A Wavelet Based Data Compression Technique for Power Quality Events Classification

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Abstract: - This paper proposes a wavelet –based data compression for classification of PQ events. The Compression technique is performed through signal decomposition, signal reconstruction and according to the criterion of the maximum wavelet energy coefficients. To justify the proposed method, data are simulated under disturbances in which various power quality events which include voltage sag, swell, momentary interruptions and harmonics were simulated and used for testing the performance of various order and scale for daubechies and symlet functions. Simulation results indicate that the order 2 and scale 5 of wavelet functions offers superior compression performance compared to various other levels.

Key-Words: - Power Quality, wavelets, Multiresolution signal decompositions, data compression

1 Introduction

Power quality issues have captured attention from Utility and their customer in recent years. Information about power quality will become a valuable commodity after deregulation subject to negotiation, pricing and ownership. The performance of a power system is frequently affected by various power quality events by their severity and duration. In this paper disturbance with a shorter duration in terms of milli seconds been considered. A Voltage sag may be caused by switching operation associated with temporary disconnection of supply, swell may be caused by switching off of heavy motors loads, use of electronic equipment in distribution system may degrade and produce significant amount of different harmonics and momentary interruption due to short-circuits and can be considered as voltage sags with 100% amplitude also[1].Since these disturbance occur in the order of micro seconds , a single captured event recorded using monitoring instruments can produce mega bytes of data[2].As a result the volume of the recorded data increases significantly. Therefore it is necessary to develop an effective compression technique which has capability to reduce the volume of data necessary for storing and to speed up transmitted data for remote monitoring and for classification of power quality events for to design various mitigating devices.Several kinds of compression techniques have been used in satellite communication and commercial telephony [3].These compression schemes highlight the principal of encoding of data. These schemes are known as predictive coding schemes and two major parts of the encoding algorithm are a predictive and a quantizer. Some error is involved in quantization which can be improved by improving the performance of the predictor which is time consuming one.

Some of the reduction techniques in power distribution monitoring use a “wraparound” scheme which recycles the existing memory capacity by writing over the oldest data, which represents a group of similar waveforms as a single entity. Both of the above methods conserve more memory space, but do not compress data in the usual sense of the data compression [4].

The discrete Fourier transform (DFT) yields frequency coefficient of a signal representing the projection of an orthogonal sine and cosine basis function, this is an adequate method if a signal is predominantly sinusoidal, periodic and stationary, as power system disturbance are subject to transient and nonperiodic components, so DFT is inadequate for data compression.

The short-time Fourier transform (STFT) uses a time-frequency window to localize sharp transition .The STFT time window is fixed, however, and this method can be inadequate for accurate analysis for other than shorter and sharp duration disturbances .

The discrete cosine transform(DCT) is conventionally used for data compression because of its orthogonal property[6].For denoising and compression of different signals it provides relatively efficient representation of piecewise smooth signals[5].The degree to which the transform basis can yield sparse representation of different signals depends on the time-localization and smoothness property of the basis function, it is usually carried out by filter bank iteration but for a fixed number of zero moment it does not yield a discrete time basis that is optimal with respect to time-localization. So it will lead to inadequacies in compression.

The Slantlet transform (SLT) has been developed by employing the length of the discrete time and their moment as the vehicle in such a way that both time-localization and smoothness properties are achieved . But compression ratio (CR) and percentage of energy retained is not up to the level to identify the signals.

An algorithm to optimize the efficiency of compression is performed by Minimum Description Length [7].This MDL criterion aims to gain the compromise between the number of retained coefficients but the error of signal reconstruction is more which will lead to improper solution of filter for filtering [6].

For image processing a splines-based compression scheme have been used to show how one could use spline to interpolate equally spaced samples of a function. Spline wavelets transform stand apart in the general theory of wavelets transform .The most worrying factor in this construction is about the delicate issues of the convergence of the iterated filter bank[7].In which even after filtering a large-quantity of data is present in the form of white noise.

The enhanced disturbance compression method (EDCM) aims to prove the storage capacity of the monitoring equipments as well as its effective bit rate when the data transmission is required for PQ matters. It is done based on a previous estimation of the fundamental components of the signal under analysis. So that this component can be subtracted from the analyzed signal revealing a non stationary type of error signals [8].In this the error was not up to tolerable level.

