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Research Article

Image Resolution Enhancement Using PCA Based Post Filtering

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Abstract: In this study an image resolution enhancement method is presented that uses the NEDI method to generate an initial image. To increase the detail of this initial image, the given low resolution image is fused with it to achieve a new image. Then the final high resolution image is obtained by using a PCA based filtering to reduce the distortion of this new image. Experimental results on test images demonstrate that the proposed method provides competitive performance.

Keywords: Distortion reduction, image interpolation, image resolution enhancement, principle component analysis

INTRODUCTION

Image resolution enhancement, which constructs a High Resolution (HR) image from its Low Resolution (LR) counterpart, plays an important role in many image processing applications, such as High Definition Television (HDTV) displays, medical imaging, satellite remote sensing and video surveillance, etc. Image resolution enhancement methods can be categorized into two major classes: the first class is the spatial method, the second one is the transform-domain based method (Celik and Tjahjadi, 2010).

The most common spatial methods, such as bilinear interpolation, cubic spline interpolation and bicubic interpolation, are well founded on the approximation theory. The relatively low computational complexity of these algorithms allows their use in real-time image processing systems. However, all of them deal with aliasing, blurring and ringing effects because they do not utilize any information relevant to edges and texture patterns in the original image (Lehmann *et al.*, 1999). Many improved methods have been developed in the literature, which incorporate more prior knowledge into image models to improve the visual quality of images. In the reference (Li and Orchard, 2001), a New Edge-Directed Interpolation (NEDI) method was proposed. Zhang and Wu proposed an adaptive method based on soft-decision estimation (SAI) (Zhang and Wu, 2008).

The transform-domain based methods often perform the resolution enhancement in the wavelet domain, which enhance image resolution by estimating preserved high frequency information from the LR image. Following this scheme, Temizel and Vlachos proposed the Wavelet Zero Padding (WZP) method in which unknown high frequency coefficients are replaced with zeros and then the inverse wavelet transform is applied to generate an initial HR approximation (Temizel and Vlachos, 2005).

Anbarjafari and Demirel applied the bicubic interpolator to estimate the missing high frequency coefficients in the wavelet domain (Anbarjafari and Demirel, 2010). In the reference (Demirel and Anbarjafari, 2011), the authors used high frequency subbands through stationary wavelet transform to correct the interpolated discrete wavelet high frequency sub bands. These methods assume that the LR image is a low pass output of the wavelet transform applied to the HR image. However, this assumption is not tenable because the LR image also contains high frequency information. In practice, therefore, the wavelet-based interpolation methods are inefficient due to leading the resulting images to be over smoothed.

In this study, we propose an image resolution enhancement method based on a post filtering process by using Principal Component Analysis (PCA). The proposed method exploits the NEDI interpolator to generate an initial estimate of the HR image. Then the observation constraint provided by the given LR image is enforced on the initial estimate of HR image to lead a combined estimate of HR image. Finally, a HR image is obtained by using the PCA based filtering which reduces distortion of the combined estimate of HR image.

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PROPOSED METHODOLOGY

Without the loss of generality, we assume that the observed LR image y is generated by decimating the ground-truth HR image x by two. Specifically, the down sampling process is applied row-wise then column-wise in the ground-truth HR image. The observation constraint for LR image can be expressed as follows:

$$y = x * D \tag{1}$$

where,
D : A noninvertible logical down sampling operator
* : The element-wise multiplication operation

Due to the edge-preserving advantage of NEDI, the proposed method first exploits the NEDI interpolation method to generate an initial image x_0 as an approximation estimate of the HR image x. Then we use the prior information to increase the detail component of x_0. The prior information y can be fused with the initial estimate x_0 to attain a new estimate x_1. The process of fusing y and x_0 can be formulated as follows:

$$x_1 = y + x_0 * \widetilde{D} \tag{2}$$

where, $\widetilde{D}$ is a logical NOT matrix of the matrix D.

The above described fusion process is not perfect because it can introduce distortion in the HR image estimate x_1. PCA, which has been widely used in image processing, is an efficient tool for distortion reduction. We use an adaptive PCA-based filtering as a post-processing step to reduce this distortion, as in Muresan and Parks (2003).

Denote by C the covariance matrix of x_1, which can be calculated as:

$$C = \frac{1}{N} zz^T \tag{3}$$

where, z, the centralized matrix of x_1, is defined as:

$$z = x_1 - \mu \tag{4}$$

with

$$\mu = \frac{1}{N}\sum_{j=1}^{N} x_1(j) \tag{5}$$

For the covariance matrix C, we can apply the diagonalization:

$$C = U \Lambda U^T \tag{6}$$

where,
$\Lambda = diag\{\lambda_1, \lambda_2, \ldots, \lambda_{N-1}, \lambda_N\}$ is the diagonal eigen value matrix with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N$
U = eigen vector matrix

