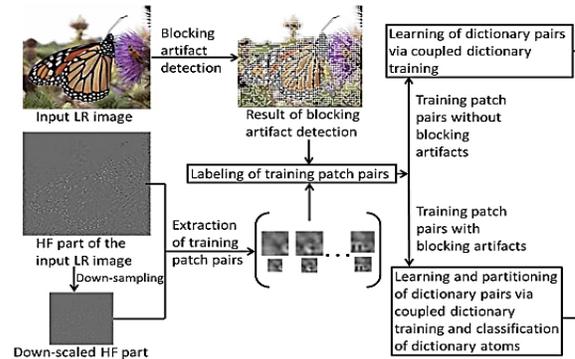


Fig. 2. Illustration of the proposed training patch extraction and dictionary learning processes in the proposed framework

C. Dictionary Learning for Image Decomposition

For the extracted HR/LR training patch pairs with blocking artifacts, we need to not only learn a coupled dictionary pair D^{HR}_B and D^{LR}_B for SR purpose, but also identify the “blocking/non-blocking atoms” in the two dictionaries for achieving MCA-based deblocking.

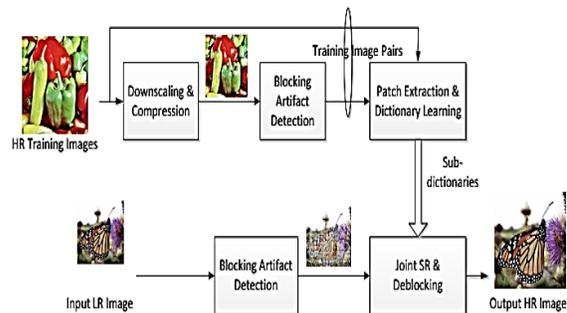


Fig. 3. Extension of the proposed framework to non-self-learning-based SR methods

D. Joint SR and Deblocking via Sparse Reconstruction:

After learning the six dictionaries based on the training patches extracted from I_{HF} , joint SR and deblocking of I_{HF} can be efficiently achieved via patch-wise sparse recovery.

E. Extension to Non-Self-Learning-Based SR

Besides the self-learning-based scheme mentioned above, the proposed framework can also be easily integrated into other non-self-learning SR methods as illustrated in Fig. 3. Note that the main difference is that the dictionary used in self-learning SR is learned from the input LR image itself, whereas the non-self-learning SR algorithms (e.g., the sparse-coding SR

in[9]) needs to learn a dictionary from a pre-collected training image set. In the extension shown in Fig. 3, each HR image in the training set is first downsampled and compressed to obtain its LR version with blocking artifacts, which are then localized by the following blocking artifact detection, so as to form a HR/LR training pair. Subsequently, the training patch extraction and dictionary learning processes described in Fig. 2.

IV. CONCLUSION

In this paper, we suggested a learning-based SR framework to attain joint single-image SR and deblocking for image sparse representation for modeling the association between LR and HR image patches in terms of the learned dictionaries, respectively, for image patches with and without blocking artifacts. Accordingly, image SR and deblocking can be concurrently achieved via sparse representation and MCA-based image decomposition.

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