Wavelet transform have recently emerged as powerful tools for a broad range of applications, which makes suitable for time-frequency analysis . In data compression the wavelet transform is used to exploit the redundancy in the signal. The performance of wavelet transforms for data compression lies in its ability in concentrating a large percentage of total signal energy in a few coefficients.Therefore the related coefficients are kept ,while others that are not related to disturbance event are discarded without losing significant information, moreover with the rapid development of computing techniques, the algorithm of MRA can be implemented for online application[9].In addition ,WT is capable of depressing the sinusoidal and white noise in the data .This property could benefit the preprocessing of the data in the measuring device [10-11].Nevertheless without loss of generality, the proposed approach is capable of compressing any type of signal in to the format of a time series.

The paper is organized as follows in section II WT-Based MRA and its properties are briefly introduced. In section III, the selection of wavelet function and decomposition scale for disturbance signal are conducted for data compression, in section IV results and discussion is carried out to justify the effectiveness of WT-based MRA on data compression, the conclusion is presented in section V

2 Wavelet Transforms

Wavelet transformation has the ability to analyze different power quality disturbances in both time and frequency domain. The wavelet transform is useful in extracting features of various power quality disturbances. Wavelet analysis deals with expansion of function in terms of a set of basis function. However, wavelet analysis expands functions not in terms of trigonometric polynomials but in terms of wavelets.Moreover another important property that the wavelet posses is perfect reconstruction, which is the process of reassembling a decomposed signal or image into its original form without loss of information.

2.1 Multiresolution Analysis

Representation of signals at various levels of resolution is the ultimate goal of MRA .Scaling function and wavelet function are used as building blocks to decompose and construct the signal at different resolution levels in a multiresolution analysis (MRA). MRA consists of two filters in each level and they are low pass and high pass filters.

The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up-sampling and down-sampling operations. Sub-sampling a signal corresponds to reduce the sampling rate, or removing some of the samples of the signal. On the other hand, upsampling a signal corresponds to increase the sampling rate of a signal by adding new samples to the signal. MRA decomposition and reconstruction are shown in Fig.1(a) and (b).

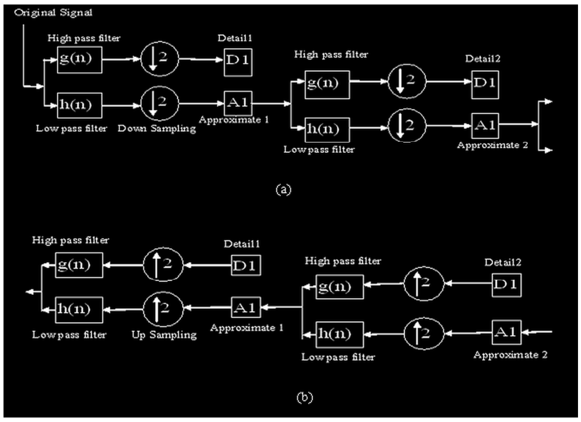

Fig.1.Multiresolution Analysis (a) Decomposistion (b) Reconstruction.tif

Assume a signal x[n], discrete time signal is distributed in 2 level. This signal is filtered into high frequency component in level 1 by using high pass filter (g(n)) and low frequency components in level 2 by using low pass filter (h(n)). This signal is passed through down sampling and in MRA level 2. The components in level 1 are used as initial signals. These signals are passed through high-pass filter and low-pass filter. The outputs of filter can be mathematically expressed as in equation (1)-(2) as follows.

$y1[k] = \sum_n x[n].g[2k-n]$ ………….. .(1)

$y2[k] = \sum_n x[n].h[2k-n]$ …………… (2)

Where g(n) is high pass filter.

h(n) is low-pass filter.

Where $y1[k]$ and $y2[k]$ are the outputs of the high-pass and low-pass filters, respectively.

