Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IMPACT FACTOR: 6.017

IJCSMC, Vol. 5, Issue. 12, December 2016, pg.82 – 85

DWT and Sparse Representation Based Image Super Resolution

Upendra Bhatt, Arti Bahuguna, Shail Ratna Bhatt

Computer Science and Engg. Department, HNBGU Srinagar Garhwal

Uttrakhand (246194)-India

Upendra.bhatt12@gmail.com, artibahuguna999@gmail.com, shailrbhatt@gmail.com

Abstract— ***Spatial resolution of images are restricted by the size of CMOS sensors. Spatial resolution can be increased by increasing no of COMS sensors resulting in decrease in size of CMOS sensors which cause shot noise. In this paper attempts have been made to enhance the spatial resolution of different images. DWT is applied to obtain the sub bands and sparse representation is used to get the better results. Bicubic interpolation is being applied in the intermediary stage and HR image is retrieved through this method and the result of this method is being compared with some other state of the art works and this work shows better result than other super resolution algorithms based on image quality parameter PSNR and MSE.***

Keywords— ***Super-resolution, DWT, Sparse representation, PSNR, MSE.***

I. INTRODUCTION

Resolution has been frequently referred as an important aspect of an image. Images are being processed in order to obtain more enhanced resolution. One of the commonly used techniques for image resolution enhancement is Interpolation. Interpolation has been widely used in many image processing applications such as facial reconstruction [1], multiple description coding [2], and super resolution [3]-[6]. There are three well known interpolation techniques, namely nearest neighbor interpolation, bilinear interpolation, and bicubic interpolation. Image resolution enhancement in the wavelet domain is a relatively new research topic and recently many new algorithms have been proposed [4]-[7] . Discrete wavelet transform (DWT) [8] is one of the recent wavelet transforms used in image processing. DWT decomposes an image into different subband images, namely low-low (LL), low-high (LH), high-low (HL), and high-high (HH). Another recent wavelet transform which has been used in several image processing applications is stationary wavelet transform (SWT) [9]. The wavelet technique as a simple sparse representation also plays a significant role in many image processing applications, in particular in resolution enhancement, and recently, many novel algorithms have been proposed [10]. In this paper DWT is used to obtain the sub bands than bicubic interpolation is applied on sub bands. Sparse representation is used to sharpen the result and finally inverse discrete wavelet is used to obtain the HR image. To compare the results of this algorithm with other algorithm PSNR and MSE is calculated which is mentioned in result and discussion section.

II. PRELIMINARIES

- ***Interpolations With Sparse Wavelet Mixtures***

The subsampled image $x(m, n)$ is decomposed with one level DWT in the LL, LH, HL, and HH image sub bands, which are treated as matrices Ψ whose columns (approximations and details) are the vectors of a wavelet image on a single scale $\{\psi d,n\}0 \le d \le 3, n \in G$. The decomposition process is performed with a dual frame matrix _Ψ whose columns are the dual wavelet frames[11]. The wavelet coefficients are written as follows:

$$z(d, n) = (x, \psi d,n) = \Psi x(m, n) \tag{1}$$

The WT separates a low-frequency (LF) image z_l (an approximation) that is projected over the LF scaling filters$\{\psi 0,n\} n \in G$ and an HF image z_h (details) that is projected over the finest scale wavelets HF in three directions $\{\psi d,n\}1 \le d \le 3, n \in G$, i.e.

$$z_l = \sum_{n \in \mathcal{G}} z(0,n)\tilde{\psi}_{0,n} \quad z_h = \sum_{d=1}^{3} z(d,n)\tilde{\psi}_{d,n}. \tag{2}$$

z_l has little aliasing and can thus be interpolated with a Bicubic interpolator V^+. z_h is interpolated by selecting directional interpolators V^+_θ for $\theta \in \Theta$, where Θ is a set of angles uniformly discretized between 0 and π. For each angle θ, a directional interpolator V^+_θ is applied a block $B = B_{\theta,q}$ that is interpolated with a directional interpolator $V^+_B = V^+_\theta$. The HF z_h and LF z_l images are interpolated with a separable and Bicubic interpolator V^+. The resulting interpolator can be written in the following form [11]:

$$X_{LL}(m,n) = V^+ z_l(m,n) + \sum_{\theta \in \Theta} \left(V_\theta^+ - V^+\right) \times \tilde{\Psi}\left(\sum_{q \in \hat{z}^\theta} \tilde{a}(B_{\theta,q}) 1_{B_{\theta,q}} z_h(m,n)\right) \tag{3}$$

For each angle θ, an update is computed over wavelet coefficients of each block of direction θ multiplied by their mixing weight $a(B_{\theta,q})$, with the difference between the separable Bicubic interpolator V^+ and a directional interpolator V^+_θ along θ. 1_B is the indicator of the approximation set B. This overall interpolator is calculated with 20 angles, with blocks having a width of 2 pixels and a length between 6 and 12 pixels depending on their orientation.

III. PROPOSED SUPER RESOLUTION METHOD

In order to increase the quality of the super resolved image, preserving the edges is essential. In this work, DWT has been employed in order to preserve the high frequency components of the image. In this correspondence, one level DWT (with Daubechies 9/7 as wavelet function) is used to decompose an input image into different subband images. Three high frequency subbands (LH, HL, and HH) contain the high frequency components of the input image. In the proposed technique, Bicubic interpolation with enlargement factor of α is applied to high frequency sub band images as shown in figure 1.

