Neurocomputing 285 (2018) 204–219

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

CISRDCNN: Super-resolution of compressed images using deep convolutional neural networks

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ARTICLE INFO

Article history:
Received 12 September 2017
Revised 29 December 2017
Accepted 17 January 2018
Available online 31 January 2018

Communicated by Jun Yu

Keywords:
Super-resolution
Compressed images
Deep convolutional neural networks
Low bit-rate coding
JPEG

ABSTRACT

In recent years, many studies have been conducted on image super-resolution (SR). However, to the best of our knowledge, few SR methods are concerned with compressed images. The SR of compressed images is a challenging task due to the complicated compression artifacts that many images suffer from in practice. The intuitive solution for this difficult task is to decouple it into two sequential but independent subproblems, the compression artifacts reduction (CAR) and the SR. Nevertheless, some useful details may be removed in the CAR stage, which is contrary to the goal of SR and makes the SR stage more challenging. In this paper, an end-to-end trainable deep convolutional neural network is designed to perform SR on compressed images, which jointly reduces compression artifacts and improves image resolution. The designed network is named CISRDCNN. Experiments on JPEG images (we take the JPEG as an example in this paper) demonstrate that the proposed CISRDCNN yields state-of-the-art SR performance on commonly used test images and imagesets. The results of CISRDCNN on real low-quality web images are also very impressive with obvious quality improvements. Further, we explore the application of the proposed SR method in low bit-rate image coding, leading to better rate-distortion performance than JPEG.

1. Introduction

Single image super-resolution (SISR) refers to the estimation of a high-resolution (HR) image from a single low-resolution (LR) observation. It is of great significance to many image processing and analysis systems. However, the SISR problem is very challenging due to the ill-posed condition. In other words, an LR image corresponds to a set of HR images, while most of them are not expected. In general, the reconstructed HR image should be visually pleasant and close to the real one as much as possible.

The SISR problem has been widely researched over the past 20 years and plenty of algorithms have been proposed. Roughly speaking, interpolation-based [1–9], reconstruction-based [10–20], and learning-based [21–44] algorithms are the three main classes of SISR methods. Meanwhile, some researchers attempted to combine different kinds of SR methods and integrate their respective merits [45,46]. Generally, the interpolation-based super-resolution (SR) approaches estimate unknown HR pixels using their neighborhoods (the known LR pixels) according to local structural properties. For the reconstruction-based methods, the observation model of the given LR image and the prior knowledge of the HR image are integrated to formulate an energy function. Thus, the SR task can be converted to an optimization problem. The prior knowledge that greatly affects SR performance is the research focus for this kind of method. The commonly used priors include gradient [10–12], sparsity [13–15], nonlocal self-similarity [14–20], and others. Many reconstruction-based SR methods use two or more priors to combine their complementary properties. The pre-trained mapping between LR images and HR images is usually adopted to guide the SR process in learning-based methods. According to the core of learning-based methods, it can be further divided into the five subclasses of neighbor embedding-based [21–23], example-based [24–27], sparse coding-based [28–32], regression-based [33–36], and deep learning-based [37–44]. With fast execution speed and outstanding restoration quality, deep learning-based methods show great potential for solving SR problems.

In some practical applications limited by storage capacity and transmission bandwidth, such as mobile communication and the internet, images and videos are generally downsampled and compressed to reduce data volume. In these cases, the observations usually suffer from both the downsampling and the compression degradations, which make the SR problem more difficult. Although

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https://doi.org/10.1016/j.neucom.2018.01.043
0925-2312/