3 Selection of Wavelets and Decomposition Scale

In this section, we provide a simple yet effective method to compress power quality disturbance, there are a number of basis functions that can be used for wavelet transformation. The wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting wavelet transform. Therefore, the details of the particular application should be taken into account and the appropriate wavelet function should be chosen in order to use the wavelet transform effectively. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application. So the best wavelet function and optimal decomposition scale need to be carefully selected. Wavelet energy is the index to reflect the energy concentration of wavelet coefficients on certain scales.The larger the wavelet energy, the more the information is preserved after decomposition.The definition of total energy and average power for a signal x[n] being expressed as follows in equation (3)-(5).

$$E = \sum_{n=-\infty}^{\infty} x^2[n] \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

And the average power is

$$P = \lim_{x \to \infty} \frac{1}{2N} \sum_{n=-N}^{N} x^n[n] \ldots\ldots\ldots\ldots(4)$$

And for a periodic signal of fundamental period N, the average power is given by

$$P = \frac{1}{N} \sum_{n=-0}^{N-1} x^2[n] \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

In this Daubechies and Symlet are taken for the further analysis.The daubechies wavelets are a family of orthogonal wavelet defining a discrete wavelet transform and characterized by a maximal number of vanishing moments and given support to each wavelet, there is a scaling function which generates an orthogonal multiresolution analysis.The symlets are nearly symmetrical wavelets proposed by daubechies as modification to the Db family, and the properties of the two wavelet families are also similar.These wavelets have been chosen because they have shown best performance in analyzing disturbance signals. The wavelet corresponding to the highest total wavelet energy is chosen as the best wavelet function, and the scale corresponding to the highest wavelet energy is chosen as the optimal decomposition scale. Four types of disturbance were taken in this paper that is voltage sag, voltage swell, momentary interruption and harmonics, the results are listed in Table I and Table II.

TABLE I
RESULTS OF SELECTION OF WAVELET FUNCTION

DB	2	3	4	5	6	7	8	9	10
Voltage sag	0.9932	0.9201	0.9463	0.8926	0.9111	0.9507	0.9614	0.9622	0.9541
Voltage swell	0.8856	0.8462	0.8817	0.8733	0.8123	0.8847	0.8957	0.8167	0.8921
Momentary Interruption	0.9241	0.9072	0.8915	0.9178	0.9176	0.9089	0.9145	0.9046	0.9188
Harmonics	0.7846	0.7812	0.7647	0.7413	0.7488	0.7312	0.7701	0.7560	0.7564
SYM	2	3	4	5	6	7	8	9	10
Voltage sag	0.9867	0.9256	0.9396	0.8814	0.8969	0.9600	0.95899	0.9710	0.9539
Voltage swell	0.9120	0.8511	0.9045	0.8875	0.8098	0.8919	0.8923	0.7901	0.8218
Momentary Interruption	0.9365	0.9173	0.8891	0.9098	0.9100	0.8945	0.9245	0.8949	0.9267
Harmonics	0.9145	0.8612	0.7749	0.8117	0.7981	0.8011	0.7609	0.7819	0.7592

The elements highlighted in yellow indicate the highest wavelet energy of a specific signal, corresponding to a certain wavelet functions. Among these db2 and sym2 seem to have highest wavelet energy levels. Either one can be chosen as the best wavelet for disturbance signals.

In this paper db2 is determined to be the wavelet function for MRA.

In table II signals are decomposed by db2 in to scales and it is evident that the wavelet energy at scale 5 is the highest and can be used as the optimal decomposition scale for MRA in this paper

TABLE II
RESULTS OF SCALE SELECTION

Scale	1	2	3	4	5
Voltage sag	0.3901	0.3945	0.4791	0.5017	0.5137
Voltage swell	0.3891	0.3919	0.4278	0.4811	0.4912
Momentary Interruption	0.0498	0.0587	0.0591	0.0614	0.0628
Harmonics	0.0844	0.0971	0.0991	0.1201	0.1279

4 Results and Discussion

The data compression uses the hard thresholding. There are two approaches available for the choice of thresholding values. The first is based on keeping the wavelet coefficients with larger absolute values. In this case, a global threshold can be set, thus only one parameter needs to be selected. The second approach applies the level-dependent thresholds, In this case, each scale level needs one threshold and the number of thresholds corresponds to the scale levels. We will use hard thresholding method. Then we discuss the application of wavelet transforms daubechies2 to compress the disturbance signals. The data that we used is the data that extracted from MATLAB simulated waveforms of various disturbances that accurse in the power system.

