

Image Resolution Enhancement using Multi Resolution Wavelet Transformations

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Abstract— In this paper an image resolution enhancement technique for Additive White Gaussian Noise (AWGN) removal is verified aiming high resolution image output. In image resolution enhancement, the main loss is on its high frequency components (i.e., edges), which is due to the smoothing caused by interpolation. In order to increase the quality of the super resolved image, preserving the edges is essential. In this work, Discrete Wavelet Transform (DWT) has been employed in order to preserve the high frequency components of the image. Along with DWT, un-decimated wavelets transform, Stationary Wavelet Transform (SWT) for image decomposition and restoration. For signal mixing techniques like bilinear and bicubic interpolation were adopted. In the process, the modified noise minimized high frequency sub bands of DWT and SWT are interpolated with the average band of the image. The resultant image then made to undergo inverse DWT for restoration of denoised image. The proposed method is verified with MATLAB simulations and the experimental results confirms high resolution of image and been verified with Peak Signal to Noise Ratio (PSNR). The proposed method is superior with PSNR when compared with other state of the art methods.

Index Terms— Additive White Gaussian Noise; Discrete Wavelet Transform; Image quality; Peak Signal to Noise Ratio; Stationary Wavelet Transform.

1. INTRODUCTION

Many algorithms and techniques for image super resolution have been suggested in the literature. A new wrinkle generation method for facial reconstruction based on extraction of partition wrinkle line features and fractal interpolation was proposed by [1], but it failed in smooth regions. Few sample coding for feature description [2] has been proposed it was indeed useful for post processing operative feature extractions. A new improved motion based localized super resolution technique using DWT for low resolution video enhancement was proposed by [3], but it was not found superior for color video signals. A conventional inter sub band correlation with wavelet domain for image resolution enhancement was developed [4]. Similarly, using pixel classification optimal image scaling was developed [6]. An improved approach of image resolution using Complex Wavelet Transform (CWT) was introduced by [5], and was very innovative. A redundant approach using DWT was introduced [7], but consumed more memory. Still many other [8-10] methods came into existence for image super resolution using wavelet domain. From the literature survey it is clear that, super resolution of image is essential and can be done using wavelet transforms. In this present scheme, both DWT and SWT are utilized for super resolution as a new approach.

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2. METHODOLOGY

The proposed system for image denoising corrupted by AWGN is built based on discrete wavelet transform and stationary wavelet transform. In this following section the theoretical background of DWT and SWT is introduced.

2.1. Discrete Wavelet Transform

Nowadays, wavelets have been used quite frequently in image processing. They have been used for feature extraction, denoising, compression, face recognition, and image super-resolution. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by “intrinsic deformations” or “extrinsic factors” into certain sub-bands. This process results in isolating small changes in an image mainly in high frequency sub-band images. Hence, discrete wavelet transform (DWT) is a suitable tool to be used for designing a classification system. The 2-D wavelet decomposition of an image is performed by applying 1-D DWT along the rows of the image first, and, then, the results are decomposed along the columns. This operation results in four decomposed sub-band images referred to as low-low (LL), low-high (LH), high-low (HL), and high-high (HH). The frequency components of those sub-band images cover the frequency components of the original image as shown in Fig.1. Clear decomposition steps of DWT are shown in Fig.3 where, the signal is denoted by the sequence CA_j , where A_j is an integer. The low pass filter is denoted by Lo_D while the high pass filter is denoted by Hi_D . At each level, the high pass filter produces detail information, while the low pass filter associated with scaling function produces coarse approximations. At each decomposition level, the half band filters

produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half.



Fig.1 Result of 2-D DWT

2.2. Stationary Wavelet Transform

The SWT was independently developed by several researchers and under different names, e.g. the un-decimated wavelet transform, the invariant wavelet transform and the redundant wavelet transform. The key point is that it gives a better approximation than the discrete wavelet transform (DWT) since, it is redundant, linear and shift invariant. These properties allow SWT to be realized using a recursive algorithm. Fig.2 shows the computation of the SWT of a signal $x(k)$, where W_{jk} , and V_{jk} are called the detail and the approximation coefficients of the SWT. The filters H_j and G_j are the standard low pass and high pass wavelet filters, respectively. In the first step, the filters H_1 and G_1 are obtained by up sampling the filters using the previous step (i.e. $H_j - 1$ and $G_j - 1$).