In order to reduce the distortion in the estimate $\hat{x}$ of the HR image, we modify the eigenvalues λ_i by a shrinkage function defined as follows:

$$T(x) = (x - \tau_i)_+ \tag{7}$$

where,
$(\cdot)_+$: Replaces negative eigen values by a small positive value
τ_i : A threshold

The modified eigen values can be used to reconstruct an estimate $\hat{z}$ of the centralized matrix z. Then an estimate $\hat{x}_1$ can be given by:

$$\hat{x}_1 = \hat{z} + \mu \tag{8}$$

The above process steps can be iterative by enforcing the observation constraint to $\hat{x}_1$ according to Eq. (2). Let x_k represent the estimate at the k^{th} step. The estimate x_{k+1} fused with the observation constraint can be given by:

$$x_{k+1} = y + x_k * \widetilde{D} \tag{9}$$

Then the quality of x_{k+1} can be improved by using the PCA based post filtering to reduce the distortion.

EXPERIMENTS

In this section, experimental results are presented to validate the effectiveness of the proposed method. In the experiments, we use a test images set including eight widely used gray-level images in the literature. To compare the performance of enhancement methods, each test image is down sampled by a factor of two to obtain the LR image y and then y is enhanced back to the original size.

Table 1: Performance comparison with interpolation methods in term of PSNR

Images	Bicubic	NEDI	Proposed
Monarch	25.27	27.97	29.45
Lena	26.15	29.29	29.90
Mandrill	21.78	23.03	23.22
Goldhill	28.67	30.40	30.68
Man	28.16	30.47	30.83
Mit	21.21	23.18	23.60
Peppers	24.19	24.28	24.54
Cameraman	23.74	25.48	25.80

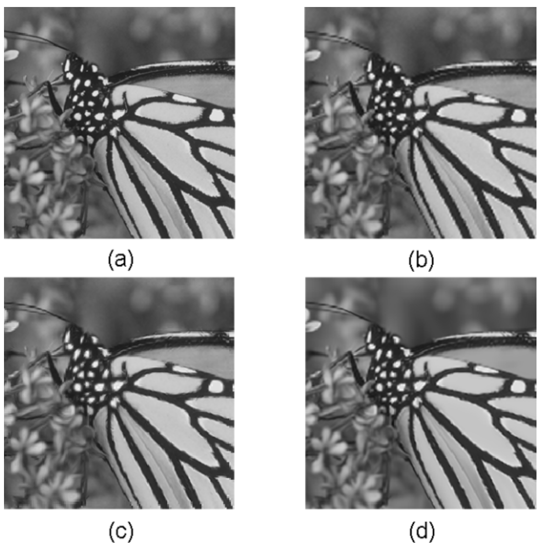

Fig. 1: Comparison of three methods on the image monarch, (a) original image, (b) bicubic method, (c) NEDI method, (d) proposed method

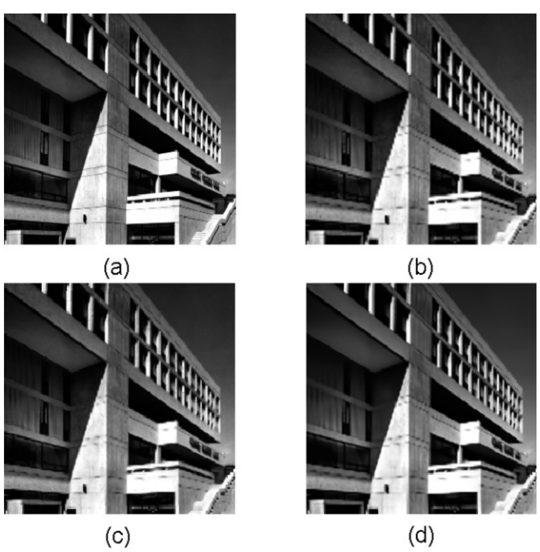

Fig. 2: Comparison of three methods on the image Mit, (a) original image, (b) bicubic method, (c) NEDI method, (d) proposed method

We compare the results generated by our proposed method with the bicubic interpolation and NEDI. All enhancement methods are coded in MATLAB 7.0 and performed on an Intel i7-2.93 GHz computer system. The performance of these methods is evaluated by the objective and subjective quality, respectively. We quantify the objective performance of all methods by Peak Signal-to-Noise Ratio (PSNR). Table 1 lists the PSNR values of results for test images. It is clearly shown that the proposed method substantially outperforms other interpolation methods. Visual comparisons for *Monarch* and *Mit* are shown in Fig. 1 and 2. We can observe that the enhanced images of the proposed method exhibit less distortion than the other two methods.

CONCLUSION

This study presents an image resolution enhancement method. Unlike conventional methods, the proposed technique first uses the NEDI interpolation method to generate an initial image of the HR image. Then the observation constraint provided by the given LR image is enforced on the initial HR image to increase the detail of the initial HR image and achieve a new image. At last, the final HR image is obtained by using a PCA based filtering to reduce the distortion of this new image. Comparisons based on visual results and PSNR show that the proposed method achieves competitive performance.

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