International Journal of Innovative Research in Computer Science & Technology (IJIRCST)
ISSN: 2347-5552, Volume-4, Issue-1, January 2016

# Single Image Super Resolution with Wavelet Domain Transformation and Sparse Representation

**Kantamani Sowmya, P. Surya Kumari, Anirudh Ranga**

***Abstract*—In this paper, we have proposed a new image resolution enhancement algorithm based on discrete wavelet transform (DWT), lifting wavelet transform (LWT) and sparse recovery of the input image. A single low resolution (LR) is decomposed into different subbands using two operators DWT and LWT. In parallel, the LR image is subjected to a sparse representation interpolation. The higher frequency sub-bands in addition to the sparse interpolated LR image are combined to give a high resolution (HR) image using inverse discrete wavelet transform (IDWT). The qualitative and quantitative analysis of our method shows prominence over the conventional and various state-of-the art super resolution (SR) techniques.**

***Index Terms*— Discrete wavelet transform, image super resolution, lifting wavelet transform, sparse representation.**

## I. Introduction

With the recent advancement of image and video imaging there is a constant need of getting a better resolution image. One promising approach is to use signal processing techniques on low resolution (LR) image(s) to achieve a HR image(s). This technique of generating a HR from a single or a multi LR images is referred as super resolution (SR). This is categorized into two form, one with input from multi source LR images with sub-pixel shift such as depicted in [1,2] and other with single LR image [3,4,5]. The work on the former has been around for a long time. The multi-frame SR suffers from the fact that it requires multiple LR input image with sub-pixel shift leading to poor image registration. This makes it an ill-posed problem, thus a regularization term is often a need but the type of prior term for regularization is an issue. These have been carefully considered in the single image version of the SR techniques.

The single image super resolution techniques are further categorized broadly into interpolation techniques, machine learning techniques and wavelet based techniques. The linear interpolation techniques like bicubic, bilinear suffer from the fact that higher frequency details are lost when magnification factor is increased leading to deprivation in edge information. Li and Orchard [6] worked on this problem and proposed a solution based on edge directed interpolation. The basic idea lies in working on geometric duality between the estimated covariance coefficients between the low resolution image and the interpolated version of the image. In spite of appreciable performance, this method of covariance-based adaptation interpolation introduces complexity. Zhang and Wu [7] further worked on enhancing the edge information by proposing a new edge guided nonlinear interpolation technique which uses directional filtering and data fusion. However owing to the complexity in estimation and computation, the research on image enhancement now focused on newer techniques like discussed below.

The second category is based on machine learning which uses a "learning step" between a HR images (like of face, fingerprint, wall etc.) and their LR counterparts. This learned knowledge is then incorporated in a priori term for the reconstruction. Notable work done by Mallat and Yu [8] focuses on adaptive estimators obtained by mixing a family of linear inverse estimators, derived from different priors on the signal regularity. The path-breaking work done by yang et al [5] is based on sparse-land local model which assumes that each patch from the LR image can be represented using a linear combinations from a dictionary. Simply, each patch is considered to be generated by multiplying a dictionary by sparse vector coefficients. However for a higher magnification factor, the results are not satisfactory.

In parallel, many techniques using wavelets decomposition operators for single image scale up problem (i.e. single image super resolution) have been around the corner for the recent times. This third category is based on enhancement using wavelet decomposition [9, 10, 11, 12]. Generally in this method, the input image is decomposed into structurally correlated sub-images which allow exploiting the self-similarities between local neighboring regions. In [12] the input image is first decomposed into subbands. Then the input image and the high-frequency subbands are both interpolated. The results of a stationary wavelet transform of the high-frequency subbands are used to improve the interpolated subbands. The super-resolved HR output is generated by combining all of these subbands using an inverse discrete wavelet transform (IDWT)

.

Manuscript received January 15, 2016.

