Analysis of Power System Disturbance Signals using Slantlet Transform for Compression and Denoising

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ABSTRACT
An orthogonal discrete wavelet transform (DWT) is a slantlet transform (SLT) with two zero moments and having improved time localization. SLT retains usual characteristics of filter bank implementation with a scale dilation factor of two. The basis is based on filter bank which uses different filters for different scales, is piecewise linear unlike iterated filter bank in DWT. This paper discusses the Compression and denoisisng of Power system disturbances through signal decomposition, thresholding of slantlet transform coefficients and signal reconstruction. Slantlet transform coefficients having values below the threshold are discarded and above are retained. The cost for data storing and transmitting for both cases is competently reduced when Compared to the energy retained of the compressed Power Quality (PQ) disturbance signals(input signals with and without noise).

.General Terms
Signal Processing, Data Compression, Orthogonal Wavelet transform, Denoising.

Keywords
Power Quality events, Slantlet transform, Compression, Energy retained, Mean Square Error.

1. INTRODUCTION
The performance of power system equipments is frequently affected by faults. Typical disturbances are signals which are having transients, sudden rise or sudden reduction in signals etc. Power quality faults phenomena spans a broad frequency spectra [1]. For example, impulsive transients due to lightening strikes could have a frequency spectrum of order of MHz. In order to capture a broad range of disturbance phenomena, including impulsive transient disturbances, dedicated PQ monitoring devices on light/medium stations with MHZ of sampling rates are used. Since transient disturbances occur in order of tens of micro seconds, a single captured event using such monitoring devices can produce megabytes of data [2].As the outcome, the volume of the recorded events increases significantly, leads to high cost in storing and transmitting such data. Therefore compression of such recorded disturbance with minimum error in reconstruction is highly needed.

A useful prerequisite in general for compression is analyzing data initially by a transform to extract the feature information in data and removal of redundancy, before doing thresholding.Transformations have been generally used in this area in recent years are discrete cosine transform, discrete wavelet transform etc. Here in this paper slantlet transform [3] is used for analysis of recorded disturbances.

The purpose of this work is to use SLT in compressing PQ system disturbances and also to compress the same by adding noise.SLT is an orthogonal DWT having two zero moments and shorter support which are competing criteria in the construction of wavelet filter banks unlike iterated filter bank in DWT[3].Octave band characteristics remains in the basis and leads to a clean DWT for finite length signals(boundary issues will not arise as long as data length is power of two)[3].Basis is specially suited for piecewise linear signals as is supported by compression and denoising examples shown further.

The organization of paper is as follows. In section 2, transformation theory issues and some important features is outlined. Data compression using thresholding and reconstruction, compression of the same by adding noise with reconstruction is presented in section 3.In section 4, simulation of data and test results are obtained and interpreted for all the events related to disturbances in PQ system. Finally conclusions have been made in section 5.

2. SLANTLET TRANSFORM THEORY
The class of bases described by Alpert [4] constructed based on Gram-Schmidt orthogonalization is used in SLT. It is based on a structure of filter bank where different filters are used for different scales. Filters used are of shorter length satisfies orthogonality and zero moment conditions. The filter bank for two zero moments used in SLT is as shown in Figure 1. Having lengths 8 and 4 [3],[6].This is one of the advantage of filter bank when compared to Daubechies-2 filter bank in terms of filter length. Every filter bank works with scale dilation factor of two and provides a multiresolution decomposition. The filters used are piecewise linear.

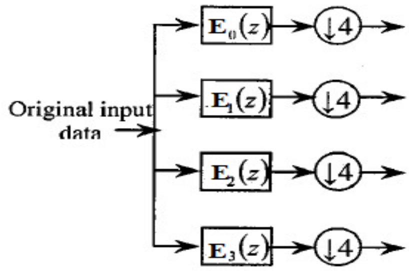

Fig 1: Filter Bank Structure using SLT

The different filters used here are not products like filters in Daubechies-2 and with this extra degree of freedom by giving up product form, filters are designed with shorter length satisfying orthogonality and zero moment conditions. The filter coefficients [3] are as follows