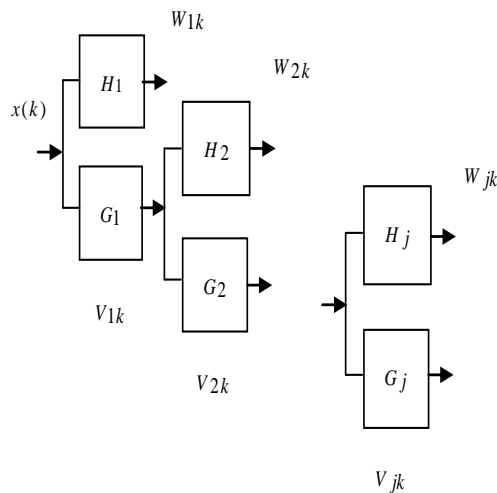


Fig.2. Stationary Wavelet Transform

SWT has equal length wavelet coefficients at each level. The computational complexity of SWT is $O(n^2)$. The redundant representation makes SWT shift-invariant and suitable for applications such as edge detection, denoising and data fusion. The functional process of SWT decomposition is shown in Fig.4.

2.3. Inverse Discrete Wavelet Transform

To reconstruct the discrete wavelet coefficients into the original signal, inverse DWT is utilized. In the process, the DWT coefficients are first up sampled (the approximation and the detail coefficients are handled separately) by placing zeros in between every coefficient, effectively doubling the lengths of each. These are then convolved with the reconstruction scaling filter for approximation coefficients (the reconstruction scaling filter is simply the original scaling filter that has been flipped left to right) and the reconstruction wavelet filter for the detail coefficients. These results are then added together to arrive at the original signal. The DWT coefficients are made periodic before convolving to obtain the original signal. This is done by simply taking the first $N/2-1$ coefficients from the DWT coefficients, and appending them to the end considering that, N is the length of our scaling filter. After the convolution and addition, to grab the part of the signal away from the convolution 'junk', the coefficients are grabbed from N to the length of the signal $N - 1$ which will provide the original signal.

3. PROPOSED METHOD

The functional block diagram of the proposed method for image resolution enhancement is depicted in Fig.5 and the functional algorithm can be summarized as

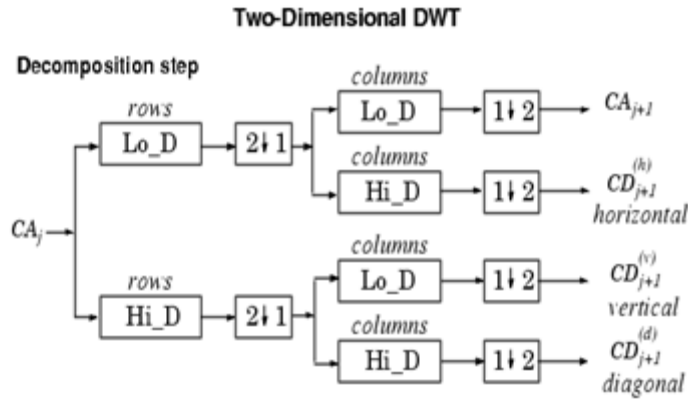
Step 1: A low resolution input image is decomposed at one level into four sub bands (LL, LH, HL & HH) with both DWT and SWT respectively. For the process Daubechies 9/7 is considered as wavelet function.

Step 2: The resultant higher sub bands of DWT is interpolated with resultant higher order sub bands of SWT with a factor of 2 to produce new estimated LH, HL and HH. For the process, bicubic interpolation with enlargement factor of 2 is applied.

Step 3: The resultant modified higher order sub bands are in-turn interpolated with the original low resolution image itself and made to undergo inverse DWT to recover the super resolution image.

