Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 92 (2016) 311 – 316
Procedia Computer Science

2nd International Conference on Intelligent Computing, Communication & Convergence

(ICCC-2016)

Srikanta Patnaik, Editor in Chief

Conference Organized by Interscience Institute of Management and Technology

Bhubaneswar, Odisha, India

Image resolution enhancement using wavelet domain transformation and sparse signal representation

Gunnam Suryanarayana *, Ravindra Dhuli

School of Electronics Engineering, VIT University, Vellore-632014, Tamilnadu, India.

Abstract

Image resolution enhancement or super-resolution (SR) problem generates a high resolution (HR) image from one or a set of low resolution (LR) images. In the past two decades, a wide variety of resolution enhancement algorithms have been proposed. These methods are confined to small scaling factors. This paper presents a novel single image resolution enhancement algorithm in wavelet domain which operates at high scaling factors. First, we perform subband decomposition on the input LR image by using discrete wavelet transform (DWT). It decomposes the LR image into different frequency subbands namely low-low (LL), low-high (LH), high-low (HL) and high-high (HH). In parallel we apply sparse representation based interpolation method on the LR image. Next, we process the three high frequency subbands in wavelet domain by applying bicubic interpolation. Finally, the interpolated high frequency subbands in addition to the sparse recovered solution are combined to produce a HR image using inverse discrete wavelet transform (IDWT). Experiments on different LR test images demonstrate that our approach produces relatively less artifacts compared to the existing methods.

Peer-review under responsibility of the Organizing Committee of ICCC 2016

* Corresponding author. Tel.: +91-7598123449.
E-mail address: surya_gunnam@yahoo.co.in

Peer-review under responsibility of the Organizing Committee of ICCC 2016
doi:10.1016/j.procs.2016.07.361

Keywords: Super Resolution; Discrete Wavelet Transform; Interpolation; Sparse Representation

1. Introduction

Image resolution enhancement or super resolution (SR) is a significant signal processing technique which generates a high resolution (HR) image from a single or multiple low resolution (LR) observations [1, 2]. It plays a vital role in numerous applications, such as medical image, infrared image, satellite image and ultra sonic image processing. Traditional approaches such as bilinear, bicubic and nearest neighbor interpolation are the well-known interpolation methods. The major advantage of these techniques is their computational simplicity. However, they produce images with artifacts, such as blurred edges and jaggy effects. Many edge guided interpolation algorithms have been proposed in the literature. Orchard and Li [3] proposed a linear interpolation approach by adapting local co-variance. The authors developed a relation between the HR co-variance and the LR counterpart by exhibiting geometric duality. Zhang and Wu [4] estimated the interlacing pixels in groups rather than pixel wise by introducing an autoregressive model. However, there is a rapid degradation in the performance of interpolation based methods when the desired magnification factor is large.

In the past few years, machine learning techniques have been proved successful in sparse resolving the images. These algorithms exploit dictionary learning and sparse representation for SR reconstruction. Yang et al. [5] enforced the sparse representation similarity between the LR and HR patch pair by jointly training two overcomplete dictionaries. Shi et al. [6–8] further developed edge guided machine learning algorithms, by employing local and nonlocal self-similarities in the traditional sparse representation model. Usually these methods provide better visual quality compared to the interpolation based techniques. But the higher order computational complexity is strictly prohibitive. Recently image SR techniques based on wavelets have been proved successful in resolving the HR images. This success is mainly due to the self-similarities between the wavelet subbands. These techniques yield better performance even at large scaling factors. In [9] the authors simultaneously applied discrete wavelet transform (DWT) and stationary wavelet transform (SWT) to decompose an input LR image in different frequency subbands. Then the interpolated DWT high frequency subbands and the SWT high frequency subbands are added with each other. Finally, the super resolved image is obtained by combining the input LR image and the estimated high frequency subbands by using inverse discrete wavelet transform (IDWT). Recently Roman and Ponomaryov [10] developed a novel edge guided SR concept for generating sharper images by employing DWT and sparse mixing estimation of the input image.