$$\begin{aligned}E_0(z) = &\left(-\frac{\sqrt{10}}{20}-\frac{\sqrt{2}}{4}\right)+\left(\frac{3\sqrt{10}}{20}+\frac{\sqrt{2}}{4}\right)z^{-1}\\ &+\left(-\frac{3\sqrt{10}}{20}+\frac{\sqrt{2}}{4}\right)z^{-2}+\left(\frac{\sqrt{10}}{20}-\frac{\sqrt{2}}{4}\right)z^{-3}\end{aligned}$$

$$\begin{aligned}E_1(z) = &\left(\frac{7\sqrt{5}}{80}-\frac{3\sqrt{55}}{80}\right)+\left(-\frac{\sqrt{5}}{80}-\frac{\sqrt{55}}{80}\right)z^{-1}\\ &+\left(-\frac{9\sqrt{5}}{80}+\frac{\sqrt{55}}{80}\right)z^{-2}+\left(-\frac{17\sqrt{5}}{80}+\frac{3\sqrt{55}}{80}\right)z^{-3}\\ &+\left(\frac{17\sqrt{5}}{80}+\frac{3\sqrt{55}}{80}\right)z^{-4}+\left(\frac{9\sqrt{5}}{80}+\frac{\sqrt{55}}{80}\right)z^{-5}\\ &+\left(\frac{\sqrt{5}}{80}-\frac{\sqrt{55}}{80}\right)z^{-6}+\left(-\frac{7\sqrt{5}}{80}-\frac{3\sqrt{55}}{80}\right)z^{-7}\end{aligned}$$

$$\begin{aligned}E_2(z) = &\left(\frac{1}{16}+\frac{\sqrt{11}}{16}\right)+\left(\frac{3}{16}+\frac{\sqrt{11}}{16}\right)z^{-1}\\ &+\left(\frac{5}{16}+\frac{\sqrt{11}}{16}\right)z^{-2}+\left(\frac{7}{16}+\frac{\sqrt{11}}{16}\right)z^{-3}\\ &+\left(\frac{7}{16}-\frac{\sqrt{11}}{16}\right)z^{-4}+\left(\frac{5}{16}-\frac{\sqrt{11}}{16}\right)z^{-5}\\ &+\left(\frac{3}{16}-\frac{\sqrt{11}}{16}\right)z^{-6}+\left(\frac{1}{16}-\frac{\sqrt{11}}{16}\right)z^{-7}\end{aligned}$$

$$E_3(z) = z^{-3}E_2\left(\frac{1}{z}\right).$$

3. DATA COMPRESSION AND RECONSTRUCTION USING SLT

A Flowchart for the process of compression and reconstruction of the signal is shown in Figure. Below.

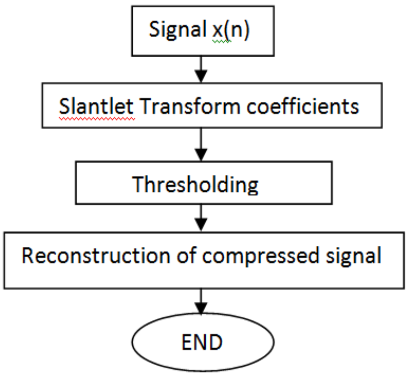

Fig 2: Flowchart for the process of compression and reconstruction.

As the flowchart says it has three different steps. Initially SLT is applied for the transformation. Then the process of thresholding is done in which suitable threshold is chosen for discarding the SLT coefficients which are not having significant energy. The above two steps will do the compression part and then inverse SLT is applied to get the reconstructed signal.

The block diagram of the entire process of compression and reconstruction is shown in figure 3.The filter coefficients used in analysis part are mentioned in section 2.The PQ system disturbance signal is applied as input to the two scale filter bank and the outputs are then getting downsampled by 4.The transformed coefficients are as shown in figure 3 is used for the analysis filter bank are $E_0(z)$, $E_1(z)$, $E_2(z)$, $E_3(z)$.The transformation retains most of the signal energy in some selective coefficients and remaining coefficients obviously are insignificant. Therefore, proper choosing of threshold is important to discard the coefficients. Also keeping reconstruction of signal and quality of the same in view, the threshold is fixed. The insignificant coefficients are set to zero once we chose the threshold value. The remaining coefficients represent the original input signal in compressed form.

