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Super Resolution of Medical Reconstructed Image Using Wavelet Transform

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Abstract — **Super resolution of the image is the process of obtaining high resolution image from low resolution image. Recently wavelet transform has been used in super resolution reconstruction for the analysis of the 2-D signal and is preferred on the other transforms such as Discrete Fourier Transform. Equally, any enhancement on the wavelet transform is added to the super resolution reconstruction. Therefore, we will deal the stationary wavelet transform (SWT), which has translation invariants property and computational complexity between (DWT) and (CWT). Shepp-Logan image of the medical image analyses, has taken, of size (256) which has down sampled from size (512) using Bicubic interpolation, where the anti-aliased filter has used before down sampling process to use it as the input image to the algorithm to enlarge it to the output of the size (512) pixels. The results show increasing the PSNR of the magnified image with respect to the original high resolution image. Where we has used the DWT and LWT with SWT and using the directional interpolation ICBI, DCC ,the results has listed in tables and figures.**

***Keywords*— Wavelet transform, Super resolution, interpolation, Edge directional interpolation, SWT, LWT, DWT, FIR filter ,DCC,ICBI.**

***Abbreviations:* SWT (Stationary Wavelet Transform) , LWT (Lifting Wavelet Transform) , DWT (Discrete Wavelet Transform), HF (High Frequency), LF (Low Frequency). PSNR (Peak Signal to Noise Ratio).CWT (Continuous Wavelet Transform).LR(Low Resolution),HR(High Resolution)**

I. INTRODUCTION

Wavelet transform is used by many researchers to achieve super resolution of the image[1][2][3][4][5][6][7][8]. The function of Wavelet transform is to disassemble signals of image and it has been used in image analysis. The original image contains LF component and aliased high frequency component so the decomposition level may obtain the fine resolution of high frequency component and edges texture. This is much important to obtain all HR component. So the interpolation is used in this transform to enhance or remove any frequency that enforce the blurring or any artifacts. This can be done in various algorithms which resolutions are different from one to one, and interpolation is achieved then fusing of the chosen sub bands that leading to large signal to noise ratio[9].

Wavelets functions $\psi(x)$ are defined over a finite interval and having an average value of zero. The basic idea of the wavelet is to represent any arbitrary function of time as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts) [10][11].

The wavelet are designed to give good time resolution and poor frequency resolution of high frequencies, and good frequency resolution and poor time resolution at low frequencies .This function is called scaling function (mother function) $\varphi(x)$,and under certain conditions which is the properties of the wavelet function the wavelet function can be generated as[12] :

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k b_k \, \varphi(2x-k)$$

$$= \sum_{k=-\infty}^{\infty} (-1)^k a_{1-k} \, \varphi(2x-k) \qquad (1)$$

The DWT is generated by sampling the wavelet parameters a_k, b_k on a grid or lattice. The reconstruction of the signal from its transform values naturally depends on the coarseness of the sampling grid[13].

A fine grid mesh would permit easy reconstruction, but with evident redundancy, i.e., oversampling. A too-coarse grid could result in loss of information[14].

The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two, as in equation below:

$$y[n] = (x * g) = \sum_{k=-\infty}^{+\infty} x[k]g[n-k] \quad (2)$$

The filter outputs down-sampled by 2, and the following equations describe the decomposition process of x[k] according to filters g and h impulse response:

$$y_{low}[n] = \sum_{k=-\infty}^{+\infty} x[k].g[2n-k] \qquad (3)$$

$$y_{high}[n] = \sum_{k=-\infty}^{+\infty} x[k].h[2n-k] \quad (4)$$

DWT decomposes an image into different sub band images; namely, average (LL), vertical (HL), horizontal (LH) and diagonal (HH) information and we have tested the SWT with the following methods as follows:

A. *DWT and SWT:*

Figure 1 uses the SWT which does not down sample the LR image as in DWT, hence the loss of HF which occurs in the DWT is compensated:

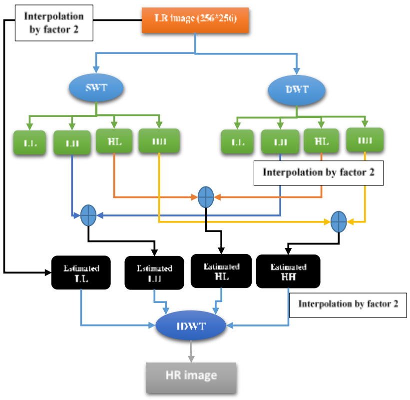

Fig. 1 SWT and DWT

B. *LWT and SWT:*

The lifting of the wavelet transform (LWT) is used to decompose the second generation wavelet, which basis function is called 'lazy wavelet'. It has the formal property of wavelet, and which are not necessarily translates and dilates of one function. The latter we refer to as first generation wavelets, the lifting wavelet transform does not need auxiliary memory, but it just replaces the wavelet transform. This lifting scheme is a new basis wavelet function added to build a new wavelet. [15] .

