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Curvature preserving image super-resolution with gradient-consistency-anisotropic-regularization prior

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ABSTRACT

Single image super-resolution (SR) often suffers from annoying interpolation artifacts such as blur, jagged edges, and ringing. In this paper, we aim to achieve artifact-free SR reconstruction from an input low resolution (LR) image using adaptive de-convolution and curvature refinement. To achieve this, we propose a curvature preserving image SR method based on a gradient-consistency-anisotropic-regularization (GCAR) prior. The gradient consistency term effectively suppresses visual artifacts such as ringing and preserves sharp edges in images while the anisotropic regularization term adaptively preserves the high frequency information according to the gradient magnitude. The complementary two terms are elaborately combined into the GCAR prior for the SR reconstruction. The GCAR prior is very effective in preserving image details and recovering high frequency information. Moreover, we use curvature refinement to remove jagged artifacts caused by aliasing due to decimation. The proposed method employs an effective feedback-control loop which contains adaptive de-convolution, re-convolution, pixel substitution, and curvature refinement. The GCAR prior is utilized in the adaptive de-convolution step. Extensive experiments on various test images demonstrate that the proposed method produces natural-looking and artifact-free SR results in terms of both visual quality and quantitative performance.

1. Introduction

With great advances in multimedia and network technologies, sharing multimedia contents through heterogeneous devices with different capabilities has become more and more popular. Although high-definition (HD) display devices such as HDTVs are becoming popular and affordable in recent years, a lot of videos have been already captured and made before such HD devices appeared. Thus, the SR reconstruction of the low-resolution (LR) videos is required. The SR reconstruction aims to reconstruct a super-resolved image from one or multiple LR input ones, and is one of inverse problems in image processing [1,2]. It is an extremely popular issue in image processing whose main goal is to recover sharp edges and textures in images while suppressing interpolation artifacts such as blur, jagged edges, and ringing [3–8]. The early SR methods have mainly focused on obtaining a high-resolution (HR) image (or sequence) from observed multiple low-resolution (LR) ones. However, the multi-frame SR approach is generally time-consuming and impractical due to the fact that the multiple input LR ones are required and motions between different observed ones should be estimated with sub-pixel precision. Thus, it is required to enhance the spatial resolution from a single observed image for achieving good SR performance in terms of both computational complexity and image quality.

1.1. Related work

Up to the present, a lot of outstanding results in the single image SR have been achieved by researchers [3–37].

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The simplest algorithms for image resizing were the interpolation methods such as the bilinear, bi-cubic, and Lanzcos algorithms. The interpolation methods run fast and were easy to implement. However, they inevitably produced blurred results when they were applied to the image SR especially with a large magnification factor. More advanced interpolation-based methods took the latent structures of images into consideration during the interpolation [9,10]. They improved the interpolation quality by adjusting the traditional interpolation methods. Example-based SR approaches assumed that the high-frequency details lost in the LR image could be effectively predicted from a set of LR and HR training image pairs. Freeman et al. proposed an example-based SR method which aimed to learn the appropriate high-frequency information from a set of training images [3]. The example-based SR method was computationally expensive, and the performance depended critically on the quality of the available examples. Recently, researchers proposed the SR methods of exploiting the natural image priors [4,6]. Glasner et al. introduced the patch similarity prior in the image SR [4]. They combined example-based SR constraints with classical SR constraints into a single unified computational framework. They attempted to recover the best possible resolution enhancement at each pixel based on its patch redundancy. Yang et al. proposed the sparse representation prior of image patches with respect to the properly chosen dictionary [6].