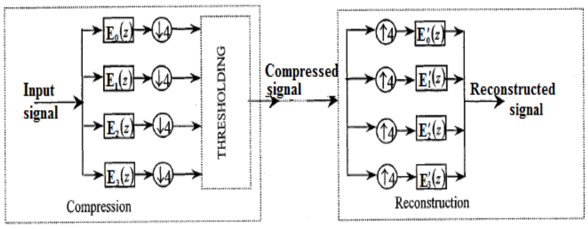

Fig 3: Block diagram for SLT based compression and reconstruction.

The coefficients in compressed form are then encoded to binary form used for storing and transmitting purpose. From the thresholded data the original PQ disturbance signal is reconstructed by using the two scale SLT synthesis filterbank as shown in the figure 4.Transformed coefficients used in synthesis filterbank are $E'_0(z)$, $E'_1(z)$, $E'_2(z)$, $E'_3(z)$ as shown in the Figure 3.These filter coefficients are the time reversal of the corresponding analysis filters. The compressed data are upsampled by four and then convolved with the synthesis filter coefficients of each channel. These data are then added to get the reconstructed PQ disturbance signal for further use. The parameters used to assess the quality of compression are energy retained in percentage and mean square error (MSE) in decibels. The percentage of energy retained is defined as

$$\left[\frac{\text{(Vector norm of the retained SLT coefficients after thresholding)}}{\text{Vector norm of the original SLT coefficients}}\right]\times 100.$$

It is used as a performance index for compression. MSE in decibels is defined as

$$\text{MSE (dB)} = 10\left[\log_{10}\left(\frac{1}{N}\sum_{i=1}^{N}\|x(i)-\hat{x}(i)\|^2\right)\right]$$

Where x(i) is the original signal and the other is the reconstructed signal[5].

The process explained above is done for the same PQ disturbance signals with addition of additive white Gaussian noise of 15dB.Again energy retained and MSE is calculated for it and compared with the other having no noise. Chosen test signals are PQ disturbance signals which are sine impulse, voltage sag, voltage swell, Harmonics, Momentary interruption, Oscillatory transient and Voltage flicker.

4. SIMULATION AND TEST RESULTS

Compression capability of SLT approach is demonstrated by taking a sine impulse signal containing impulse at some time (Figure 4.).Decomposition of the signal into two levels and the corresponding outputs of the filter are shown in the Figure 5. Information of different frequency components is shown by the outputs of filter. It also shows how accurately it localizes the disturbance point. Once thresholding is done by proper value of threshold, later the reconstruction process is done.

Reconstructed signal is as shown in the Figure 6.The ratio between the original signal coefficients to the number of signal coefficients remained after thresholding is compression ratio(CR).Here in present case CR = 10 is considered. It is observed that higher the CR values less data are retained after thresholding and hence accuracy is sacrificed in reconstructing the signal.

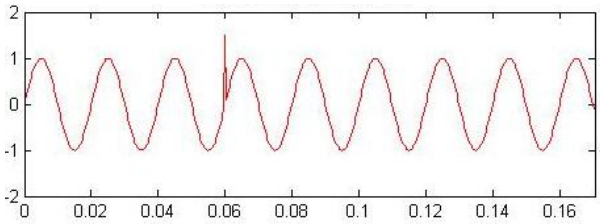

Fig 4: Original Sine impulse signal of 50 Hz.

