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KRZYSZTOF DUDA

AGH University of Science and Technology
Measurement & Instrumentation Department
Kraków, Poland
e-mail: kduda@agh.edu.pl

LIFTING BASED COMPRESSION ALGORITHM FOR POWER SYSTEM SIGNALS

The paper concerns the problem of power system signals compression with possible application in system monitoring and control. The proposed compression algorithm for power system signals ensures efficient use of available storage memory or communication channel bandwidth. It is shown that while preserving good quality, compression ratios from 20 in case of highly distorted waveforms to 340 for slightly distorted sinusoidal waves can be achieved. The presented results were evaluated with a specially prepared representative database of field- recorded electric signals. For signal decorrelation lifting implementation of wavelet transform in the compression algorithm was used. The influence of sampling frequency, length of data frame, type of wavelet function, number of wavelet decomposition stages and quantization level on the compression ratio and compression quality was investigated.

Keywords: lifting wavelet transform, signal compression, power system monitoring

1. INTRODUCTION

Most currently available long term power system monitoring equipment does not record time signals but only some parameters evaluated from the signal. Such an approach significantly reduces the amount of data to be stored or transmitted which is a strong advantage, but at the same time a lot of information is lost. The two examples of above methodology are synchronized with GPS time wide area measurements by PMU (Phasor Measurements Units) [1] and THD (Total Harmonic Distortion) measurements [2].

In the first case the signal is represented by DFT (Discrete Fourier Transform) as a complex phasor and thus the whole fundamental frequency period is represented by modulus and angle. This ensures a high compression ratio (if the signal were sampled with 2000 samples per fundamental frequency period, the compression ratio would be CR = 1000). There are significant drawbacks of phasor measurements: 1. the whole information about the spectrum of the signal (e.g. harmonics and interharmonics) is lost except the fundamental frequency component, 2. short duration time phenomena like transients are averaged and lost, 3. measurement is sensitive to fundamental frequency deviation.

In case of THD measurement the output value of THD does not carry the information which harmonics exceeded available levels.

Parameters of power system signals [3] always introduce some loss of information about the time signal, in the sense that the same parameters may be evaluated from different electric power signals as discussed in two examples above.

The most precise description of an electric power system is in the form of voltage and current time signals in this system. Straightforward recording or transmitting of time signals would require very large storage capacity or a high speed communication channel. Thus for efficient data storage or transmission, signal compression is required. As an example consider acquisition of voltage and current in a three-phase power system with a sampling frequency f_s = 10 kHz and 16 bit ADC (Analog to Digital converter). Each second requires 6×16×10000 = 960000 bits or 0.12 MB of storage memory. This gives 7.2 MB per 1 minute, 432 MB per 1 hour and 10.4 GB per day (24 h) of needed storage memory in the data acquisition system.

Rapid development of digital technology especially in the media business (i.e. digital photos, audio and video) stimulated the development of sophisticated compression algorithms like the JPEG and MPEG families [5, 6]. Many publications were also devoted to compression algorithms designed for specific, digitally acquired signals like power signals, biomedical signals etc. Significant popularity in the field of signal compression was gained by DWT (Discrete Wavelet Transform). The main advantage of DWT is the ability to concentrate the signal energy in a small number of wavelet coefficients, thus enabling efficient lossy compression by neglecting coefficients with small amplitude with simultaneous good quality. The basic works related to DWT are [7, 8] where the theoretical background of wavelet theory is presented including most popular wavelets and the Mallat algorithm (pyramid decomposition). An extension of Mallat's algorithm is called WPT (Wavelet Packet Transform) and was introduced in [9].

A number of compression algorithms was design based on DWT. The most specific are EZW [5, 6] (Embedded Zero tree Wavelet) coding algorithms that posses the feature of progressive coding (i.e. the signal can be reconstructed with progressive quality from the beginning of the bitstream). The applications of DWT for compression range from 1D (dimensional) data as: seismic data, speech signals, biomedical signals (e.g. ECG [10-13] (electrocardiogram), ECF (electroencephalogram)) power system signals [14-17] and other by 2D images (fingerprint compression, JPEG2000 standard) to 3D images (CT computed tomography data). A nice feature of wavelets is that algorithms design for one class of signals e.g. ECG can be used almost straightforward for another class e.g. power signals with minor modifications. DWT-based compression algorithms can be viewed as general purpose ones for data containing local phenomena, such as disturbances in power signals.