**K Soumya**, Electronics and Communication Engineering, Godavari Institute of Engineering and Technology, Rajahmundry, India,

**P Surya Kumari**, Electronics and Communication Engineering, Godavari Institute of Engineering and Technology, Rajahmundry, India,

**Anirudh Ranga**, School of Electronics, VIT University, Vellore, India,

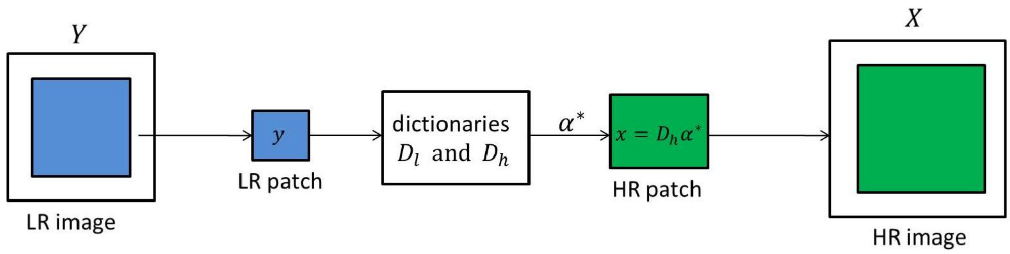


Figure 1 : Flow chart of sparse representation

However the image still persists blurriness and artifacts when the magnification factor is increased to a level of four. A new method recently developed by Roman and Ponomaryov in [13] suggest using a novel edge preservation concept for sharper image using DWT and sparse mixing estimation of the input image. Our method focuses on the concept taken up by the above authors but with modifications. In our proposed method we have not used the redundant edge preservation step rather used a lifting scheme. The lifting scheme allows one to custom-design the filters, needed in the transform algorithms, to the situation at hand. The lifting scheme builds a new wavelet, with improved properties, by adding a new basis function [14].This insures a fast in-place calculation of the wavelet transform, i.e. an implementation that does not require auxiliary memory. Another modification is in using the concept of sparse representation, developed by yang et al [5]. The proposed method is compared with the conventional and state-of-the-art methods. The qualitative and quantitative assessment shows the prominence of our method over the above mentioned methods.

## II. METHODOLOGY

### *A. Signal Recovery based on Sparse Representation*

In an image enhancement problem, given a low resolution image and we need to find its higher resolution version. This recovery is generally an ill-posed problem because there can be infinitely many solutions for a LR image to be considered a down-sampled version of its higher resolution, so a regularizer term is often required. For our case we are considering a sparse coefficient to be a regularizer. For this, suppose there exist an over-complete dictionary $D \epsilon R^{n \times K}$ having $K$ elements. Let a signal $x \epsilon R^n$ be represented as a sparse linear combination with respect to $D$. The signal $x$ can then be represented as $x = D\alpha$ where $\alpha \epsilon R^K$ is any vector with less ($\ll n$) nonzero entries. Now, since the low resolution image is considered to be a blurred and decimated version of a high resolution image so, our LR patch, $y$, can be written as a decimated version of high resolution patch. Mathematically,

$$y = Mx = MD\alpha, \quad (1)$$

where $M \epsilon R^{k \times n}$ with $k < n$ is a projection matrix which controls the decimation and blurriness factor. The equation $x = D\alpha$ is an underdetermined for the obscure coefficients α given the dictionary $D$ be an over-complete one [5]. The equation $y = MD\alpha$ is then even more underdetermined. Under mild conditions the sparsest solution $\alpha^*$ to the above equation will be unique. Further if $D$ satisfies a near-isometric condition, then any sparse representation of HR image patch with respect to dictionary $D$ can be recovered for the LR image patch. The sparse recovery process is shown in Figure 1.

**Algorithm for Sparse Recovery:**

**Input** : Take low resolution image $Y$ as input along with two training dictionaries $D_h$ and $D_l$

For 3x3 patch '$p$' of $Y$ taken in raster scan order with an overlap of one pixel , solve the optimization problem for $\alpha$

$$\alpha^* = arg\ min \lambda \|\alpha\|_1 + \frac{1}{2}\|D_l\alpha - p\|_2^2$$

place HR patch , $x = D_h\alpha^*$ in $S_o$

End

**Output** : Sparse recovered image $S_o$

In our case, we have use dictionaries trained by *yang et.al* method.

