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Signal Estimation & Reproduction In Frequency Domain Using Tunable Q-Factor Wavelet Transform

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ABSTRACT

The present patterns and development in communication and digitization builds the importance of signal and image processing concepts. This paper concentrates on former one i.e., signal processing, and mainly concentrates on receiver section in planning and actualizing the channels to recuperate the information with less measure of noise or with high SNR. In this paper, rather than processing the time domain data, spectral data nothing but frequency domain processing is executed on the approximate coefficients produced with the backing of Tunable Q-Factor Wavelet Transform [TQWT].

Keywords: Denoising, Custom Thresholding, Tunable Q-Factor Wavelet Transform [TQWT], Frequency Domain Processing and Dual Tree Complex Wavelet Transform.

I. INTRODUCTION

Processing and retaining a signal which is corrupted by unwanted entities nothing but noise has been vital to various pros for sensible and furthermore theoretical reasons. The main requirement of any signal processing scheme is to retaining majority of its critical properties (e.g. smoothness) with least error. Conventional de-noising plans depend on linear methods, as of late, nonlinear techniques, particularly those dealing with wavelets have increased their importance. Recently, many shrinkage functions are planned and changed for higher noise reduction [2-9].

One of the most punctual papers in the field of noise removal using wavelet transform[10]. They demonstrated that by utilizing wavelet-thresholding, the noise could be essentially decreased without diminishing the edge sharpness [10]. Standard Discrete Wavelet Transform DWT, being non-redundant is a great tool for some non-stationary signal preparing applications; however it experiences few noteworthy confinements. To diminish these confinements, numerous scientists grew real-valued expansions to the Discrete Wavelet Transform DWT. Complex wavelet Transform (CWT) is likewise a substitute, complex-valued augmentation to the Discrete Wavelet Transform. The underlying inspiration driving the advancement of CWT was to benefit unequivocally both magnitude & phase data. Wavelet procedures are effectively connected to different issues in signal and image processing applications. Signal compression, motion estimation, texture synthesis, segmentation, classification and denoising are just a few illustrations. Be that as it may, the fundamental issue with CWT lies in designing of filters banks.

In this paper, denoising of signals using CWT is treated as existing algorithm, which requires more computational power. So, to avoid complexities in this works, a much simpler concept is used for noise removal. The 'Tunable Q-Factor Wavelet Transform TQWT' is a flexible fully-discrete wavelet transforms. This concept is treated as proposed algorithm in this work.

This paper combines TQWT with custom Thresholding for Denoising of frequency domain signals. Since frequency domain analysis is better for noise removal[1].

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II. EXISTING METHOD

The major cons of DWT are shift invariant and selectivity can be overcome by the refinements made in dual tree complex wavelet transform (CWT) with supplementary properties. A real/complex signal will be decomposed in to approximate and detail coefficients with facilitate of analytic filters based mostly complex wavelet transform. Utilizing the obtained coefficients one can cipher amplitude and phase knowledge, which is sufficient to narrate the energy restricted to particular place.

The Fourier transform relies on complex-valued periodic sinusoids $e^{j\Omega t} = \cos(\Omega t) + j\sin(\Omega t)$. The corresponding complex-valued scaling function and complex-valued wavelet is given as

$$\psi_c(t) = \psi_r(t) + \mathrm{j}\psi_i(t)$$

A. ANALYTIC FILTER

Gabor defined how a real signal $f(t)$ can be described as complex function as $x(t) = f(t) + j\,g(t)$ where, $g(t)$ is the Hilbert transform of $f(t)$ and denoted as $H\{f(t)\}$ *and* $j = (-1)^{1/2}$.

The following figure describes the synthesis and analysis of analytic filter

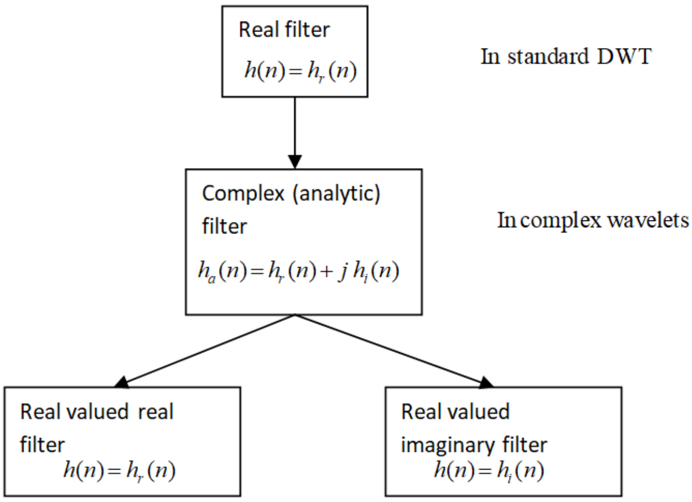

Fig.1 analysis of analytic filter by 2 real filters

The dual-tree CWT of a signal $x(n)$ is implemented using two critically-sampled DWTs in parallel on the same data. The filter bank structures for both DT-DWTs are identical. Figure shows 1-D filter banks spanned over three levels.

