Optics Communications 285 (2012) 245–248

Contents lists available at SciVerse ScienceDirect

Optics Communications

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

Adaptive regularized image interpolation using a probabilistic gradient measure

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ARTICLE INFO

Article history:
Received 29 August 2011
Received in revised form 19 September 2011
Accepted 21 September 2011
Available online 12 October 2011

Keywords:
Image interpolation
Gradient
Regularization

ABSTRACT

An adaptive image interpolation approach is proposed in this paper. The proposed approach imposes a regularization on the reconstructed high-resolution image to suppress the noise and blurring incurred in the observed low-resolution image. Furthermore, the proposed regularization scheme is steered by the local gradient information of the image, which is evaluated using a probabilistic measure. Experiments are conducted to demonstrate the superior performance of the proposed approach.

1. Introduction

Image interpolation has a capability to enlarge a lower resolution image to a higher resolution version [1,2]. It has a wide range of applications, including digital photography, video communications, object recognition, and so on. Its main purpose is to provide more details in images so as to improve content recognition ability [3,4].

The existing image interpolation approaches can be classified into two categories: *deterministic*-based interpolation and *regularization*-based interpolation. The first approach uses the single input image only to perform image interpolation. On the contrary, the second approach imposes certain prior information on the desired reconstructed high-resolution image.

There are several spatially-adaptive image interpolation algorithms, which can adjust the interpolation coefficients to preserve the geometric constraint of images, such as the local edge directions. Li and Orchard [5] proposed to adjust the interpolation based on the geometric duality between low-resolution and high-resolution covariances. Zhang and Wu [6] proposed to perform interpolation on two directions and adaptively fuse their results to be single image. Liu et al. [7] proposed an image interpolation approach using regularized local linear regression. They used the moving least square method to robustly estimate local image structure, and then estimate the geometric structure of the marginal probability distribution of the missing pixels. Hung and Siu [8] proposed to use weighted least square estimator to perform unequal variance preserving for estimating both model parameters and missing pixel intensity values.

The aforementioned deterministic image interpolation approaches cannot suppress the noise or blurring incurred in the observed image. In view of this, the prior image model can be further used as the regularization for the unknown reconstructed high-resolution image. The major challenge is the determination of the degree of regularization [9—11], since it determines the quality of the reconstructed high-resolution image. Conventional approaches impose a spatially-invariant regularization parameter to the whole image. However, these approaches have limited adaptive capability in the process of image reconstruction and cannot balance the suppression of noise against the preservation of image details.

In view of this, a regularized image interpolation is proposed in this paper by exploiting the local gradient measure to adjust the degree of regularization according to the local content of the image. Motivated by the fact that the local gradient is critical to determine the degree of image's sharpness [12,13], for the smooth region with *smaller* gradient, the proposed approach will impose a *stronger* regularization. On the other hand, for the edge/texture region with *larger* gradient, the proposed approach will impose a *softer* regularization. Furthermore, the proposed approach exploits a probabilistic scheme to measure the gradient information.

The rest of this paper is organized as follows. Section 2 presents the proposed adaptive regularization approach. Experimental results are presented in Section 3. Finally, Section 4 concludes this paper.

2. Proposed regularized image interpolation approach

The given low-resolution image can be viewed as warped, blurred, down-sampled and noisy version from the original (unknown) high-resolution image (denoted as $\mathbf{f}$). That is, their relationship can be mathematically expressed as

$$\mathbf{g} = \mathbf{hf} + \mathbf{v}, \tag{1}$$

where $\mathbf{g}$ represents the observed low-resolution image, $\mathbf{h}$ represents the above-mentioned convolving and downsampling operations, and $\mathbf{v}$ represents the additive white Gaussian noise. With such establishment, the goal of image reconstruction is to produce a single high-resolution image based on its low-resolution observation.

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0030-4018/$ – see front matter
doi:10.1016/j.optcom.2011.09.065

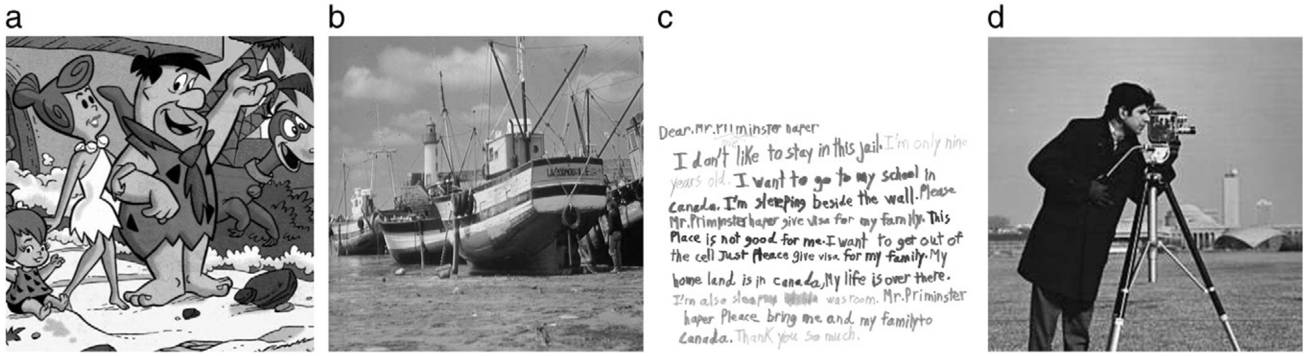

Fig. 1. Test images used in this paper: (a). *cartoon*; (b). *boat*; (c). *text*; (d). *cameraman*.