The query *wavelet & compression & power system* returns from http://ieeexplore.ieee.org database 32 answers. Among them only a few papers are dedicated to compression of power signals with wavelet transform in different implementations (e.g. DWT, WPT, multiwavelet, S-transform and slantlet) and none of them is devoted to lifting-based computations.

The paper [14] presents a DWT-based compression algorithm for power system disturbance data. Three-level wavelet decomposition with four-coefficient Daubechies' filter was used. This wavelet is not symmetric which is a disadvantage in most applications, especially when dealing with signal borders, and was the reason of designing symmetrical biorthogonal wavelets. Compression was achieved by the hard thresholding method. Significant detail coefficients were stored together with their positions. Compression ratios for the analyzed three test signals, each containing 1536 samples, were equal to 5.32, 5.73 and 2.90 with a NMS (Normalized Mean-Square) error 2.52×10^{-5}, 3.1×10^{-5} and 4.88×10^{-5} respectively. One can easily estimate the lower and upper bound, not evaluated by the authors, for an algorithm compression ratio proposed in [14]. In case of a pure sinusoidal signal all detail coefficients would be discarded (provided that the sampling frequency was high enough and fundamental frequency occupies an approximation subband on the 3-rd level) and the resulting upper bound for compression ratio is 8, as only a smoothed signal of scale 3 would be needed for reconstruction. In the worst case when all detail coefficients appeared significant under the selected threshold, the algorithm would appoint annotated positions to all detail coefficients and the data file would be actually 1.875 times bigger than the original data file!

In [15] the compression properties of the DWT and WPT were examined for one signal acquired from the DFR (Digital Fault Recorder). The compression algorithm was based on DWT or WPT decomposition, hard thresholding and entropy encoding by a LZW algorithm. Wavelet coefficients insignificant under a predetermined threshold were set to zero. For algorithm presentation a 512-point DFR signal sampled at 2400 Hz with 12-bit resolution was selected. This test signal (shown in Fig. 6 [15]) possesses values close to zero in almost half of its duration which may result in high compression (no information in this part of the signal!) i.e. overoptimistic results. A Daubechies 20 (non-symmetric) wavelet was selected for DWT and WPT. The number of decomposition levels was not specified by the authors. The quality of lossy compression was measured by the NMS error. The compression ratio CR was defined as the number of all signal samples (i.e. 512) divided by the number of retained wavelet coefficients. For the above conditions CR = 10 with NMS -48 dB was obtained. Next, an application of the compression algorithm for modem transmission was presented. In this case one record of voltage and current channels, each having 4096 integer (word) samples (8192 bytes) was used. A Daubechies 12 (non-symmetric) wavelet was chosen for DWT and WPT and after thresholding, wavelet coefficients were compressed by a LZW algorithm. The quality of compression was measured by PRD (Percentage Root mean square Difference). For the case of WPT+LZW compression a 11.7-times transmission speedup over a simulated PSTN (Public Switched Telephone Line) was obtained (as compared to the original record).

In [16] the MDL (Minimum Description Length) criterion was used for selection of the best wavelet filter and the threshold value for wavelet coefficients. DWT or WPT decomposition for 22 different wavelet filters was considered (ten Daubechies filters, five Coiflets and seven Symlets filters) with fixed four decomposition levels. The results from wavelet-based compression were combined with lossless coding (Huffman, LZW and LZH). An experimental study has been carried out for six recordings of a single-phase to ground fault event. The length of each signal was N = 8000 samples for 800 ms. One should notice that test signals (shown in Fig. 3 [16]) contain zeros for more then a half of their duration which may provide overoptimistic results. After numerical brute-force experiments the authors selected the *Symlets7* filters as the best although they noticed that a wavelet filter, which is optimal for a given signal, is not necessarily the best for another type of signal. Using the MDL the number of wavelet coefficients to be stored was computed. Positions of the coefficients were also stored. The quality of compression was measured by the percentage of MSE (Mean Square Error). Finally it was concluded that the DWT and WPT compression significantly reduce the original file size of each signal to less than 11% with the MSE about 1%. Additional lossless coding may further reduce file size by more than half of that value.