III. THE TQWT

It is beginning at right now same that the "Tunable Q-Factor wave Transform" (TQWT) is accomplice adaptable out and out DWT. The fundamental parameters for the TQWT are the Q-factor, the emphasis, and besides the proportion of stages (or levels).

The Q-factor, import alphabetic character, impacts the incidental direct the wavelet; basically. Generally, alphabetic character could be a live of the proportion of developments the wave shows up. For Q, accomplice estimation of one. 0 or extra perceived may be appeared. (Q may be real regarded.) The Q-factor of accomplice discontinuous heartbeat is that the quantitative association of its inside repeat to its information measure,

$$Q = \frac{f_o}{BW}$$

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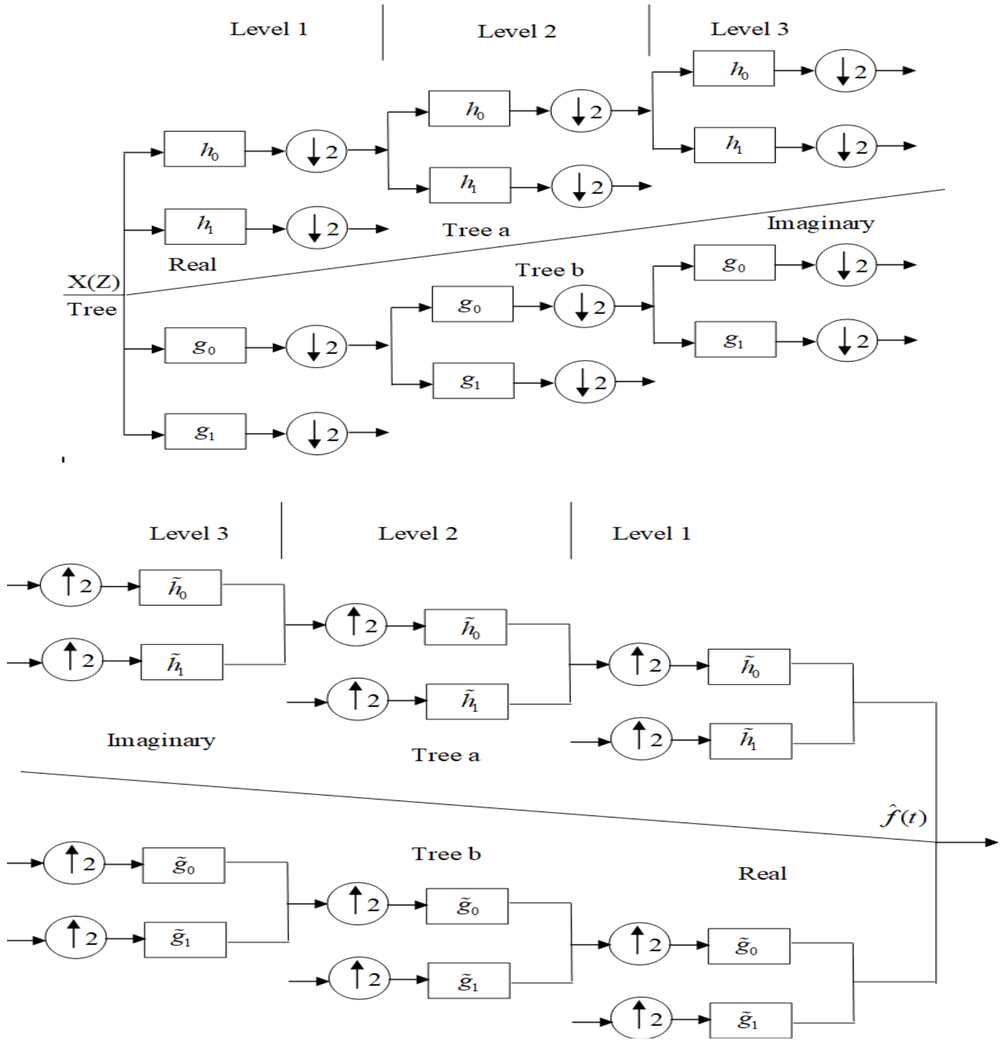

Fig.2 (a) Analysis filter bank (b) Synthesis filter bank for DT-DWT.