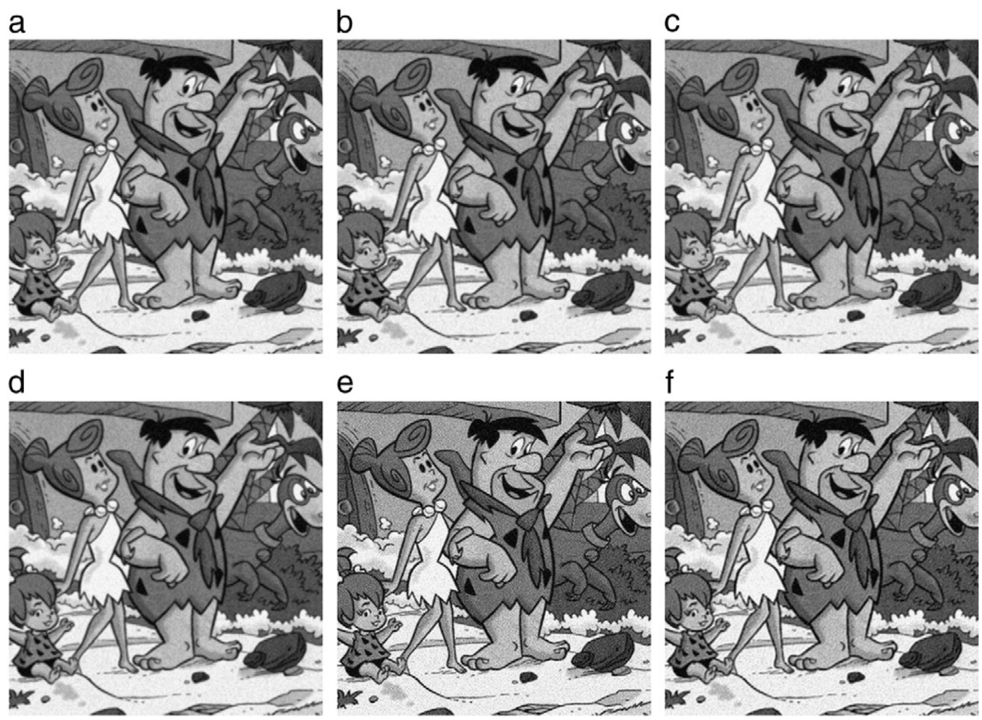

Fig. 2. Various reconstructed images of *Cartoon*: (a)–(e). Refs. [5,6,18—20], respectively; (f). Proposed approach.

The proposed approach estimates the unknown high-resolution image (denoted as $\hat{\mathbf{f}}$) by minimizing the following cost function

$$\hat{\mathbf{f}} = \underset{\mathbf{f}}{argmin}\,\{|\mathbf{f}-\mathbf{g}| + \Gamma(\mathbf{f})\}. \tag{2}$$

where $|\mathbf{f}-\mathbf{g}|$ is the data term, representing the fidelity between the estimated high-resolution image with the observed low-resolution images. On the other hand, $\Gamma(\mathbf{f})$ is the regularization term, which can be formulated using a conventional total variation model [14,15] as

$$\Gamma(\mathbf{f}) = \sum_i \sum_j \left(|f_{i,j}-f_{i-1,j}| + |f_{i,j}-f_{i+1,j}| + \left|f_{i,j}-f_{i,j-1}\right| + |f_{i,j}-f_{i,j+1}|\right). \tag{3}$$

The novelty of the proposed approach is to adaptively adjust the regularization according to the local content of the image as

$$\begin{aligned}\Gamma(\mathbf{f}) = \sum_i \sum_j \Big(&\lambda_{i-1,j}\left|f_{i,j}-f_{i-1,j}\right| + \lambda_{i+1,j}|f_{i,j}-f_{i+1,j}| \\ &+\lambda_{i,j-1}\left|f_{i,j}-f_{i,j-1}\right| + \lambda_{i,j+1}|f_{i,j}-f_{i,j+1}|\Big)\end{aligned} \tag{4}$$

where the weighting factor λ is measured in terms of edge strength of the local neighbor for each pixel. Comparing Eqs. (3) and (4), one can see that the degree of regularization is spatially adjusted in the proposed approach, rather than being spatially-invariant in conventional approach. Therefore, the proposed approach will impose a stronger regularization for the smoother region, while imposing softer regularization for edge/texture region.

The weighting factor λ is calculated based on a probabilistic measure using local gradient information.

$$\lambda_{i,j} = \frac{1}{Z}\sum_i \sum_j \phi\left(\lambda_{i,j} - \frac{1}{\delta_{i,j}}\right), \tag{5}$$

where Z is normalizing factor, $v_{i,j}$ measures local gradient defined as

$$\delta_{i,j} = \left|f_{i,j}-f_{i-1,j}\right| + |f_{i,j}-f_{i,j-1}| + \xi, \tag{6}$$

in which $\xi = 10^{-3}$, the function $\phi(\cdot)$ is a non-negative kernel function that integrated to one [16], and a Gaussian function with a standard deviation 1 is used in this paper.

Finally, the steepest descent algorithm [17] is used in this paper to find the closed-form solution for estimating the full-resolution image at each iteration step n as

$$\hat{\mathbf{f}}^{(n+1)} = \hat{\mathbf{f}}^{(n)} - \alpha\left\{\mathbf{h}^T \mathrm{sign}\left(\mathbf{h}\hat{\mathbf{f}}^{(n)} - \mathbf{g}\right) + \mathbf{C}^{-j}\mathbf{R}^{-i}\mathrm{sign}\left(\hat{\mathbf{f}}^{(n)} - \lambda\mathbf{R}^i\mathbf{C}^j\hat{\mathbf{f}}^{(n)}\right)\right\}, \tag{7}$$