### *B. Proposed Method for SR*

In this paper, the input LR image is of resolution 128 x 128. The LR subjected to DWT operation which down samples the image leading to decomposition into several sub bands, viz., LL (Low-Low), LH (Low-High), HL (High-Low) and HH(High-High). The three higher frequency sub-bands LH, HL,HH give important information regarding horizontal, vertical and diagonal components of the image while the lower sub-band give approximate coefficient. Next, to preserve the edges and curves of the image, we have used a second generation wavelet operator LWT. It uses two dimensional Taylor series. The first order preserve the edges while the second order preserves the curves of an image. The wavelet function used for this operation is biorthogonal 1.1. To have a factor of four i.e. to enhance the resolution from 128x128 to 512x512 we used Lanczos interpolator. After applying the DWT and LWT the higher frequency subbands are added up. Since these higher sub-bands contain significant frequency components so interpolation is applied to them and not LL sub-bands.

In parallel, the LR image is applied to sparse interpolation algorithm with a factor of $A$. The algorithm used for this step has been explained in the previous section. This sparse interpolated version of input image and the three higher sub-bands are then applied IDWT. The result of this step is our super resolved image with dimension of $2A$ times

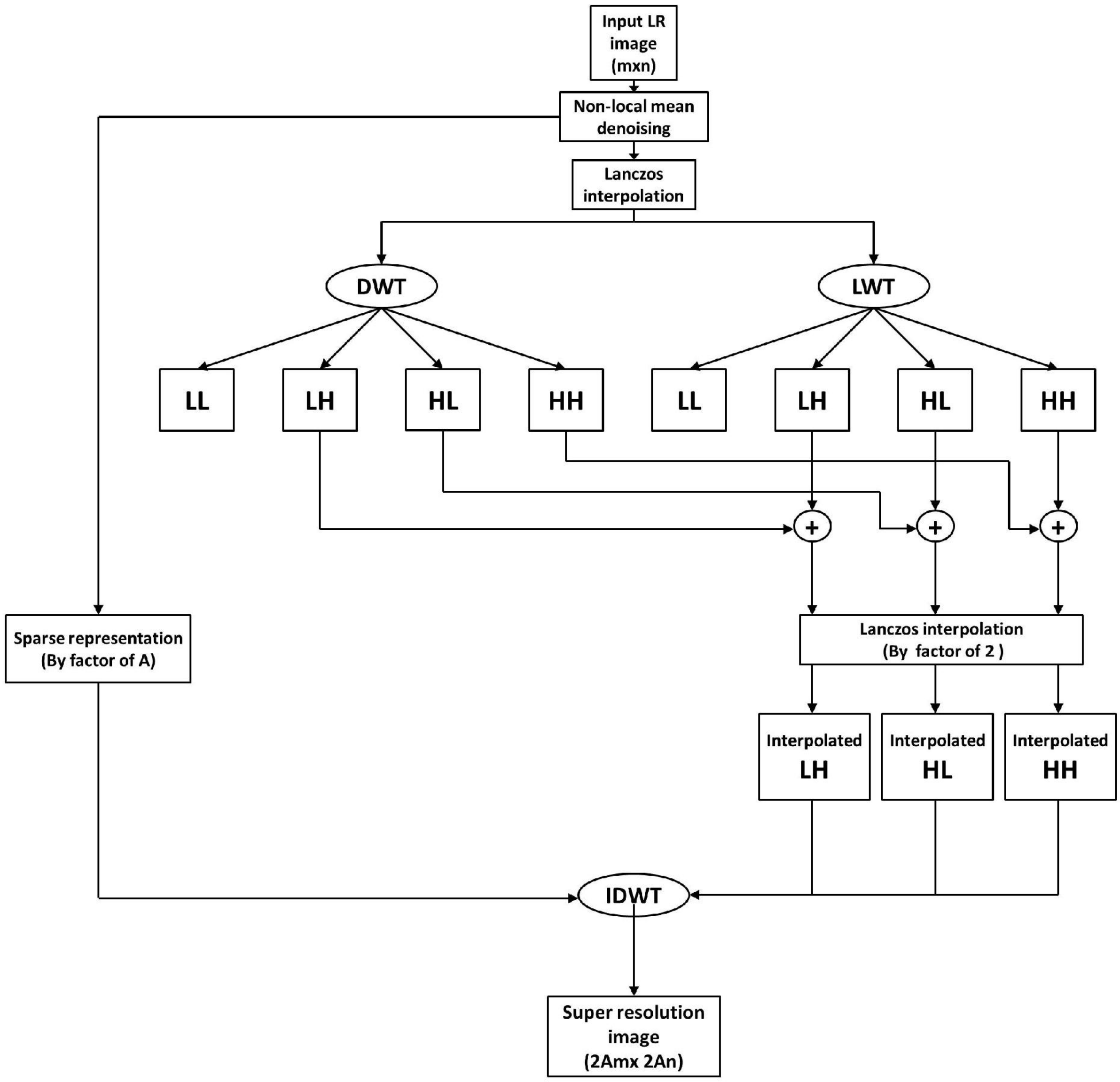


Figure 2 : Block diagram of the proposed SR algorithm

its LR version, where A is factor of sparse interpolation. The block diagram used for our proposed algorithm is shown in Figure 2.