The operative facts on the above methods can be summarized as:

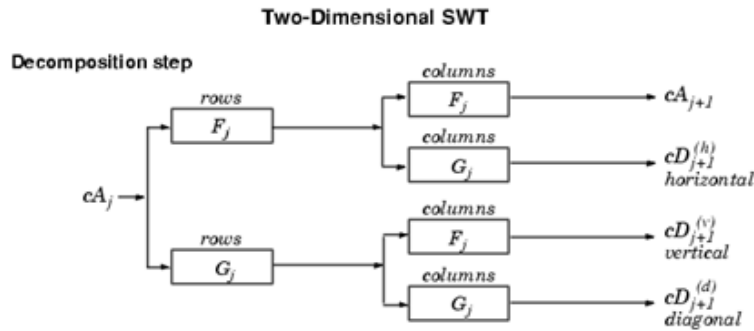
1. Down sampling in each of the DWT sub bands causes information loss in the respective sub bands. An un-decimated transform like SWT is employed to minimize this loss.



Where $\begin{matrix} \boxed{2 \downarrow 1} \end{matrix}$ Downsample columns: keep the even indexed columns
 $\begin{matrix} \boxed{1 \downarrow 2} \end{matrix}$ Downsample rows: keep the even indexed rows
 $\begin{matrix} \text{rows} \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry
 $\begin{matrix} \text{columns} \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry

Initialization $cA_0 = s$ for the decomposition initialization

Fig.3. A 2-D DWT functional process.



where $\begin{matrix} \text{rows} \\ \boxed{X} \end{matrix}$ Convolve with filter X the rows of the entry
 $\begin{matrix} \text{columns} \\ \boxed{X} \end{matrix}$ Convolve with filter X the columns of the entry

Initialization $cA_0 = s$ for the decomposition initialization

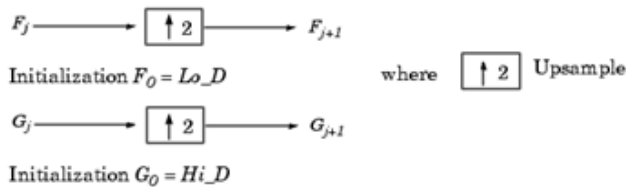


Fig.4. A 2-D SWT functional process.