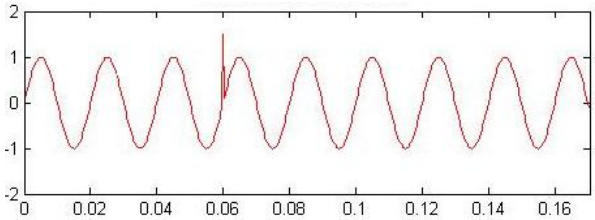

Fig 5: Multiresolution analysis, (a) Original sine impulse signal of 50 Hz

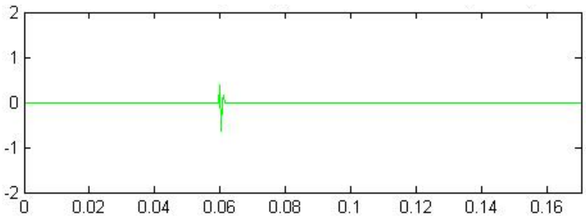

Fig 5(b) First filter output

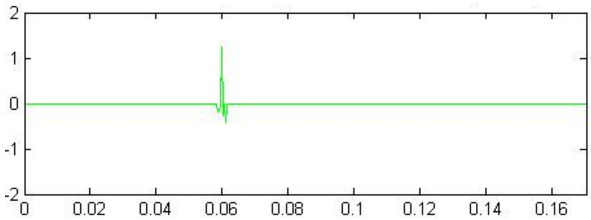

Fig 5(c) Second filter output

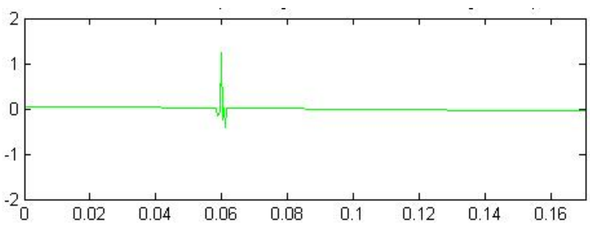

Fig 5: (c) Third filter output

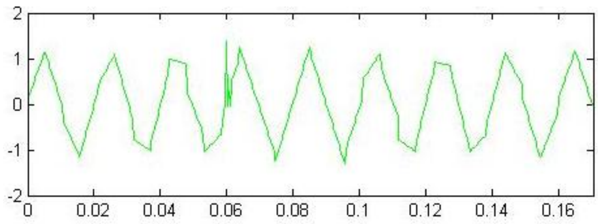

Fig 6: Reconstructed sine impulse signal

All the input signals are generated in the MATLAB code at the sampling rate of 3 kHz. Simulation is done with sinusoidal signals of 50Hz and 1 p.u. amplitude. MSE and percentage of energy retained is calculated for all the PQ disturbance signals and listed in the Table 1.

Table 1.Percentage of Energy retained and MSE in dB obtained using SLT based compression approach for all signals at CR=10

Input Signals without noise	ER (%)	MSE
Impulse	98.2191	-20.4826
Sag	98.6136	-22.9437
Swell	98.6104	-19.6933
Harmonics	91.9063	-13.3416
Momentary Interruption	98.9159	-24.5668
Oscillatory Transient	98.1121	-20.2475
Voltage Flicker	98.7521	-21.9107

In the same way for the entire PQ disturbance signals a white Gaussian noise of 15dB is added and then compression and reconstruction is done. Again the percentage of energy retained and MSE is calculated for all the PQ disturbance signals having SNR of 15dB and listed in Table 2.

Table 2. Percentage of energy retained and MSE in dB obtained using SLT based compression approach for all signals with SNR of 15dB at CR=10

Input Signals with noise	ER (%)	MSE
Impulse	93.7501	-14.7121
Sag	92.8994	-15.6653
Swell	95.4906	-14.3391
Harmonics	87.1272	-11.1386

Momentary Interruption	91.1185	-15.1829
Oscillatory Transient	93.0431	-14.3747
Voltage Flicker	94.0553	-14.8708

Figure 7 Shows the original sine impulse signal with added noise and Figure 8.shows the reconstructed signal from the thresholded data. From figure 8 it can be easily seen that signal which is reconstructed contains much less noise and pattern of reconstructed signal without noise is kept. Therefore good denoising can be done through data compression. It is because the slantlet transform coefficients caused by noise are generally small and mostly concentrated in high frequency bands, i.e., the first several scales. So that any thresholding can reach the denoising to a certain degree.

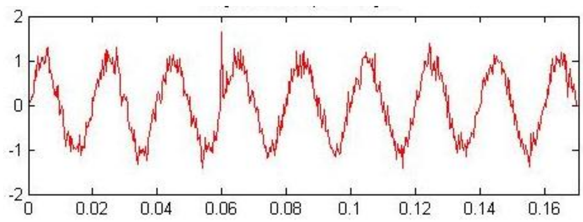

Fig 7: Sine impulse signal with AWGN of 15dB SNR.

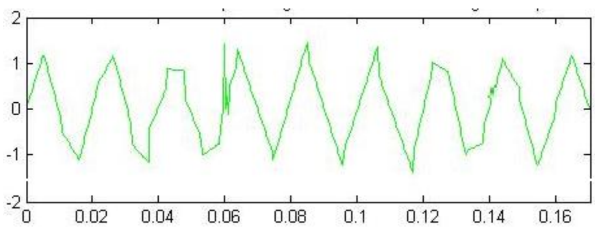

Fig 8: Reconstructed sine impulse signal.