In this paper, we propose a wavelet based SR method based on sparse representation and DWT. The DWT operator is applied to decompose an image into different subbands. We use the sparse representation model introduced by Yang et al. [5] on the initial HR estimate. To show the prominence of the proposed method, our algorithm is implemented on various test images and the results are compared with the conventional and state-of-the-art methods.

The rest of this paper is organized as follows. Section 2 provides the implementation of sparse representation method. The proposed sparse representation based resolution enhancement approach is outlined in section 3, followed by various experimental results provided in section 4. Finally, the conclusions are drawn in section 5.

2. Sparse Representation

The input LR image is decomposed by DWT into different subbands, namely low-low (LL), low-high (LH), high-low (HL) and high-high (HH). The LL subband contains no edge information, since it is the low frequency version of the input image. So, the LL subband is replaced by the input image through sparse representation model (SRM) [5]. The SRM model jointly trains two over complete dictionaries D_h and D_l in such a way that, they have same sparse representations with respect to each HR-LR patch pair. Now, if X, Y represents the LR and HR frames and x, y be the corresponding image patches. Then from the SRM model,

$$x = D_h \alpha \quad \text{and} \quad y = D_l \alpha,$$

where $\alpha \in R^k$ is the sparse representation vector with the $||\alpha||_0 \leq k$. Here, we use the dictionaries trained in Yang's method [5].

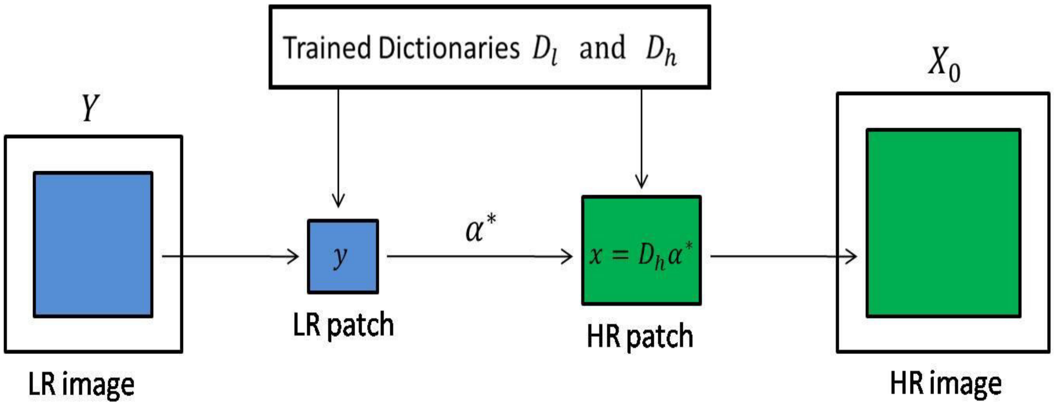

Fig. 1. Image recovery using sparse representation

First, the given LR image Y is divided into 3×3 patches. For each LR patch y we estimate the sparse vector α using the LR dictionary D_l. Now, the same sparse representation is used to linearly combine the columns of D_h, to generate the HR patch x. The task of computing the sparse vector is modeled as the following optimization problem.

$$\min_{\alpha} \left\| \begin{bmatrix} FD_l \\ PD_h \end{bmatrix} \alpha - \begin{bmatrix} Fy \\ \omega \end{bmatrix} \right\|_2^2 + \lambda \|\alpha\|_1,$$

where F is the feature extraction operator which enables close approximation in the SRM, p is a matrix that extracts the overlapped region between the current patch and the previously reconstructed HR patch and ω preserves the reconstructed HR image on the overlap.

The sparsest solution α^* of the above optimization problem is used to reconstruct the HR patch as $x=D_h\alpha^*$. Similarly, the other LR patches are processed in a raster-scan order with one pixel overlap in every direction. The recovered image X_0 is substituted in the LL subband after normalization. This process is outlined as a block diagram in Fig. 1.