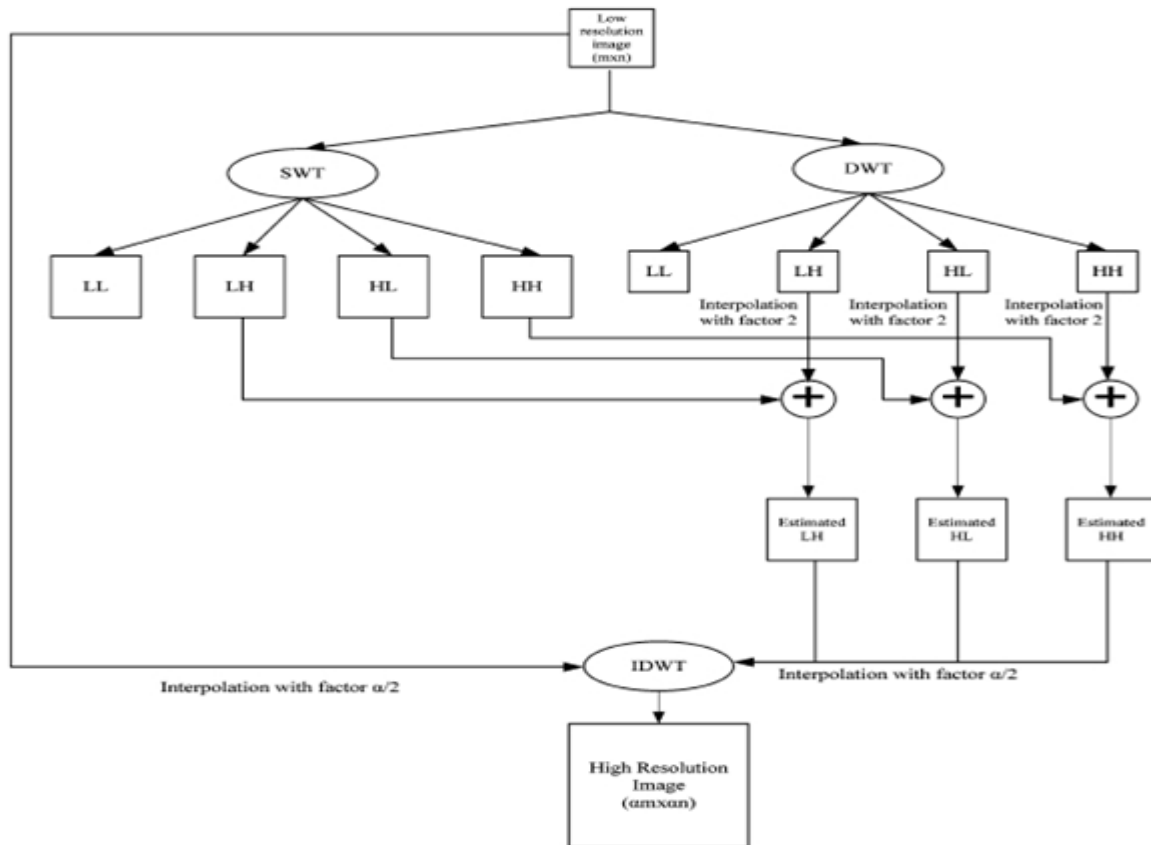


Fig.5 Functional block diagram of the proposed method.

2. The interpolation of DWT and SWT higher order bands are always possible since the size of the DWT and SWT decomposed signals are equal.
3. Also from literature of wavelet domain we could say, the low resolution image is obtained by low pass filtering of high resolution image. So, instead of using low frequency sub band, which contains less information than the original high resolution image, in the process input image itself is used for final interpolation. This change enables and increases the quality of the super resolved image. Thus the final output image contains sharper edges.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed method is been evaluated using the Peak Signal to Noise Ratio (PSNR). PSNR is the quality measurement between the original image and the reconstructed image which is calculated through the Mean Squared Error (MSE). The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The MSE and PSNR are derived using Equations (1.1) and (1.2) respectively.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M \times N} \quad (1.1)$$

$$PSNR = 10 \log_{10} \left[\frac{R^2}{MSE} \right] \quad (1.2)$$

The decomposition results of Lena test image of DWT and SWT are presented in Fig.6 and Fig.7 respectively.

