Neurocomputing 194 (2016) 340–347

Contents lists available at ScienceDirect

Neurocomputing

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

Incorporating image priors with deep convolutional neural networks for image super-resolution

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ARTICLE INFO

Article history:
Received 29 July 2015
Received in revised form
13 January 2016
Accepted 18 February 2016
Available online 5 March 2016

Keywords:
Super-resolution
Deep convolutional neural network
Image gradient priors
Multi-task learning

ABSTRACT

Deep convolutional neural network has been applied for single image super-resolution problem and demonstrated state-of-the-art quality. This paper presents several prior information that could be utilized during the training process of the deep convolutional neural network. The first type of prior focuses on edges and texture restoration in the output, and the second type of prior utilizes multiple upscaling factors to consider the structure recurrence across different scales. As demonstrated by our experimental results, the proposed framework could significantly accelerate the training speed for more than ten times and at the same time lead to better image quality. The generated super-resolution image achieves visually sharper and more pleasant restoration as well as superior objectively evaluation results compared to state-of-the-art methods.

1. Introduction

Image super-resolution (SR) aims to overcome the resolution limitation of the sensors and restores high resolution (HR) images from low resolution (LR) inputs with information complementing. Image super-resolution is a classic yet an inherently ill-possed problem as different HR images can be degenerated into the same LR image. To handle the under-determined nature of the problem, various prior knowledge have been utilized. For instance, both the interpolation methods [1] and the reconstruction methods [2,3] assume that pixels change only gradually in a local area, such that the former utilizes local smooth functions for interpolation, and the latter uses coherence constraints in the optimization problems for reconstruction.

In another evolving and promising line of methodology, the example based approach [4,5,20], the recurrence priors between LR and HR image examples are modeled by learning a mapping from internal/external examples [4,6] or from combined sources [7]. In the pioneer work by Freeman et al. [4], the co-occurrence prior between LR and HR image patches were integrated into an Markov Random Field model [4] to restore locally coherent HR images. Yang et al. [5,8] proposed to combine the learned dictionary with sparse coding coefficients estimated among signals to restore
HR image patches. Zhang et al. [9] further explored non-local multi-scale similarity to get better results. Some researchers have also attempted analyzing the blurring kernel that causes the degeneration between HR examples and LR examples. For example, Michaeli and Irani [10] estimated the optimal blur kernel by the inherent recurrence property of small image patches. Timofte et al. [11] and Yang and Yang [12] grouped the feature spaces of image patches into numerous subspaces which indirectly distinguished the blur model and got better performance. Yang et al. [13] systematically analyzed the impact of the blur kernel and made a benchmark comparison for several state of the art methods.

In fact, the structure recurrence among examples and the low degree of freedom in local image structures [9] make it possible for a feasible learning of a mapping, such that the problem becomes learning a regression model. The promising performance demonstrated by deep-learning methods in recent years has inspired researchers to attempt deep models for optimal HR restoration. For instance, Dong et al. [14] proposed a deep convolutional neural network for image super-resolution. It directly learned end-to-end mappings from LR to HR images which achieved state-of-the-art restoration quality. However, the parameters in a deep model are usually highly free, and learning the purely end to end mappings would often fall into local minimum, especially when only limited training images are available as that in the SR problem. On the other side, as demonstrated in [14,15], it needs days for training given large amount of training samples. Thus, how to incorporate useful prior to constrain or regulate the learning process of a deep model is a critical issue both for speeding up the training and improving image quality in the SR task. Lee et al. [16] argued that

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http://dx.doi.org/10.1016/j.neucom.2016.02.046
0925-2312/© 2016 Published by Elsevier B.V.

supervised constraints would contribute to learning discriminative features and accelerating the convergence process. Besides, Dong et al. [14,15] emphasized that large sub-image examples were important.

In this paper, we incorporated the image priors such as image gradients into constructing deep convolutional neural network and further extend the deep convolutional network with multi-scale information regulated by multi-task learning. As in Fig. 1, fixed feature extraction layers were concatenated with the SR-Net [14] and feature of image gradients were obtained. Thus, the training process could pay special attention to the image gradients. A loss function was optimized together with mapping from LR to HR sub-images. The consistency of features extracted between reconstructed images and original images was propagated to supervise the training of mapping from LR to HR sub-images. Besides, we naturally extend the framework to support multi-task learning in order to simultaneously train deep convolutional neural network with different magnification factors, as illustrated in Fig. 2. The local structures in natural images usually tend to reoccur across different scales, and therefore the multi-scale information could be shared in all the tasks. With weight sharing, less parameters are needed and better results are achievable. Finally, we combined the two priors to give a superior result with a faster training convergency rate.