The parameter r is the abundance of the TQWT when it is readied utilizing unendingly different levels. Here 'excess' construes demonstrate over-inspecting rate. The predefined estimation of r must be more basic than 1.0, and an estimation of 3.0 or progressively prominent is suggested

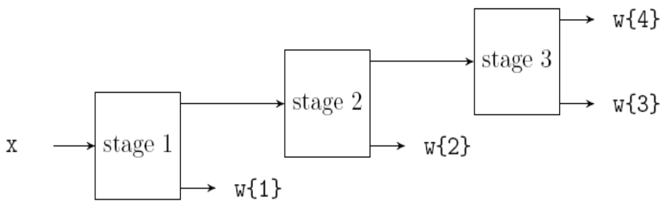

Fig.3. Wavelet transform with three stages (J = 3).

The amount of stages (or levels) of the change is implied by J. The change includes a course of action of two channel banks, with the low-pass yield of each channel bank being used as the commitment to the dynamic channel bank. The parameter J shows the amount of channel banks. Each yielded sign establishes one sub-band of the wavelet channel. There will be J +1 sub-gatherings: the high-pass channel reaction of each channel bank, and the low-pass channel reaction of the last channel bank. For example, a 3-arrange wavelet change is portrayed in Figure 2.

IV. Results & Discussion

In this segment, the outcomes for the purging of spectrum for complex test information in light of the current and proposed techniques are displayed. The information is produced by applying a Gaussian irregular

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contribution to a complex framework. As the genuine spectrum isn't accessible variance is taken as the measure for evaluating the algorithm, rather than mean-square error. The variance is ascertained as

$$\frac{1}{N}\sum_{k=0}^{N-1}\left(Y(k)-\sum_{k=0}^{N-1}Y(k)\right)^2$$

A complex valued function is produced and Fourier transform is figured for that signal. To test the method within the presence of AWGN, another signal $y_1(n)$ is produced as $y_1(n)=y(n)+\alpha\upsilon(n) \quad \mathit{for}\ n=0,1,2,......N-1;$

where $\upsilon(n)$ is a complex Gaussian noise with zero mean and unit variance and α is the amplitude related with $\upsilon(n)$. The quantity of samples in every acknowledgment is thought to be 512, i.e., N = 512. The outcome in view of the Monte Carlo simulation utilizing existing technique i.e, utilizing CWT is appeared in figure 4. The outcomes for same calculation in time domain are appeared in the figure 5. The two outcomes were obtained when custom thresholding is connected to the coefficients of CWT.

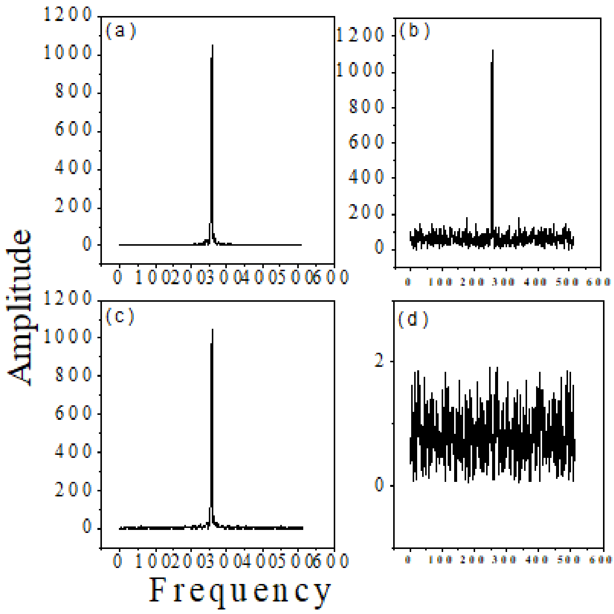

Fig. 4 (a) original Spectrum (b) Noisy Spectrum (c) Denoised Spectrum (d) variance

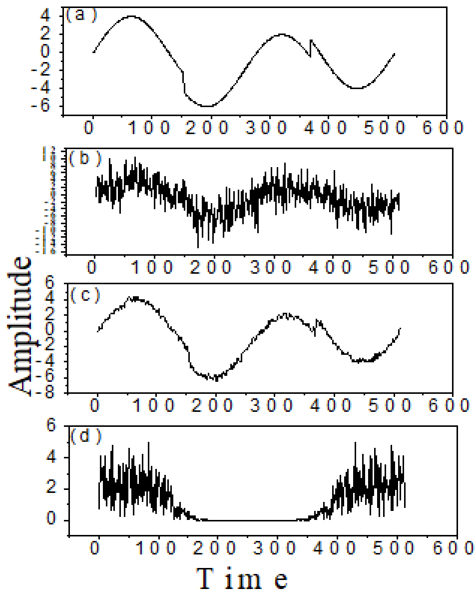

Fig. 5 (a) original Signal (b) Noisy Signal (c) Denoised Signal (d) variance

Table 1 gives the enhanced SNR and Variance of denoised motions by handling time domain information and freqency domain information utilizing complex wavelets. From the table 1 clearly the denoised information got by preparing frequency domain information utilizing CWT has improved performance than handling the time-domain information. The same is spoken graphically in figure 6.