This method first recovered the sparse representation coefficients from the LR patches over a LR dictionary, and then reconstructed a HR patch using the coefficients over the HR dictionary which was jointly trained with the LR dictionary. The edge statistics of natural images were exploited in [15–17] as a prior for the SR reconstruction. To enhance the image details in the estimated SR images, several approaches were proposed using texture priors based on domain-specific modeling [18–20]. Natural image statistics such as the heavy-tailed distributions were also used in the SR reconstruction [21–23]. Another approach to the single image SR was the de-convolution based SR methods which used the prior information of images to make sure that the solution is unique [12,14,34]. With the assistance of the reasonable prior information, it was able to recover high frequency information effectively. However, when the input LR image was not able to provide enough information for the SR reconstruction, it leaded to the loss of the high frequency information especially with a large magnification factor. Above all, the most important issue in the single image SR is to effectively remove interpolation artifacts such as blurring, jagged, and ringing ones, and successfully recover the image features of sharp variations such as edge and texture which are lost during the sampling process.

1.2. Contributions

In this work, we aim to achieve artifact-free SR reconstruction from an input LR image using adaptive de-convolution and curvature refinement. We propose an effective curvature preserving image SR method based on a gradient-consistency-anisotropic-regularization (GCAR) prior. To effectively preserve the image details such as edge and texture, we combine the gradient consistency (GC) term and the anisotropic regularization (AR) term into the gradient-consistency-anisotropic-regularization (GCAR) prior. The GC term effectively preserves the consistency of pixel values between LR images and their corresponding SR results. It suppresses visual artifacts such as blur and ringing which usually occur along the boundaries of objects, thus preserving sharp edges in images. The AR term adaptively preserves the high frequency information according to the gradient magnitude, thus enhancing the details in texture regions. Moreover, curvature refinement successfully removes annoying jagged artifacts and improves the SR results in images. Thus, the proposed SR is able to effectively remove interpolation artifacts such as blur, jagged edges, and ringing, as well as successfully recover the high frequency information as shown in Fig. 1. Compared to the conventional de-convolution based methods [12,14,34], the proposed method uses the GC and AR terms in smooth and complex regions, respectively, which leads to the content adaptive de-convolution. Moreover, the anisotropic property of the AR term is very effective in enhancing the image details in complex regions and producing natural-looking SR results. Therefore, the proposed method produces more natural-looking and clearer SR reconstruction results than the other de-convolution based ones (see Fig. 1).

The rest of this paper is organized as follows. In Section 2, we explain the proposed SR method using the GCAR prior in

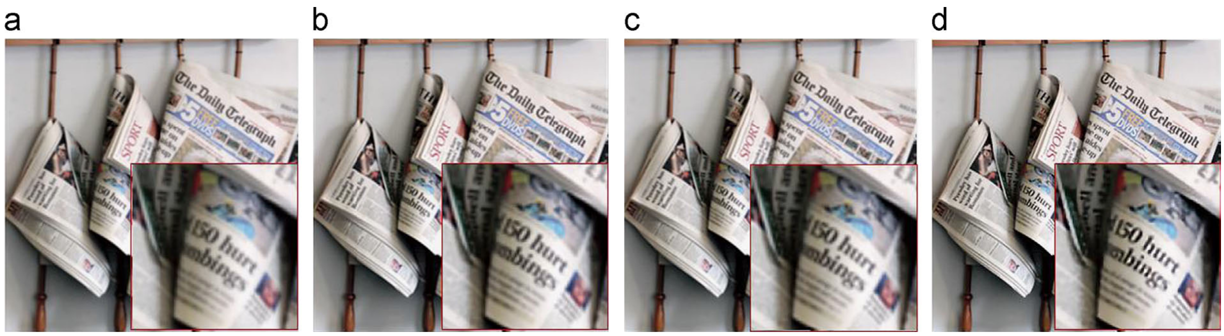

Fig. 1. Super-resolution results in the *Newspaper* image. (a) Bi-cubic. (b) [12]. (c) [14]. (d) Proposed method. The proposed method produces more natural-looking and clearer SR reconstruction results by effectively removing interpolation artifacts such as blurring, jagged, and ringing ones as well as successfully preserving the details in images.