The rest of this paper is organized as follows. In Section 2, we describe the proposed framework consisting of a deep convolutional neural network with image gradient priors. We denote the framework as SRCNN-Pr. In Section 3, we present our multi-task learning deep convolutional network which was further combined with image multi-scale magnification priors, denoted as SRCNN-Multitask-

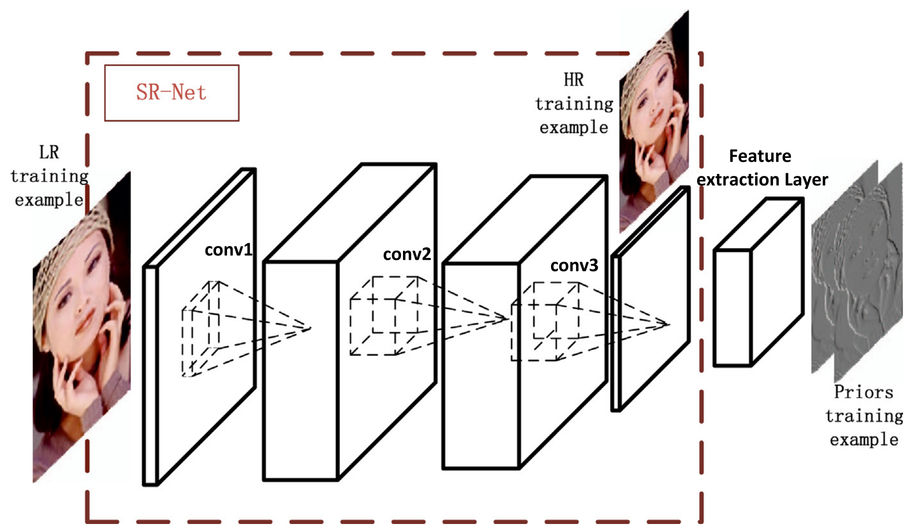

Fig. 1. The proposed Convolutional network framework with gradient and texture priors modeled, denoted as SRCNN-Pr.

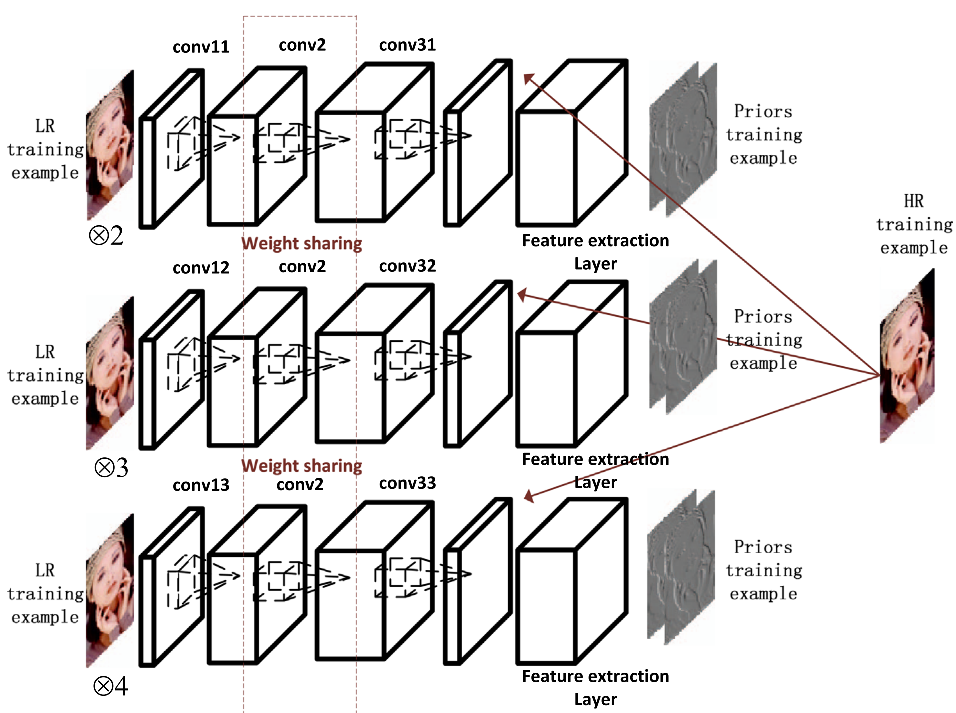

Fig. 2. The proposed Convolutional network framework with gradient priors modeled, denoted as SRCNN-Pr.