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Single image super-resolution based on subpixel shifting model

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ABSTRACT

This paper presents a novel single image super-resolution (SR) reconstruction method using shifted kernel regression. Assuming that a low-resolution (LR) image is made by the shifted regression-based image degradation model, the proposed SR process shifts pixels in a regularly sampled LR image with a subpixel precision according to local gradient. The optimum displacement of each pixel is estimated using the Gaussian filtered second derivatives. The shifted low-resolution image is finally up-scaled by estimating the regression coefficients of the shifted kernels in the spatially adaptive manner. Experimental results show that the proposed method overcomes the limitation of existing intensity-based SR algorithms. The proposed SR algorithm can successfully restore sharp, clear edges without undesired artifacts such as ringing, inverted gradient, halo effects, etc. Without using an iterative process, the proposed single image SR algorithm can easily be implemented in the form of either pre- or post-processing filters for further enhancing the SR result of existing methods.

1. Introduction

High-resolution (HR) image acquisition is widely used in various image processing applications including contents creation, intelligent video surveillance, radiography, bioengineering, medical imaging, etc. Since HR image sensors increase the production cost and sensing noise, digital image processing-based super-resolution (SR), or HR imaging, is an alternative way to increase the spatial resolution without using a higher-density image sensor [1].

Existing SR techniques can be categorized into the following [1]: (i) functional interpolation-based, (ii) example-based, and (iii) reconstruction-based methods. Functional interpolation algorithms are further classified by the type of basis functions such as zero-order hold, bilinear, bicubic, and the discrete Fourier transform (DFT) [2]. These algorithms have been developed under the assumption that the original HR image is band-limited. Since the above mentioned assumption cannot completely cover practical applications, a functional interpolation-based SR algorithm cannot successfully reconstruct the original HR image.

Example-based methods try to retrieve the most similar high-frequency patterns from a set of a priori acquired image samples [3–5]. The fundamental assumption is that the high-frequency information lost in the sub-sampling process can be restored if a sufficient number of example images are provided. If this assumption does not hold, the fake high-frequency artifact occurs, and it significantly degrades the quality of the reconstructed image.

Reconstruction-based methods adopt spatial adaptivity which can preserve the high frequency components along the edge orientation in a restored HR image [6–9]. This type of spatially adaptive algorithms consist of two steps: (i) a given LR image serves as the input of the adaptive regularized image interpolation, and (ii) the spatially adaptive fusion is implemented based on the orientation analysis such as steerable filters. Common problems of reconstruction-based methods include an insufficient number of LR images and the ill-conditioned nature of the restoration process. As far as the isotropic smoothness is used as a priori constraint, reconstruction-based interpolation method cannot preserve edges in various orientations since there is no direct effort to restore the directional high-frequency details lost in the sub-sampling process.

Recently, kernel estimation-based image reconstruction methods have been proposed for both regularly and irregularly sampled images. Multiframe SR is considered as an interpolation of irregularly sampled images, where several low-resolution (LR) images are fused (interlaced) onto a single HR grid [10]. In order to enhance the regression-based SR results, the non-local means filter learns a global prior called the non-local prior, whereas the steering kernel regression learns a local prior [11,12]. In this case the SR artifact can be considered as a special case of the kernel estimation error. In order to remove such artifacts, kernel or region-based analysis

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has been widely used in other applications: denoising and digital image stabilization.

The main contribution of the proposed research is that a novel image degradation model is formulated using shifted regression with a subpixel precision and the corresponding SR algorithm is presented using locally adaptive kernel regression. Since the proposed SR method does not need a deconvolution process, it can restore the HR image without restoration artifacts such as ringing and halo effects. In order to estimate the subpixel shifting vectors, we analyze the gradient of the image based on the proposed degradation model. Experimental results show that the proposed method can not only preserve the image sharpness but also minimize restoration artifacts near the edge. The proposed reconstruction method is suitable for wide range of imaging devices such as digital cameras, digital TVs, and mobile phone cameras.

2. Image degradation model based on subpixel shifting

Conventional regression-based SR algorithms estimate a regression function using an observed LR image, and then compute the intensity values at the HR grid using the estimated regression function [10]. There is a mismatch between the result of regression-based resampling and the original HR image since the estimated regression function does not contain the original high-frequency details. In practical applications where noise is present, the measurements in a local window are modeled as

$$y_i = z_g(\mathbf{x}_i) + \eta_i, \quad \text{for} \quad i = 1, \ldots, P \tag{1}$$