Definitions of all the PQ system disturbance signals used here in this paper are described [5] and MATLAB simulated PQ signals are shown in Figures (9,10,11,12,13,14).The reconstructed signals of original disturbance signals with noise are comparable to reconstructed signals of original disturbance signals. For example if we look into the table 1,the energy retained in percentage for the sine impulse signal is 98.2191 and energy retained for the same with noise is 93.7501 as mentioned in Table 2.The difference in percentage between these two values is 4.55 which is tolerable. Similarly for all the signals the difference in percentage of energy retained of the signals with and without noise is around 5. From this observation we can say that a good denoising has happened through compression. As the SLT approach is the efficient method for data compression when compared to DCT and DWT [5].SLT based compression technique is also the efficient technique for compression as well as denoising through compression.

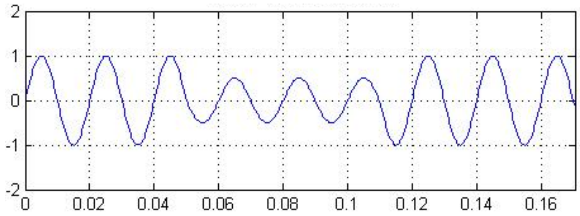

Fig 9: Voltage Sag signal of 50 Hz.

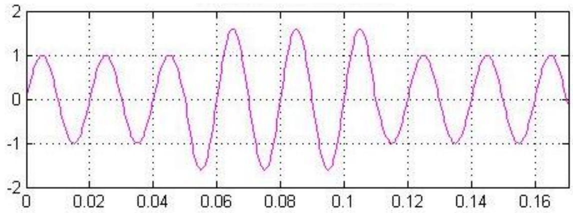

Fig 10: Voltage Swell signal of 50 Hz.

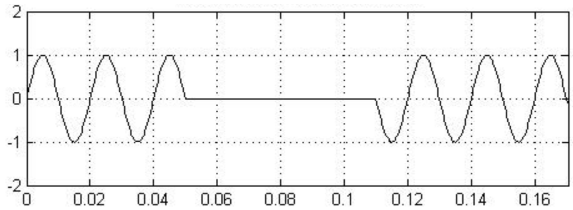

Fig 11: Momentary interruption signal of 50 Hz.

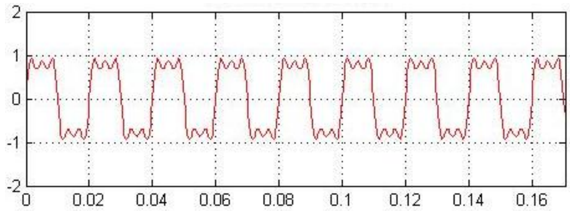

Fig 12: Signal with third and fifth Harmonics of 50 Hz.

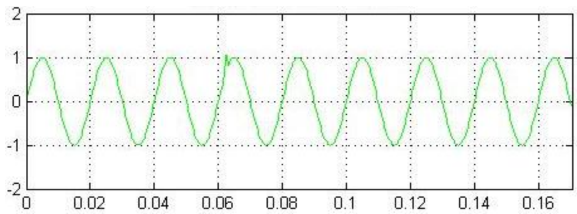

Fig 13: Oscillatory transient signal of 50 Hz.

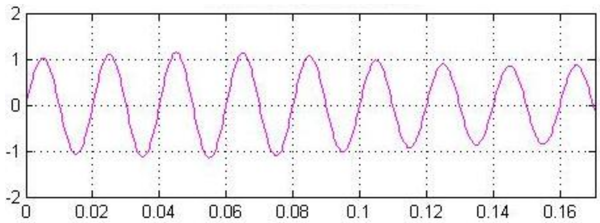

Fig 14: Voltage Flicker signal of 50 Hz.

5. CONCLUSION

SLT is applied for compression of PQ disturbance signals and the same is done for the original signals with additive white Gaussian noise of signal to noise ratio of 15dB.The performance is evaluated through computer simulation for both the cases. Considering percentage of energy retained and mean square error in dB of different disturbance signals, it is in general observed from analysis that accuracy is good for efficient compression, high quality compression and good denoising effect. Thus it is, in general, conclude that SLT based compression technique is efficient for compression of transient signals with noise and without noise upto certain degree.

6. REFERENCES

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