3. Proposed SR technique

In this paper, we assume the input LR image X of size $m \times n$, which is a downsampled version of the original HR image Y of size $4m \times 4n$. In practice, the blurring and noisy effects are also taken into consideration. Thus, the SR problem can be formulated as

$$X = BHY + n,$$

where H denotes the downsampling followed by the blurring operation B and n is the additive noise.

Fig. 2 shows the flow-chart representation of the proposed SR technique. Firstly, we apply bicubic interpolation on the input LR image to get the initial estimate (LR version) of HR image. However, this image consists of blurred edges due to the ringing and jagging artifacts. So, we process this HR estimate in transformed domain to add more edge information.

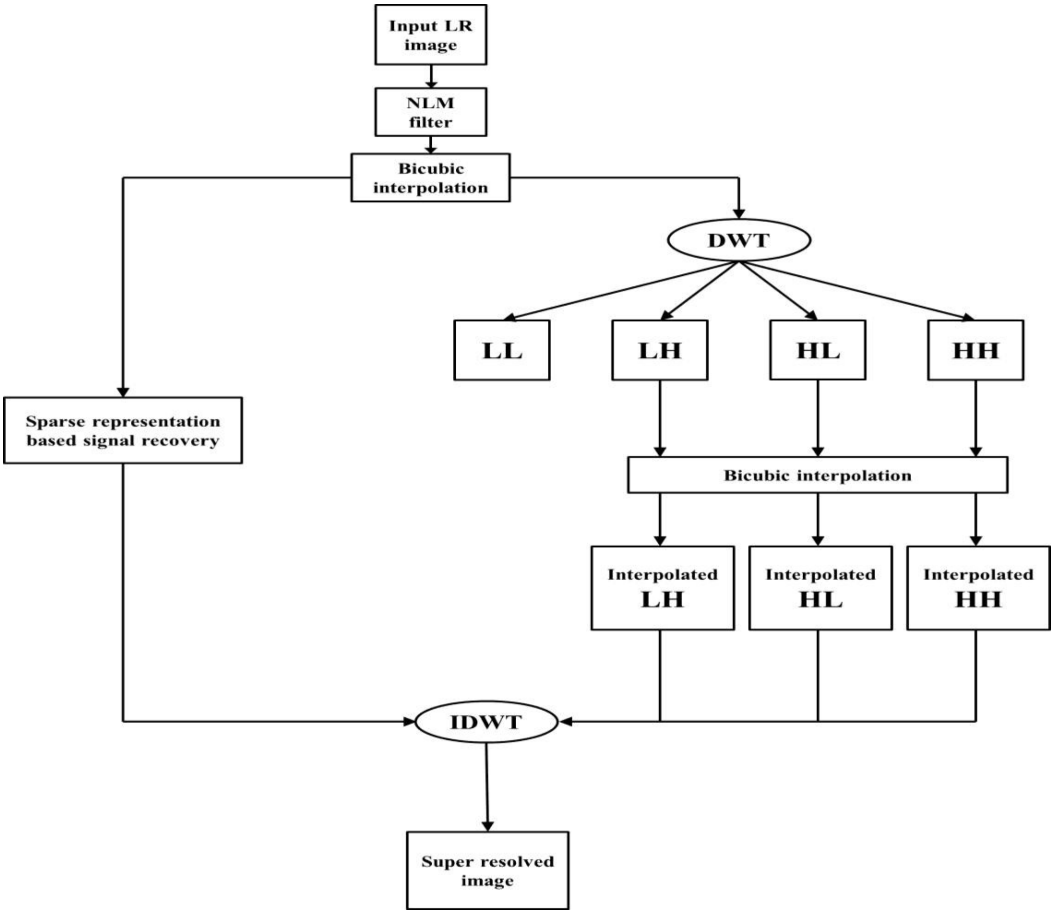

Fig. 2. Flow-chart representation of the proposed SR method

In this scenario, one level DWT is operated on the initial HR estimate, which decomposes into several subbands namely: LL, LH, HL and HH. Here, the LL subband contains no edge information, whereas the LH, HL and HH subbands inherently include the edge information in horizontal, vertical, diagonal directions respectively. Now the three high frequency subbands LH, HL and HH are further interpolated using bicubic interpolator. As the LL subband contains no high frequency details, we replace it with sparse recovered version of the denoised LR image. The concept of sparse representation based signal recovery is explained in section 2. Finally, we apply IDWT process on the sparse solution and the three interpolated high frequency subbands to extract the SR image.