Since to apply wavelet transforms, we need the data in terms of dyadic number, we can use any methods such as zero padding, But for analysis, we need to consider only the size of the original data. The reason for using this wavelet is because as mentioned earlier, it has the highest wavelet energy of the different signal. So Db2 seems suitable for this type of data sets. Before we do the compression, we decompose the signals by using Db2 at level 5, from the Fig.2 and Fig.3.

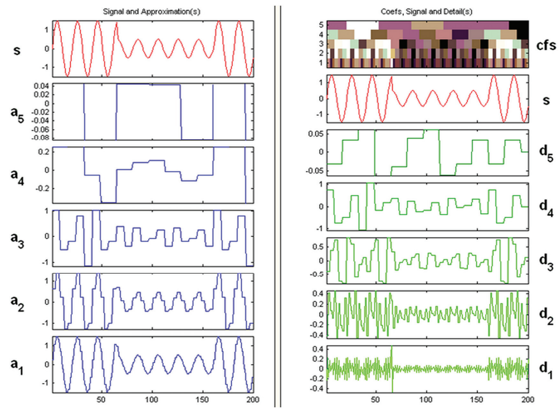

Fig.2. Wavelet decomposition at level 5 for voitage sag.tif

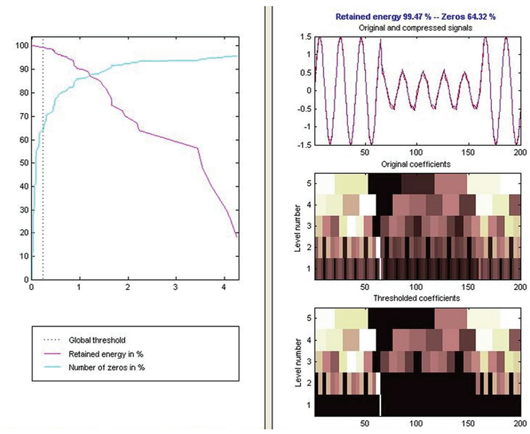

Fig.3. comparision result for voltage sag.tif

We can notice that at level 5, the approximation (a5) and detail (d5) have shown clearly the shape and characteristics of the original data. From level 1 until level 5 in detailed coefficients, all of the higher frequencies have been filtered out and finally we obtained the smooth version of the original signal at level 5 by using the summation of approximation and detail. Subsequently to compress the data we need to calculate threshold values for every level. But in this paper we have calculated the threshold values one time since we apply global threshold. With the hard threshold values, we apply compression to the original data. Based on statistical result in table III and table IV which indicates that the compressed signal, which are almost perfect and the length of the compressed signal for voltage swell, momentary interruption and for harmonics are all considered to be best compressed value. Therefore, by using Db2 wavelet function and applying level 5 compression with hard threshold value (0.8242), we obtained a good compressed data.

TABLE III
STATISTICAL ANALYSIS FOR COMPRESSION BY DB2 FOR POWER QUALITY EVENTS

Disturbances	Retained Energy %	Zero details %	Standard deviation	Median Absolute deviation	Mean Absolute deviation
Voltage sag	99.47	64.32	0.2805	0.1615	0.2143
Voltage swell	99.55	59.62	0.2902	0.2587	0.2444
Momentary Interruption	99.31	73.24	0.2951	0.03584	0.1843
Harmonics	99.46	22.54	1.5131	1.3567	1.3194

TABLE IV
LENGTH OF THE COMPRESSED SIGNAL FOR VOLTAGE SAG

Before Compression		After compression	
a5	7	a5	7
b5	7	b5	7
b4	13	b4	8
b3	25	b3	12
b2	50	b2	14
b1	100	b1	21
Total	202	Total	69

5 Conclusion

This paper proposes a modified approach of data compression for detection and classification of power quality events. The order 2 daubechies wavelet and scale 5, respectively are the best wavelet function and scale for signals, with maximum wavelet energy. A numerical simulation is conducted, the results by appling WT-based MRA shows better performance compared with conventional methods in terms of compression. Thus, we can clearly observe the difference in energy distribution between different signals, further the signals can be perfectly reconstructed from the compressed signal. There by data storage requirement and transmission time will be minimized and can have faster PQ event classification.

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