In [17] two-scale SLT (slantlet transform), which is an orthogonal DWT, was used for compression of power quality events. Computational complexity of the SLT is of the same order as that of the DWT. The compression algorithm relied on a judiciously fixed threshold level and setting all insignificant coefficients to zero. Compression quality was measured by MSE in decibels. Test signals were generated using the MATLAB code at a sampling rate of 3 kHz, amplitude resolution was not considered. Visual inspection of signals before and after compression for CR = 10 gives the impression of rather significant quality deterioration (compare Fig. 4 and Fig. 5 or Fig. 8 in [17]) and more reliable results were obtained for CR = 5 (Fig. 1 [17]). Best results were obtained for simulated voltage flicker CR = 10 and MSE = -19.78 dB. Results for SLT were compared with DWT with unknown configuration (i.e. the wavelet and the number of decomposition levels was not specified) and a method called by the authors 'standard DCT', without specifying any implementation details (e.g. it is known from the JPEG standard [6] that quantization of DCT coefficients should be frequency-dependent which for images is achieved by zig-zag ordering and DCT should be computed in blocks for images of 8x8 pixels or 64 samples, additionally the DC component is coded separately from AC components).

The above citations [14-17] are a demonstration of ideas rather than thorough studies of properties of the methods. All methods work well for selected test signals but their effectivness was not checked for a broad range of field signals.

The paper presents a compression algorithm for electric power signals that enables very efficient usage of available storage memory or communication channel bandwidth. It is shown that while preserving good quality compression ratios from 20 in case of highly distorted waveforms to 340 for undistorted sinusoidal waves can be achieved. That means that continuous monitoring can be extended 20 times (e.g. from about 1 day to about 1 month) in the worst case. The presented results were evaluated with signals recorded in the field with different sampling frequencies and possessing different disturbances and those selected by IEEE experts [4].

The main contribution of the paper is a broad analysis of how wavelet decomposition parameters (i.e. different configurations of the number of decomposition levels and kind of wavelet filters) influence compression efficiency. Additionally, numerical experiments were conducted with a representative data set of 12 field power signals containing different disturbances and acquired with different sampling frequencies. The presented results were obtained by using a brute force method, checking every possible configuration for the selected range of parameters. Such an approach was possible thanks to significant computational power of today's PC (Personal Computers) (computations took 5 days in the MATLAB environment with software not optimized for speed).

The originality of the presented work lies in applying Lifting Wavelet Transform (LWT) for signal decorrelation in the compression algorithm. Additionally the influence on compression ratio and compression quality of the sampling frequency, length of data frame, type of wavelet function, number of wavelet decomposition stages and quantization level was investigated for a representative set of electric power signals.

2. COMPRESSION ALGORITHM

Compression algorithms [5, 6] can be divided into one of two major categories**:** lossless (like ZIP or ARJ) and lossy (like JPEG or MPEG). While the previous group ensures that the signal after encoding and decoding is exactly the same; the former allows some degradation of the signal after encoding and decoding, which most often is measured by MSE, PRD, PNSR (Peak Noise Signal Ratio) or other e.g. subjective test. The advantage of lossy compression algorithms lies in significantly higher compression ratios.

The block diagram of proposed compression algorithm is presented in Fig. 1. The input signal $x[n]$ is decomposed with integer LWT [19], next the wavelet coefficients are rescaled by Q ($0 < Q \leq 1$) and rounded. Finally the bitstream is formed by an entropy encoder (Huffman, arithmetic or other). The decoding stage works just in the opposite direction as shown in Fig. 1b. For special case when Q =1 compression algorithm is lossless i.e. $x[n] = x_r[n]$, otherwise $x_r[n]$ slightly differs from $x[n]$. Compared to [14-17] hard thresholding is replaced by quantization, which can be viewed as a kind of soft thresholding. Quantization is easier in implementation and can be computed efficiently, especially in the case when Q possesses values in the form of powers of 2. Another feature of the proposed method is lossless compression for Q = 1. For integer LWT reconstruction the error is equal 0, which is particularly important for biomedical data [11-13] as law regulation does not allow lossless compression.