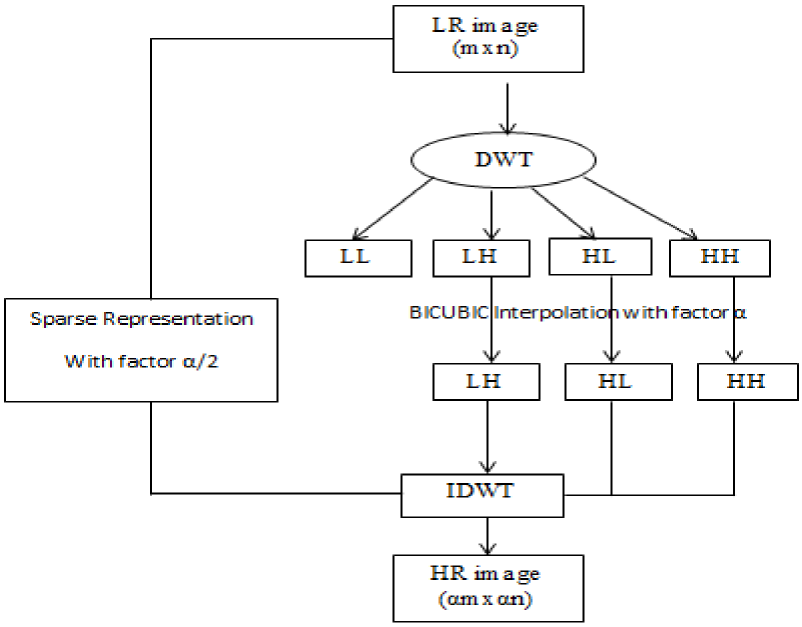

Fig. 1. DWT and Sparse based super resolution

In the proposed SR procedure, the LR image is used as the input data in the sparse representation for the resolution enhancement process in the following way (see in Fig. 1). The LR image is calculated by using a 1-D interpolation in a given direction θ and then following the computations of the new samples along the oversampled rows, columns, or diagonals. Finally, in this step, the algorithm computes the missing samples along the direction θ from the previously calculated new samples, where the entire sparse process is performed with the Bicubic interpolation (factor α/2), reconstructing the LL sub band. Finally all the high-frequency sub bands and LR which is sparsed is inputted to inverse DWT to achieve the HR image of factor α.

IV. RESULTS AND DISCUSSION

The proposed algorithm has been tested on different images like Lena, Mandrill and Pirate and the results are shown in figure 2 and table 1. Test are conducted on 128x128 size LR images and 512x512 size HR images are obtained after that PSNR and MSE has been calculated for each state-of-the-art works.

Fig.2. Super resolved images of Lena and Mandrill from 128x128 to 512x512

Table1. Quality Parameter for Proposed algorithm

SR Algorithm	Lena		Mandrill		Pirate	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
DWT-SR	34.3732	87.8782	28.7281	192.7211	31.7321	100.7371
IRSEDWT	35.6362	72.7372	30.7372	150.7382	32.7382	92.8921
CWT-SR	30.7382	156.7838	27.7282	187.8822	28.8822	109.8821
Proposed	36.7882	56.8838	32.7832	99.7882	34.6722	78.8282

V. CONCLUSIONS

This work proposed an image resolution enhancement technique based on the interpolation of the high frequency sub bands obtained by DWT then the high frequency subband images have been interpolated. An original image is interpolated with half of the interpolation factor used for interpolation with sparse representation. Afterwards all these images have been combined using IDWT to generate a super resolved imaged. The proposed technique has been tested on well-known benchmark images, where their PSNR and MSE results show the superiority of proposed technique over the conventional and state-of-art image resolution enhancement techniques.

References

[1] L. Yi-bo, X. Hong, and Z. Sen-yue, "The wrinkle generation method for facial reconstruction based on extraction of partition wrinkle line features and fractal interpolation," in Proc. 4th Int. Conf. Image Graph., Aug. 22–24, 2007, pp. 933–937.

[2] Y. Rener, J. Wei, and C. Ken, "Downsample-based multiple description coding and post-processing of decoding," in Proc. 27th Chinese Control Conf., Jul. 16–18, 2008, pp. 253–256.

[3] H. Demirel, G. Anbarjafari, and S. Izadpanahi, "Improved motion based localized super resolution technique using discrete wavelet transform for low resolution video enhancement," in Proc. 17th Eur. Signal Process. Conf., Glasgow, Scotland, Aug. 2009, pp. 1097–1101.

[4] Y. Piao, I. Shin, and H. W. Park, "Image resolution enhancement using inter-subband correlation in wavelet domain," in Proc. Int. Conf. Image Process., 2007, vol. 1, pp. I-445–448.

[5] H. Demirel and G. Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform," IEEE Geoscience and Remote Sensing Letter, vol. 7, no. 1, pp. 123–126, Jan. 2010.

[6] C. B. Atkins, C. A. Bouman, and J. P. Allebach, "Optimal image scaling using pixel classification," in Proc. Int. Conf. Image Process., Oct. 7–10, 2001, vol. 3, pp. 864–867.

[7] W. K. Carey, D. B. Chuang, and S. S. Hemami, "Regularitypreserving image interpolation," IEEE Trans. Image Process., vol. 8, no. 9, pp. 1295–1297, Sep. 1999.

[8] S. Mallat, A Wavelet Tour of Signal Processing, 2nd ed. New York: Academic, 1999.

[9] J. E. Fowler, "The redundant discrete wavelet transform and additive noise,"Mississippi State ERC, Mississippi State University, Tech. Rep. MSSU-COE-ERC-04-04, Mar. 2004.

[10] A. Temizel and T. Vlachos, "Image resolution upscaling in the wavelet domain using directional cycle spinning," J. Electron. Imaging, vol. 14, no. 4, p. 040501, 2005.

[11] S. Mallat and G. Yu, "Super-resolution with sparse mixing estimators," IEEE Trans. Image Process., vol. 19, no. 11, pp. 2889–2900, Nov. 2010.