## III. Results and Discussion

The proposed algorithm is applied on well-known gray-level test images (Boat and Elaine) and color test images (Lena, Mandrill and Pepper) obtained from the USC-SIPI image database [15]. The test images are directly down-sampled by 4 and then interpolated by others techniques. For color images interpolation steps are (i) convert the RGB to YCbCr space, (ii) interpolate the Y channel by the proposed method while Cb and Cr by basic technique like Bicubic interpolation and (iii) convert the interpolated channel back to RGB color space. We have applied our algorithm only on luminance channel because human visual system is more sensitive to luminance changes. For the proposed algorithm, the code is written in MATLAB version 12b on Intel Core 2 Duo P8600 at 2.4GHz with 4 GB of RAM PC. The wavelet function used is bior 1.1. For effective sparse recovery of the image we have used the patch size to be 3x3. The dictionaries used are pre-trained dictionaries with regularizer, $\lambda$ as 0.4.

For quantitative measurement and analysis, structural similarity index (SSIM) [16] is used here. SSIM is a full reference metric i.e. measuring the image quality by taking the initial uncompressed or distortion free image as a reference as shown in Table I. From table I, it is shown our method clearly outperforms the conventional techniques and competitive enough to the state-of-the-art techniques. In Figures 3 and 4 we show the HR images with the cropped portions of important regions from strategic point of view. From Figures 3 and 4, we see that [6] and [7] are not able remove the blur in images. The Yang's [5] and Mallat's [8] methods although give pleasant view of the results but the edges but failed to provide a ringing free output. However, the wavelet based methods of [12] and [13] are able to reduce ringing effects but could not provide satisfactory


Figure 3 – Reconstructed HR images (for magnification factor of 4) of *Lena* by different SR methods: (a) Bicubic (b) [6] (c) [7] (d) [5] (e) [8] (f) [12] (g) [13] (h) Proposed Technique