Fig. 3. LR test set images

4. Experimental results

In this section, we compare the proposed SR technique with conventional approaches, viz., bicubic upsampling (Bicubic); edge guided directional filtering (EGDF) [4] and state-of-the-art approaches, viz., sparse representation model (SRM) [5]; DWT and SWT (DWT-SWT) [9]; DWT based sparse mixing model (DWT-Sparse) [10] to demonstrate the effectiveness of our method. These algorithms are implemented on two gray level images (Boat and Elaine) and three RGB color images (Lena, Peppers and Mandrill).

Fig. 3 shows the LR test images, which are downsampled by a factor of 4. These images are reconstructed back using various SR techniques. For color images, the SR procedure involves three steps: 1. RGB to YCbCr space transformation; 2. Apply the proposed algorithm on the Y channel and simple bicubic interpolation on Cb and Cr channels; 3. Transform the Y, Cb and Cr channels back to the RGB color models.

We use Daubechies (Db1) wavelet to decompose the image into subbands. The input image is denoised by choosing $\sigma_R=2$. For effective sparse recovery of the image we have set the patch size to be 3×3 and λ as 0.4. All the experiments were tested on Matlab 2013b using an Intel Core i3, 2.30 GHz and 4GB RAM.

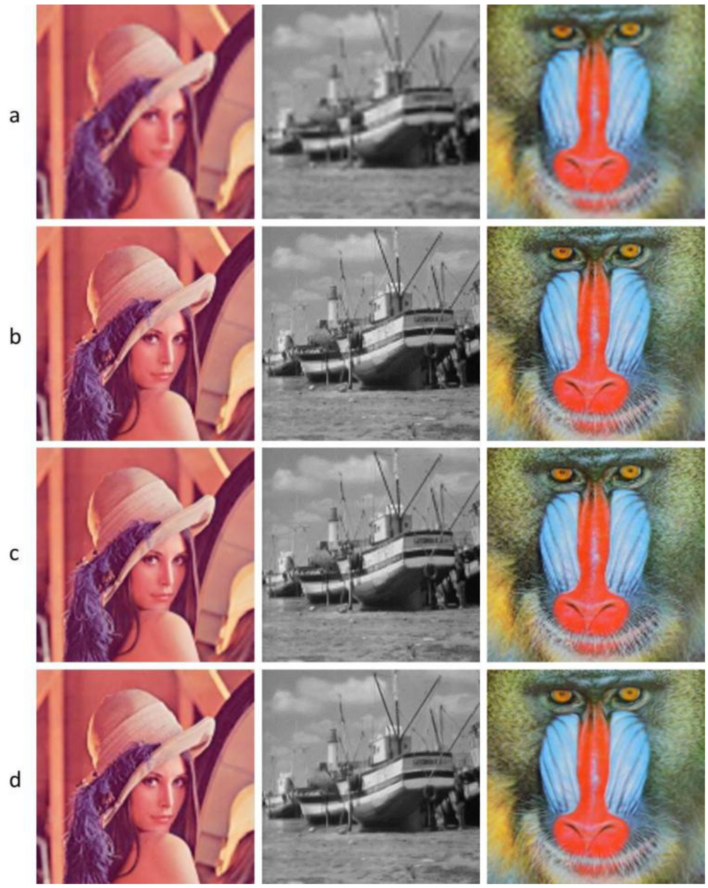

Fig. 4. Reconstructed SR images of Lena, Boat and Mandrill using various methods:
(a) Bicubic (b)DWT-SWT [9] (c)DWT-sparse [10] (d)Proposed method