Table 1 Performance of Existing Method With respect to input SNR.

Input SNR [dB]	Frequency Domain		Time Domain	
	Output SNR[dB]	Variance	Output SNR[dB]	Variance
-10	12.9608	2900	10.3287	3980
-5	21.5316	800.6487	17.6794	1790
0	24.3023	231.35	22.1051	498.1208
5	26.6103	78.7414	24.9066	101.4611
10	30.9121	25.2987	28.9177	57.5245

Table 2 gives the enhanced SNR and Variance of denoised functions by frequency domain information utilizing CWT and TQWT. From the table clearly the denoised information acquired by handling frequency domain information utilizing TQWT has showed signs of improvement than preparing the with CWT i.e, existing calculation. The same is spoken graphically in figure 7.

Table 2 Performance of Proposed Method With respect to input SNR [Frequency Domain]

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Input SNR [dB]	CWT		TQWT	
	Output SNR[dB]	Variance	Output SNR[dB]	Variance
-10	12.9608	2900	19.3522	1900
-5	21.5316	800.6487	24.4267	754
0	24.3023	231.35	31.4278	183.4523
5	26.6103	78.7414	39.9582	68.1663
10	30.9121	25.2987	50.9188	18.8697

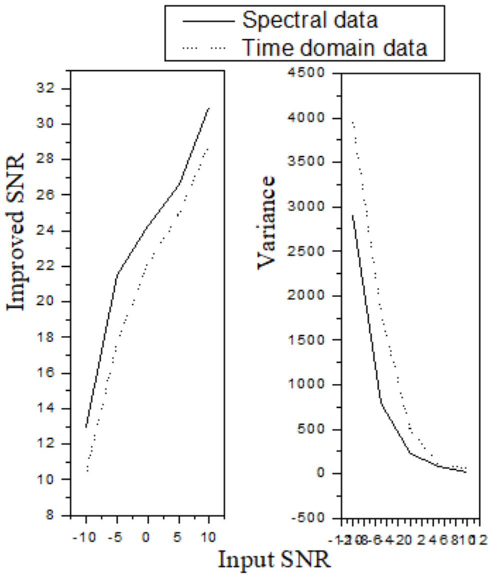

Fig. 6 (a) Input SNR vs. Output SNR (b) Input SNR vs. Variance

V. CONCLUSION

Wavelet transforms permits preparing of non-stationary signals, for example, MST radar data. This helps extraordinarily to evacuate the noise in the specific pass band of frequency. To test our calculations, right off the bat a complex signal was created and handled with complex wavelet transform (CWT) in time and frequency domains, from the outcomes obviously preparing of information in frequency domain is giving better outcomes that as well if joined with custom thresholding.At long last proposed calculation i.e. denoising spectral information preparing with Tunable Q-Factor Wavelet transform is giving promising outcomes when joined with custom thresholding.

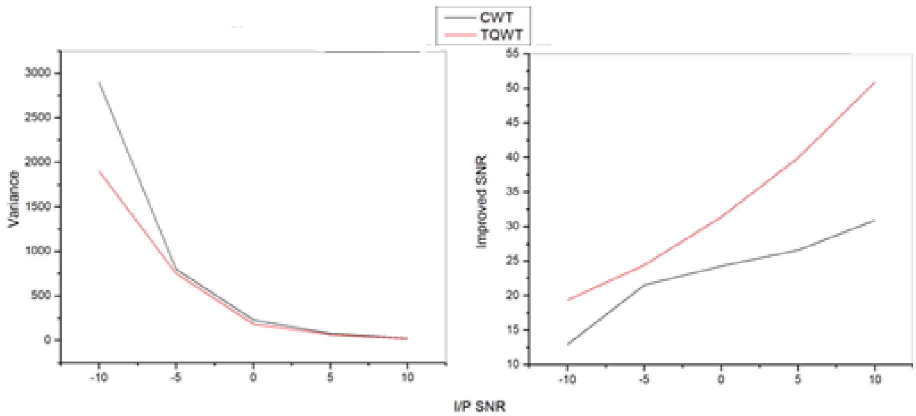

Fig. 7 (a) Input SNR vs. Output SNR (b) Input SNR vs. Variance

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This calculation is later connected to MST radar information, there additionally TQWT beats the Complex wavelet transform regarding Variance, SNR and fundamentally the computational multifaceted nature consequently lessening the time factor. Handling with CWT requires 2.419411 seconds and our proposed calculations just requires 110 milli seconds.

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