Image Super-Resolution via Online Convolutional Sparse Coding with Perceptual Loss

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Abstract—Image super-resolution (SR) aims to reconstruct a high-resolution (HR) image from a low resolution (LR) image. Recently, sparse coding has become an increasingly popular method for SR. Despite its popularity, sparse coding can not capture shifted local patterns in images. Convolutional Sparse coding (CSC) addresses this problem by learning a shift-invariant dictionary composed of many filters. However, CSC oparates in the batch mode which needs large space and is computationally expensive. In this paper, we propose an online convolutional sparse coding based SR (OCSC-SR) to alleviate the above problems. Our proposed scheme consists of three components: a set of scalable LR filters, a set of scalable HR filters and a mapping function from LR feature maps to HR ones. In addition, we propose a novel perceptual loss function to achieve higher perceptual quality. Experiments demonstrate our OCSC-SR method outperforms state-of-the-art methods in terms of both peak signal-to-noise ratio (PSNR), visual perception and space complexity.

Index Terms—image super-resolution, convolutional sparse coding, online learning, perceptual loss

I. Introduction

Single image super-resolution (SISR) plays an important role in various computer vision tasks, such as surveillance imaging [1], medical imaging, [2] hyperspectral imaging [3], and natural image generation [4]. SISR is an inherently ill-posed inverse problem which aims to recover a high-resolution image from a low resolution input. In order to resolve this inverse problem, numerous SISR algorithms have been proposed, including interpolation-based methods [5], reconstruction-based methods [6], and learning-based methods [7]. Since interpolation-based methods attempted to estimate the missing pixels in HR images with simple smooth assumptions, it could not restore complex structures in natural images. Due to the complexity and diversity of natural scene images, reconstruction-based methods, which utilized the regular constraints with priori information to implement SR, could not meet the requirements of SISR with large upscaling factors. In contrast to the former two kinds of methods, the learning-based methods, such as markov random field (MRF) [8], neighbor embedding [9], sparse coding [10] and deep neural networks [11], adaptively learned mapping between LR and HR pairs to recover missing edge and texture details in LR images.

Recently, sparse coding has become an increasingly popular method for SISR. Yang et al. [10] firstly provided a sparse coding based super-resolution method (SC-SR) which jointly trained two dictionaries for the LR and HR image patches. In SC-SR, overlapping patches cropped from the input image are encoded by a LR dictionary. Then, the sparse coefficients are passed into a HR dictionary to reconstruct HR patches. Several approaches have been suggested to learn and optimize the dictionaries [12], [13], [14] or build efficient mapping functions [15]. However, conventional sparse coding can not capture local interactions as it assumes the patches of an image are independent of one another. Gu et al. [16] proposed a CSC based SR method to demonstrate the effectiveness of consistency constraint and the advantage of global image based CSC over conventional patch based sparse coding. CSC explicitly models local interactions through the convolution operator, however the resulting optimization problem is considerably more complex than traditional sparse coding. Bristow et al. [17] produced a fast convolutional sparse coding (FCSC) to address this problem. [18], [19] also considered extending online learning to CSC.

In this paper, we present a OCSC-SR method to address the aforementioned issues. The main contributions of our work include:

- We propose a scalable online convolutional sparse coding method for image SR. The proposed OCSC-SR method requires much less space space and converges much faster than existing CSC algorithms while

having better reconstruction performance for image SR.
- Our OCSC-SR introduces a novel perceptual loss function utilizing the image features generated by the convolutional sparse representation, which are more robust to changes in pixel space.
- We evaluate OCSC-SR on three public benchmark datasets. The results show our model outperforms the state of the arts for SISR with high upscaling factors(4×).

II. Related Works

A. Convolutional Sparse Coding for Super-Resolution

The IEEEtran class file is used to format your paper and style the text.

B. Online Convolutional Sparse Coding

C. Perceptual Loss Function

III. Online Convolutional Sparse Coding based Super-Resolution

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A. Scable LR Filter Learning

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, ac, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

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- Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as "3.5-inch disk drive".
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C. Maping Function Learning

Number equations consecutively. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$a + b = \gamma \tag{1}$$

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D. Testing

Please use "soft" (e.g., \eqref{Eq}) cross references instead of "hard" references (e.g., (1)). That will make it possible to combine sections, add equations, or change the order of figures or citations without having to go through the file line by line.

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IV. Experiments

A. Figures and Tables

a) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation “Fig. 1”, even at the beginning of a sentence.

TABLE I
Table Type Styles

Table Head	Table Column Head		
	Table column subhead	Subhead	Subhead
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[a]Sample of a Table footnote.

Fig. 1. Example of a figure caption.

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetization, M”, not just “M”. If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

V. Conclusion

Acknowledgment

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks …”. Instead, try “R. B. G. thanks…”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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