Data flow in the compression algorithm is organized in frames made of a chosen number of $x[n]$ input samples (e.g. 512) while the output works in an asynchronous manner and the bitstream can be stored or sent when the output buffer is filled. The proposed compression algorithm is designed for *on-line* application.

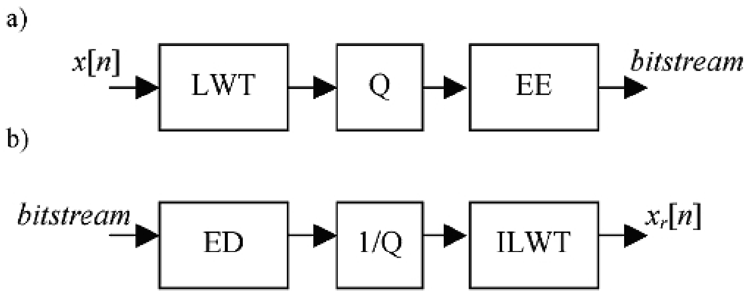

Fig. 1. Compression algorithm a) encoding, b) decoding, denotations: $x[n]$ – input signal, $x_r[n]$ – reconstructed signal, LWT – integer Lifting Wavelet Transform, ILWT – Inverse integer Lifting Wavelet Transform, EE – Entropy Encoder, ED – Entropy Decoder, Q – quantization $0 < Q \leq 1$.

2.1. Integer Lifting Wavelet Transform

LWT is the way of computing DWT coefficients. It was shown in [18] that every DWT filterbank can be factored into lifting steps. The lifting-based DWT has many advantages over the filterbank approach. Some of them are as follows (according to [6]): 1) Computational efficiency: usually the lifting-based DWT requires less computation (up to 50%) compared to the filterbank approach. 2) Memory savings: during the lifting implementation, no extra memory buffer is required because of the in-place computation feature of lifting. This is particularly suitable for hardware implementation with limited available on-chip memory. 3) Integer-to-integer transform [19]: the lifting-based approach offers integer-to-integer transformation suitable for lossless compression. 4) No boundary extension: In the lossless transformation mode, boundary extension of the input data can be avoided because the original input can be exactly reconstructed by integer-to-integer lifting transformation. The boundary problem can also be solved by using second generation wavelets [20] which is the approach applied in the proposed method, 5) Parallel processing.

Lifting computations can be also extended to adaptive computations [12, 21] or for integer to integer (i.e. lossless) FFT (Fast Fourier Transform) or DCT (Discrete Cosine Transform) implementation [22].

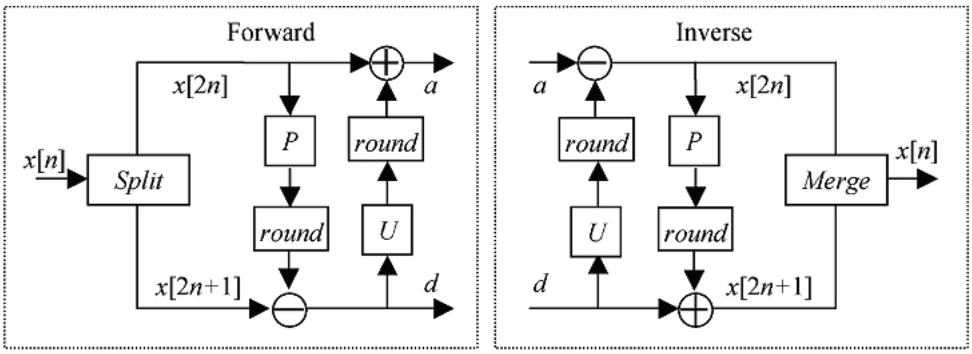

Fig. 2. Integer LWT computations: $x[n]$ – input signal – length N, a – approximation coefficients length – $N/2$, d – detail coefficients length – $N/2$.