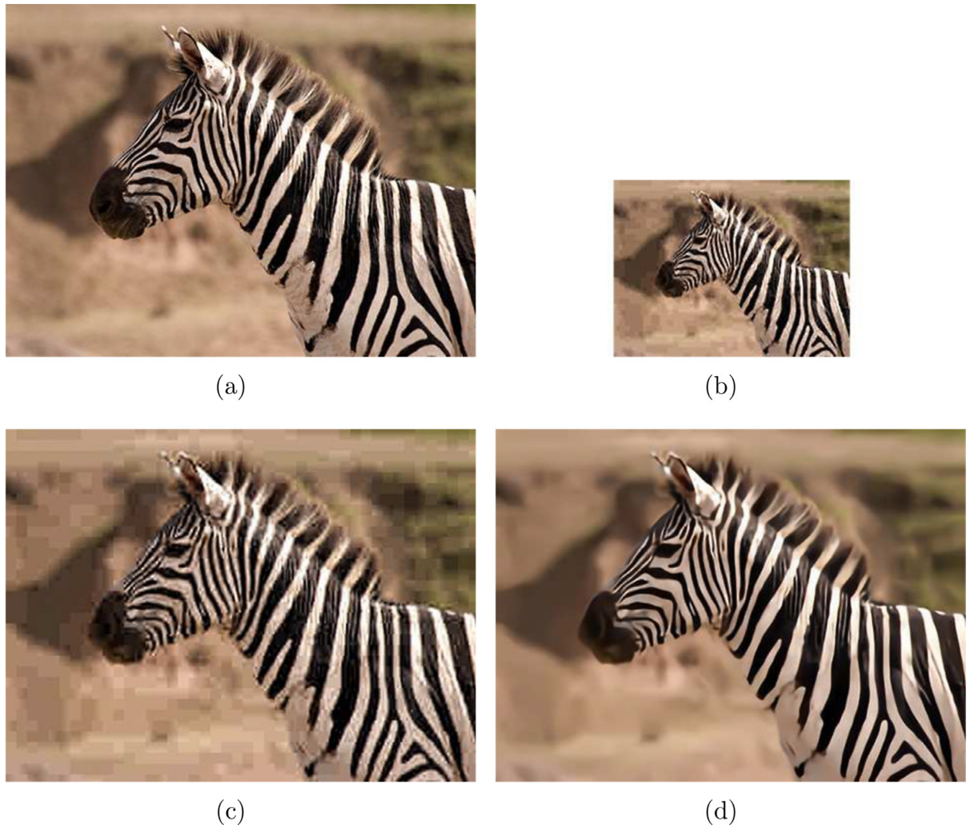

Fig. 1. Illustration for JPEG compressed image SR on test image *Zebra* (SR factor: 2, Quality factor (QF): 10). (a) Original image. (b) JPEG compressed LR image. (c) Result of the Bicubic on (b). (d) Result of the CISRDCNN on (b). Obviously, our result (d) is more visually pleasant than (b) and (c). Please zoom in to view details and make comparisons.

a lot of research has been done on the SISR problem and plenty of effective SISR methods have been proposed over the past few decades, very few methods were concerned with compressed images [47–52]. Roughly, there are two frameworks for compressed images SR. Some researchers converted this task to an optimization problem via compression process modeling and prior knowledge regularization. In SRCDFOE [47], the compression distortion is seen as the spatially correlated Gaussian noise, and the Markov random field and total variation are used to regularize the estimated HR images. To simultaneously realize decompression and SR, the DCSRMOTV [48] incorporates the multi-order total variation model into the JPEG image acquisition model. For this type of method, the main difficult is how to realize the accurate modeling of the compression process. In addition, it is difficult to balance compression artifacts reduction (CAR) and details preservation. Another commonly used strategy is to decompose this task into two subproblems (i.e., CAR and SR) and use a cascading framework to address them. For example, Xiong et al. [49] combined the adaptive regularization and the learning-based SR to reduce compression noise and compensate for details, respectively. Kang et al. [50] proposed a sparse coding-based SR method for compressed images, in which the patches with/without compression artifacts are processed differently. Using a denoised training dataset, Lee et al. [51] presented a dual-learning-based algorithm for compression noise reduction and SR. More recently, Zhao et al. [52] constructed a three-steps-process framework for compressed images SR, which is composed of BM3D filtering-based compression noise reduction, local encoding-based patch classification, and mapping-based reconstruction. However, for most of this kind of algorithm, the compression noise reduction and upsampling are treated as two independent stages. Consequently, the resultant images using existing methods are likely to still contain compression noise or be over-smoothed. On the whole, the research on compressed images SR is lacking and there is still much room for performance improvement.

The core issue of compressed images SR is how to reduce compression noise and preserve details as much as possible when enhancing image resolution. On the one hand, it is hard to remove compression artifacts in super-resolved images without a CAR or denoising stage. Moreover, the compression noise in the LR input may be significantly amplified in the upsampling process. However, the CAR and SR operations should not be separated since some of the details removed in the CAR stage are useful for the SR. On the basis of the above insights, an end-to-end trainable *D*eep *C*onvolutional *N*eural *N*etwork is designed to perform *SR* on *C*ompressed *I*mages in this paper, and we term our network CISRDCNN. The CISRDCNN takes a compressed LR image as input and directly outputs the resultant HR image without any preprocessing or postprocessing. Fig. 1 illustrates an example of the result of the CISRDCNN, in which we can see that our result is much more visually pleasant than the LR input and the resultant image of Bicubic interpolation. The framework of the proposed CISRDCNN is illustrated in Fig. 2. Our contributions in this work are mainly in the following aspects:

- We propose a deep convolutional neural network-based SR framework for compressed images, namely CISRDCNN, which simultaneously reduces compression artifacts and enhances image resolution.
- To preserve the functions of different modules in CISRDCNN and achieve joint optimization of the CAR and SR, a special strategy is used to train the proposed network, i.e., individual training and joint optimization.