Table 1.PSNR and SSIM indices of the reconstructed SR images

Method	Lena	Peppers	Mandrill	Boat	Elaine
Bicubic	28.83	28.20	27.92	26.78	29.07
	0.942	0.883	0.758	0.841	0.923
EGDF[4]	21.25	20.66	20.17	19.21	18.84
	0.931	0.899	0.829	0.915	0.959
SRM[5]	28.26	27.79	27.55	26.32	28.76
	0.871	0.902	0.834	0.930	0.875
DWT-SWT[9]	33.11	32.39	30.11	29.92	34.13
	0.949	0.910	0.847	0.889	0.965
DWT-Sparse[10]	33.25	31.75	30.25	30.51	32.44
	0.941	0.905	0.851	0.940	0.973
Proposed Method	33.52	32.41	30.30	30.53	34.50
	0.950	0.905	0.862	0.943	0.965

The peak signal to noise ratio (PSNR) and the structural similarity index measure (SSIM) are applied to examine the objective quality. Table 1 shows the measured PSNR and SSIM values of various methods. Besides, Fig. 4 provides visual quality comparison of the test images Lena, Boat and Baboon. By looking at these tabulated values and figures one can notice the outstanding performance of the proposed method over the existing methods.

5. Conclusion

In this paper, we proposed an image resolution enhancement approach using sparse recovery and wavelet transformations. The proposed method uses DWT to separate the low frequency and high frequency content of an LR image, and then the high frequency subbands alone are interpolated. Besides, the sparse recovered signal tends to produce sharper output image when combined with the interpolated high frequency subbands using IDWT operation. The experimental results demonstrated the prominence of our method over the existing approaches.

References

1. P. Vandewalle, S. E. Susstrunk, M. Vetterli, Superresolution images reconstructed from aliased images, in: Visual Communications and Image Processing 2003, International Society for Optics and Photonics, 2003, pp. 1398–1405.
2. G. Suryanarayana, Sparse representation based super-resolution algorithm using wavelet domain interpolation and nonlocal means, TELKOMNIKA Indonesian Journal of Electrical Engineering 16 (2).
3. X. Li, M. T. Orchard, New edge-directed interpolation, Image Processing, IEEE Transactions on 10 (10) (2001) 1521–1527.
4. D. Zhang, X. Wu, An edge-guided image interpolation algorithm via directional filtering and data fusion, Image Processing, IEEE Transactions on 15 (8) (2006) 2226–2238.
5. J. Yang, J. Wright, T. S. Huang, Y. Ma, Image super-resolution via sparse representation, Image Processing, IEEE Transactions on 19 (11) (2010) 2861–2873.
6. W. Dong, L. Zhang, G. Shi, X. Li, Nonlocally centralized sparse representation for image restoration., IEEE Transactions on Image Processing 22 (4) (2013) 1620–1630.
7. W. Dong, D. Zhang, G. Shi, Centralized sparse representation for image restoration, in: Computer Vision (ICCV), 2011 IEEE International Conference on, IEEE, 2011, pp.1259–1266.
8. W. Dong, L. Zhang, R. Lukac, G. Shi, Sparse representation based image interpolation with nonlocal autoregressive modeling, IEEE Transactions on Image Processing 22 (4) (2013) 1382–1394.
9. H. Demirel, G. Anbarjafari, Image resolution enhancement by using discrete and stationary wavelet decomposition, Image Processing, IEEE Transactions on 20 (5) (2011) 1458–1460.11
10. H. Chavez-Roman, V. Ponomaryov, Super resolution image generation using wavelet domain interpolation with edge extraction via a sparse representation, Geoscience and Remote Sensing Letters, IEEE 11 (10) (2014) 1777–1781.