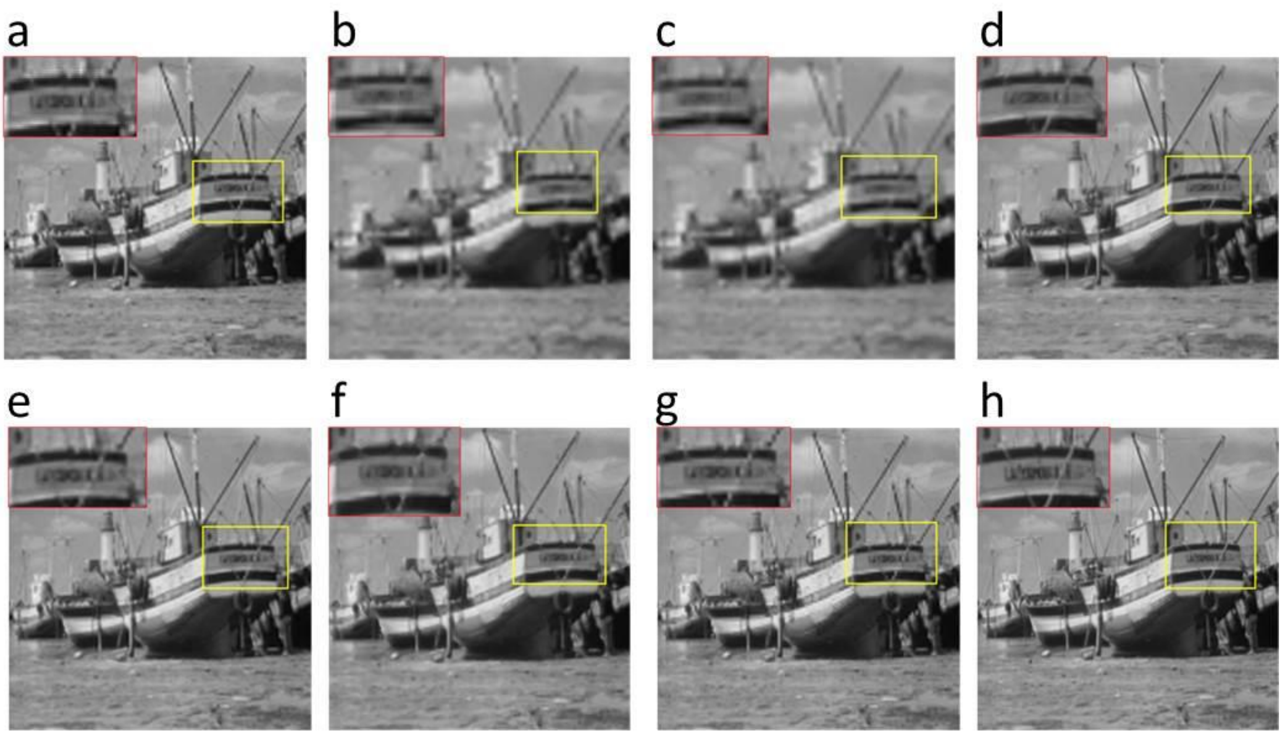


Figure 4 – Reconstructed HR images (for magnification factor of 4) of *Boat* by different SR methods: (a) Bicubic (b) [6] (c) [7] (d) [5] (e) [8] (f) [12] (g) [13] (h) Proposed Technique

**Table I**: SSIM values of standard test images for various state-of –the-art and conventional SR techniques for a resolution of 128x128 to 512x512.

| Method / Images | SSIM | | | | | |
|---|---|---|---|---|---|---|
| | **Lena** | **Mandril** | **Pepper** | **Boat** | **Elaine** | ***Average*** |
| Bilinear | 0.812 | 0.779 | 0.885 | 0.852 | 0.902 | 0.846 |
| Bicubic | 0.821 | 0.786 | 0.883 | 0.839 | 0.913 | 0.848 |
| [6] | 0.743 | 0.732 | 0.897 | 0.910 | 0.919 | 0.840 |
| [7] | 0.712 | 0.767 | 0.899 | 0.918 | 0.911 | 0.841 |
| [5] | 0.801 | 0.804 | 0.912 | 0.911 | 0.920 | 0.869 |
| [8] | 0.934 | 0.857 | 0.900 | 0.929 | 0.924 | 0.908 |
| [12] | 0.940 | 0.831 | 0.910 | 0.932 | 0.939 | 0.910 |
| [13] | 0.921 | **0.899** | 0.920 | 0.941 | 0.958 | 0.927 |
| **Proposed** | **0.961** | 0.859 | **0.924** | **0.956** | **0.960** | **0.932** |

results in areas of sharper edges (for example in fig 3-f,3-g, fig 4-f,4-g.). Our method not only reduces the ringing effect but also able to enhance the sharp edges information as evident from Figures 3-h and 4-h.