Lifting is a transform, which uses two operations in the decomposition; these are the update, and differences. As can be seen, the splitting of the even and odd samples is to predict the correlation between consecutive samples (even and odd) which result has no difference if it is equal. Similarly, the update gives the mean to the output sj-1 while the predict gives the gradient to the dj-1 output value [16]. See Fig.2:

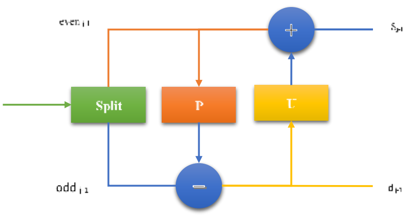

Fig. 2 LWT block diagram

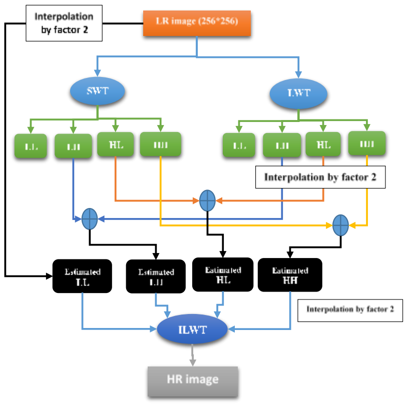

Fig. 3 LWT and SWT

In Fig.3, the SWT does not down sample the input LR image and the LWT does the down sampling of the input image that causes a loss of HF component. This is compensated by SWT by adding the HF component to the decomposition of LWT.

But the LWT in super resolution uses the directional interpolation to achieve fine results, therefore, we limit the result on how we use the interpolation in LWT and the reconstruction of it, also, we present the results of the DWT and DWT&SWT and the result of the FIR filter in the case of DWT&SWT in the tables illustrated, and we present the other results in the form of figures with different reconstruction options.

II. FIR FILTER FOR SWT AND DWT:

The FIR filter has been used in the image processing due to linear phase characteristics and any filters with non-linear phase can introduce artifacts that are visually annoying. The linear-phase FIR filter has been classified into four basic types as in Table 1 below:

TABLE 1 FIR FILTERS TYPES

Type	Impulse response	
I	symmetric	Length is odd
II	symmetric	Length is even
III	Anti-symmetric	Length is odd
IV	Anti-symmetric	Length is even

The chosen filter length N=35 is less than the all input samples and symmetric type I is convenience as a low pass filter. The use of the hamming window in time domain is to design FIR filter by convolving with 0.5 amplitude *sinc* function to reduce the Gibbs ripples and reduce the side loop amplitude but the disadvantage is the increasing in the transition width.

The test of the medical image used (Shepp-Logan) of size (512 × 512) filtered using anti-aliased filter, and then down sampled to (256× 256) in Bicubic interpolation to gives the input low resolution image [17] , see Fig.8 and Fig.9:

Fig. 8 Shepp- Logan low resolution image size (256× 256)

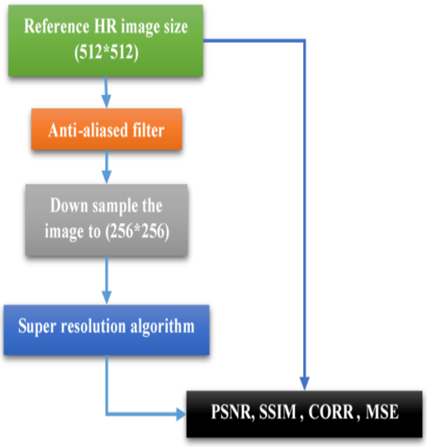

Fig.9 LR image measurement

III. Discussion of the results:

The results are placed in two parts where the highly differences have been placed in the form of figures and the little differences have been placed in the form of tables of PSNR, Mean Square Error(MSE), Correlation ,and Structure Similarity Measurement(SSIM). The results of using FIR filter with various nonlinear interpolation methods increased the quality of the medical image as seen in the tables 2, 3, 4:

Table 2 Discrete Wavelet Transform

	PSNR	PSNR (db)	SSIM	MSE	CORR
Nearest	18.8168	29.3475	0.9030	0.0131	0.8593
Bilinear	23.9074	31.7419	0.9295	0.0041	0.9562
Bicubic	24.8367	32.1232	0.9324	**0.0033**	0.9635
Box	24.1001	31.8222	**0.9388**	0.0039	0.9566
Triangle	24.0506	31.8016	0.9317	0.0039	0.9574
Lanczos2	24.8382	32.1238	0.9324	**0.0033**	0.9635
Lanczos3	24.7458	32.0865	0.9199	0.0034	0.9628
Spline	**24.8504**	**32.1287**	0.9328	**0.0033**	**0.9636**
Makima	24.7802	32.1005	0.9345	**0.0033**	0.9630