where y_i represents a noisy observed image, $z_g(\cdot)$ is a regression function of the LR data, and η_i is an independent and identically distributed (i.i.d) zero-mean noise. $\mathbf{x}_i = [x_{i1}, x_{i2}]^T$ represents the uniform sampling position in the Cartesian coordinate, and P is the total number of sampling positions in the local window centered at $\mathbf{x}_i$. Conventional image degradation model based on the convolution of a space-invariant linear filter and the regression function of the original image is given as

$$z_g(\mathbf{x}_i) = h * z_f(\mathbf{x}_i), \tag{2}$$

where * denotes the convolution operation, z_f represents the regression function of the original signal, and h the image degradation kernel implying atmospheric blur, motion blur, out-of-focus blur, or anti-aliasing filtering followed by down-sampling, to name a few. Since the estimation of z_f by solving (2) is an ill-posed problem, restoration artifacts such as a ringing and overshooting are unavoidable in the deconvolution process.

Instead of the conventional convolution-based model, we propose a shifted regression-based image degradation model as

$$z_g(\mathbf{x}_i) = z_f(\mathbf{x}_i + \mathbf{s}_i) \tag{3}$$

where $\mathbf{s}_i = [s_{i1}, s_{i2}]^T$ represents the shifting vector with a subpixel precision. Based on the proposed model, an LR image is made by shifting the position of pixels in the uniformly sampled HR image.

Fig. 1 compares the conventional and proposed image degradation models in one-dimensional (1D) case. Fig. 1(a) shows the conventional degradation model that manipulates the intensity value in the uniform sampling grid, whereas Fig. 1(b) shows the shifted regression-based model. The 1D shifting vector s_i should be zero at the center of edge x_C and its length increases with the distance from x_C. Although an image generally consists of multiple, possibly mixed edges, we assume that each degraded edge region is generated by a single edge at the corresponding position and the intensity value in the edge region is monotonically increasing or decreasing. Under the shifted regression-based model, restoration can be performed by simply moving back the pixel position by s_i.

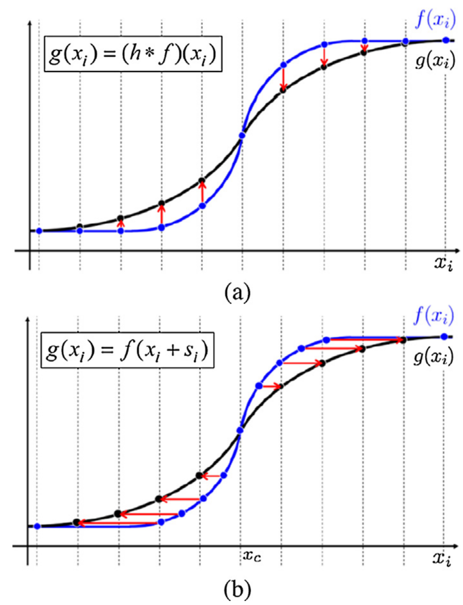

Fig. 1. Two different models for the same one-dimensional (1D) edge degradation: (a) conventional convolution-based degradation model in the uniformly sampled grid where the intensity values change in the fixed pixel position and (b) the shifted regression-based degradation model where the pixel position moves with preserving the same intensity value.

Based on the shifted regression-based degradation model, the proposed SR algorithm consists of three parts: estimation of the edge orientation, subpixel shifting vectors estimation, and kernel regression-based SR on HR grid as shown in Fig. 2.

3. Edge orientation estimation

This section presents an edge orientation estimation method for the forthcoming shifting vectors estimation and orientation-adaptive image interpolation. Oriented or orientation filters are used in many vision and image processing tasks such as texture analysis, edge detection, image compression, motion analysis, and image enhancement [13,14]. The proposed orientation estimation method uses the first order derivative of a Gaussian filter called steerable filter whose size is easily adjustable by changing the standard deviation of Gaussian.

Freeman proposed the steerable filter that is synthesized in an arbitrary direction as a linear combination of a set of basis filters, such as two-dimensional (2D) circularly symmetric Gaussian functions as [14]

$$G(x_1, x_2) = e^{-\left(x_1^2 + x_2^2\right)}, \tag{4}$$

where scaling and normalization constants are set to unity for notational simplicity. Let G_n^0 be the nth partial derivative of a Gaussian

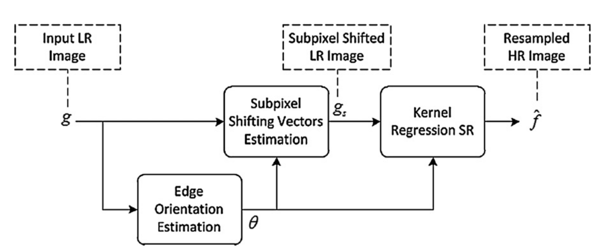

Fig. 2. Block diagram of the proposed SR algorithm.