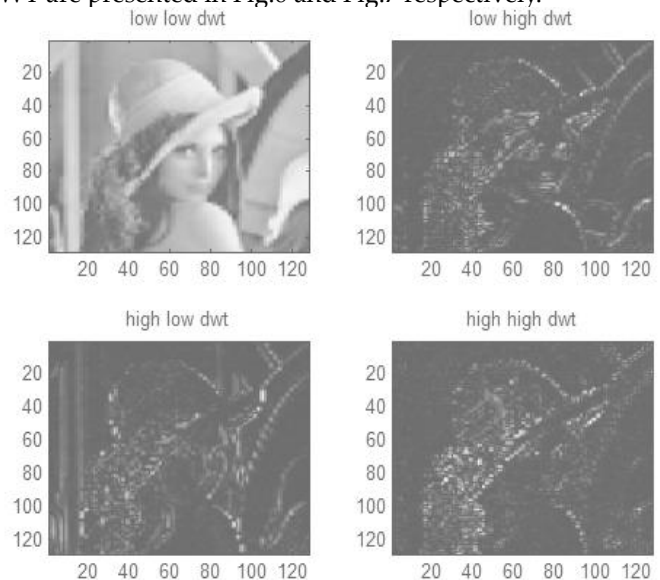


Fig.6 Result of 2-D DWT decomposition at level 1

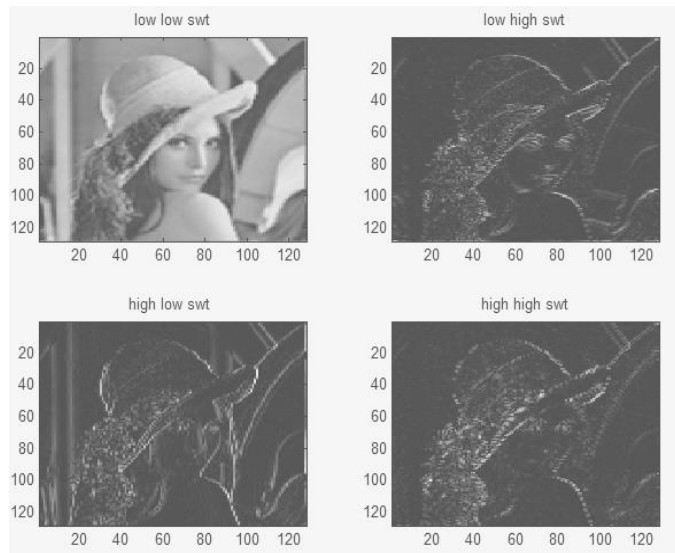


Fig.7 Result of 2-D SWT decomposition at level 1

Table.1 gives comparative PSNR values derived with various standard test images, between the proposed method with other state of the art super resolution methods using Bilinear, Bicubic and Zero padding techniques respectively. The schematic of the same is depicted in Fig.8 for easier visual comparison. Fig.9 gives the visual quality comparison of the Lena test image of the proposed method compared with other state of the art methods. The proposed method gives approximately 7.29 dB increase when compared to conventional bilinear super resolution technique, and with respect to bicubic and zero padding techniques the proposed advances with 5.825 dB and 3.4 dB respectively. From the PSNR values and visual quality comparisons it is observed that the proposed method for image super resolution is superior and scope full. This proposed method has huge scope for improvement in code optimization and memory space management.

5. CONCLUSIONS

This work proposed an image resolution enhancement technique based on the interpolation of the high frequency sub bands obtained by DWT and SWT, correcting the high frequency sub bands and further interpolating with half factor of original image. The proposed method is tested with well-known benchmark images, and the obtained PSNR confirms that, the proposed method is superior with both parametric and visual quality when compared to other state of the art methods.

6. REFERENCES

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Table.1 PSNR of the proposed method with various test images

Technique / Image	Lena	Elaine	Baboon	Peppers	Boatman	Football	Woman dark hair	<i>Average</i>
Bilinear	26.34	25.38	20.51	25.16	25.9	20.28	25.03	23.93
Bicubic	26.83	28.93	20.61	25.66	29.45	20.38	25.53	25.31
Zero Padding	28.84	30.44	21.47	29.57	30.96	21.24	29.44	27.09
Proposed method	29.74	31.45	29.32	30.45	31.97	29.09	30.32	30.34

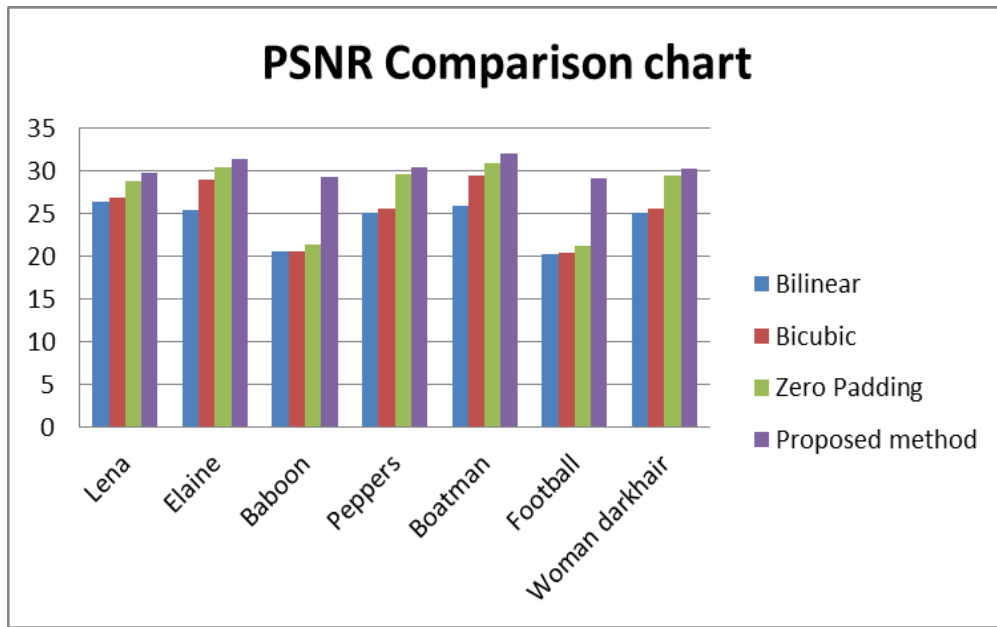


Fig.8 PSNR Comparison of proposed method VS. Other state of the art techniques



Fig. 9 Visual quality comparison of the proposed method tested with Lena gray scale image of size 128 x 128. From left to right: low resolution input, Bilinear, Bicubic, Zero padding, proposed method output.