Table 3

DWT and SWT

	PSNR	PSNR (db)	SSIM	MSE	CORR
Nearest	18.9862	29.4371	0.9015	0.0126	0.8686
Bilinear	23.6013	31.6130	0.9283	0.0044	0.9528
Bicubic	24.4631	31.9717	0.9307	0.0036	0.9601
Box	23.7044	31.6566	**0.9377**	0.0043	0.9525
Triangle	23.6013	31.6130	0.9283	0.0044	0.9528
Lanczos2	24.4532	31.9676	0.9309	0.0036	0.9600
Lanczos3	24.2487	31.8836	0.9147	0.0038	0.9584
Spline	24.2192	31.8714	0.9251	0.0038	0.9578
Makima	**24.5016**	**31.9874**	0.9331	**0.0035**	**0.9606**

Table 4

FIR filter enhancement of DWT&SWT

	PSNR	PSNR(db)	SSIM	MSE	CORR
Nearest	19.2541	29.5772	0.9014	0.0119	0.8709
Bilinear	23.9085	31.7423	0.9295	0.0041	0.9562
Bicubic	24.8451	32.1266	0.9323	**0.0033**	0.9635
Box	24.5438	32.0046	**0.9420**	0.0035	0.9609
Triangle	24.0516	31.8020	0.9317	0.0039	0.9575
Lanczos2	24.8471	32.1274	0.9323	**0.0033**	0.9636
Lanczos3	24.7576	32.0913	0.9201	**0.0033**	0.9629
Spline	**24.8588**	**32.1321**	0.9327	**0.0033**	**0.9637**
Makima	24.7883	32.1037	0.9344	**0.0033**	0.9631

We have seen in the tables 2, 3, 4 the Makima interpolation outperforms others interpolations used in DWT in MSE and CORR, PSNR, but less than in SSIM value of Box interpolation. The spline interpolation has preferred in the case of DWT &SWT and FIR filter and the Box is more than in SSIM than other methods. Moreover, the lifting wavelet transform , in which the DCC [18] (Directional Cubic Convolution) interpolation and ICBI [19] (Iterative Curvature Based Interpolation) is used to achieve the finer result for the super resolution image .As seen in the table below:

Table 5

Lifting Wavelet Transform

LWT	DCC Haar	DCC db2	ICBI Haar	ICBI db2
PSNR	**21.695**	20.9399	21.6621	21.6875
PSNR (db)	**30.7710**	30.4166	30.7557	30.7674
MSE	**0.00676**	0.0081	0.0068	0.0068
SSIM	**0.90387**	0.8822	0.8988	0.8658
CORR	0.92489	0.9111	0.9240	**0.9252**

Likewise, the ICBI and DCC uses the local derivative weighting interpolation to achieve the interpolation in the same direction of edges.

The results state that 'Haar' wavelet with DCC (Directional Cubic Convolution) outperform the other methods in all measurement except the correlation between the two images. Where the ICBI with 'db2' wavelet gives the higher value in Correlation (**0.9252**). The nonlinear interpolations does not work with the lifting wavelet transform, as it gives bad image reconstruction in all measurements. Therefore, we have used the edge interpolation above to achieve the LWT super resolution with the result stated above.

The other results have illustrated in Figures (9, 10), in which lifting wavelet reconstruction with SWT has been used, as seen in figures (9, 10), where the difference with the original image illustrated has different colour and compared with Fig.11 which show the DWT and SWT output image. Fig 12, 13 is the output image of the FIR filter and Fig.14 uses the Bicubic interpolation only:

Fig. 9 LWT&SWT, DCC

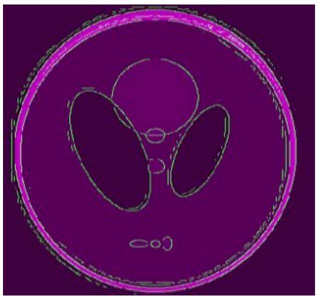

Fig. 10 LWT & SWT, ICBI

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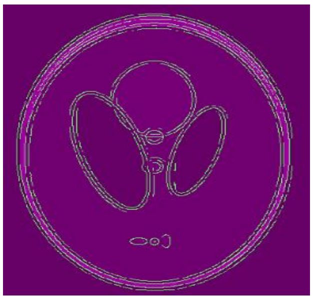

Fig. 11 DWT& SWT

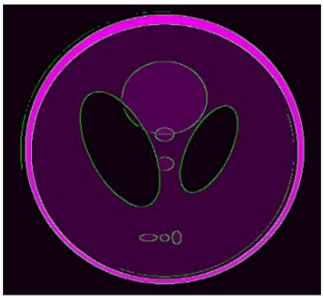

Fig. 12 DWT & SWT FIR DCC

Fig. 13 DWT &SWT, ICBI ,FIR

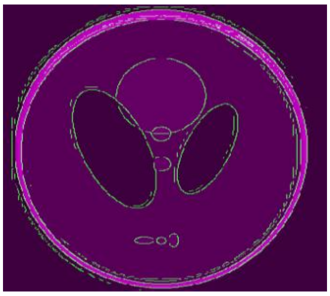

Fig. 14 Bicubic Only

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