## IV. CONCLUSION

In this paper, we have developed an effective image enhancement technique using concept of sparse recovery and wavelet transformations. The input image is decomposed into different subbands using DWT. Since using DWT decimates an image and loss in high frequency components, so we have used a second generation wavelet transformer LWT, whose first derivative preserves the edges and second take care of the curves present in the image. Then, the higher frequency components are added up. In parallel, we sparsely recover the input image with an interpolation factor of two. The three higher subbands and the sparse recovered image is applied to IDWT and finally to a reconstruction based algorithm to give a super resoled image. This method is applied on five well known test images and the experimental results shows prominence over traditional and other state of the art techniques.

## REFERENCES

[1] T. S. Huang and R. Y. Tsay. "Multiple frame image restoration and registration". In Advances in Computer Vision and Image Processing, volume 1, pages 317-339, 1984.

[2] S. Lertrattanapanich and N. Bose. "High resolution image formation from low resolution frames using delaunay triangulation". IEEE Transactions on Image Processing, Volume11 Number 12 :1427-1441, December 2002.

[3] X. Gao, K. Zhang, D. Tao, and X. Li. "Joint learning for single-image super-resolution via a coupled constraint". IEEE Transactions on Image Processing, Volume-21 Number 2 : 469- 480, February 2012.

[4] S. Dai, M. Han, W. Xu, Y. Wu, Y. Gong, and A. Katsaggelos. "Softcuts: A soft edge smoothness prior for color image super-resolution". IEEE Transactions on Image Processing, Volume-18 Number-5:969-981, May 2009.

[5] J. Yang, J. Wright, T. S. Huang, and Y. Ma. "Image super-resolution via Sparse Representation". IEEE Transactions on Image Processing, Voluem-19 Number-11 : 2861-2873, November 2010.

[6] X. Li and M. T. Orchard, "New edge-directed interpolation," IEEE Transactions on Image Processing ,Volume 10, 1521–1527, October 2001

[7] L. Zhang and X. Wu, "An edge-guided image interpolation algorithm via directional filtering and data fusion," IEEE Transactions on Image Processing, volume 15, 2226-2238, August 2006

[8] S. Mallat and G. Yu, "Super-resolution with sparse mixing estimators," IEEE Transactions Image Processing, volume-19, Number-11, 2889–2900, Nov. 2010.

[9] Y. Piao, I. Shin, and H. W. Park, "Image resolution enhancement using inter-subband correlation in wavelet domain," in Proceedings International Conference on Image Processing , volume 1, 445–448, 2007

[10] H. Demirel and G. Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform," IEEE Geoscience and Remote Sensing Letter, volume 7, number 1, 123–126, January 2010.

[11] C. B. Atkins, C. A. Bouman, and J. P. Allebach, "Optimal image scaling using pixel classification," in Proc. International Conference on Image Processing, volume 3, 864–867 ,October 7–10, 2001

[12] Hasan Demirel and Gholamreza Anbarjafari, "Image Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition", IEEE Transactions on Image Processing volume-20, Number- 5, 1458-1460, May 2011.

[13] Herminio Chavez-Roman and Volodymyr Ponomaryov, "Super Resolution Image Generation Using Wavelet Domain Interpolation With Edge Extraction via a Sparse Representation" , IEEE Geoscience and remote sensing Letters ,volume-11, Number- 10 , 1777-17781, May,2014.

[14] Sweldens W, "Wavelets and the Lifting Scheme: A 5 Minute Tour," International Journal ZAMM Zeitschrift fur Angewandte Mathematik und Mechanik, Volume -76, Number- 2, 41-44 , 1996.

[15] A. Weber, USC-SIPI Image Database. [Online] Available: http://sipi.usc.edu/database/database.php

[16] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity", IEEE Transactions on Image Processing, Volume-13, Number-4, 600-612, 2004

**K. Soumya** received B.Tech degree in electronics and communication engineering from Sri Prakash College of Engineering, India, in 2013. Currently, she is pursuing M.Tech in digital electronics and communication systems, Godavari Institute of Engineering and Technology, India. Her research interests are in signal and image processing.

**P. Surya Kumari** is currently working as an assistant professor in ECE department, Godavari Institute of Engineering and Technology, India. Her research interests include signal processing, image processing and mathematical modeling.

**Anirudh Ranga** received M.Tech degree in school of electronics from VIT University, Vellore, India, in 2015.