A computation diagram of integer LWT is depicted in Fig. 2 [19]. The input signal $x[n]$ is split into samples with even and odd indices. The error of prediction of odd index samples from even ones forms detail coefficients d and updating even index samples with detail coefficients results in approximation coefficients a. Thus the signal x of length N is decomposed into low-pass approximation a and high-pass details d, both of the length $N/2$. For integer valued input signal x wavelet coefficients a i d are also integers. The computations are made in-place with no need for additional memory. The decomposition can be iterated on the approximation signal according to the Mallat algorithm or on approximation and detail signals according to WPT. The P and U are called predict and update filters. The most popular P filters are: P = [1], P = [1/2, 1/2], P = [-1/16, 9/16, 9/16, -1/16] and P = [3/256,

-25/256, 150/256, 150/256, -25/256, 3/256]. U coefficients can always be computed as $U = P/2$. In implementation filters P and U do not have to be of the same length (one can choose any combination e.g. $P = [1/2, 1/2]$, $U = P/2 = [1/2]$ and not necessarily $U = P/2 = [1/2, 1/2]$). For $P = [1/2\ 1/2]$ and $U = [1/4\ 1/4]$ LWT is equivalent to the Le Gall (5,3) spline filter which was chosen for lossless coding in JPEG2000 standard [6]. The second LWT from the JPEG2000 standard is the (9, 7) filter [6]. (9,7) LWT is not considered in the proposed implementation as it requires 4 lifting stages and scaling. For the sake of simplicity the proposed algorithm exploits only two lifting stages without scaling (see Fig. 2). The resulting wavelets belong to a biortogonal family and are symmetric. The input signal is decomposed with the Mallat algorithm.

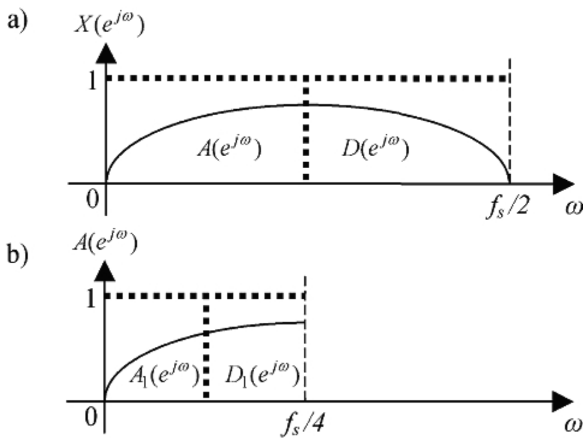

Fig. 3. Frequency interpretation of Mallat decomposition. Spectra of discrete signals are shown in the range from 0 to $f_s/2$ Hz. Denotations consistent with Fig. 2, f_s – sampling frequency: a) first decomposition level, b) second decomposition level.

Frequency interpretation of 2 level Mallat decomposition is illustrated in Fig. 3. Every decomposition level divides the spectrum of the input signal to low-pass and high-pass subbands. In compression algorithms only detail coefficients are quantized (or thresholded). From Fig. 3 two main conclusions can be drawn: 1) the value of sampling frequency f_s determines the division of the signal spectrum (e.g. for f_s = 150 Hz after second level decomposition 50 Hz is present in detail coefficients, but for f_s = 250 Hz after the second level 50 Hz is present in approximation coefficients); 2) compression of signals with reach spectrum will result in a low compression ratio for given quality, as detail coefficients posses information and cannot be significantly quantized.

2.2 Measurement of compression performance

As depicted in Fig. 1, after LWT wavelet coefficients are rescaled by Q. For efficient implementation Q in the form $Q = 1/2^m, m = 1,..., M$ was chosen and integer valued wavelet coefficients are rescaled by bit shifting instead of multiplication and rounding. This procedure causes some loss of information during compression and is the reason of quality loss of the reconstructed signal x_r. For evaluation of compression quality PRD was used [10]:

$$PRD=\sqrt{\sum_n \left(x[n]-x_r[n]\right)^2/\sum_n x[n]^2}\,100 \tag{1}$$

where: $x[n]$ – original signal, $x_r[n]$ – reconstructed signal (see Fig. 1). For comparisons with other works (e.g. [14-17]) one can notice that the following relation holds $PRD = \sqrt{NMSE}$ and $MSE=\frac{1}{N}\sum_{n=1}^{N}\left(x[n]-x_r[n]\right)^2$.

The definition of entropy in information theory was introduced by Shannon. For a discrete memoryless source entropy E is defined by equation:

$$E=-\sum_{i=1}^{n} p_i \log_2 p_i\,, \tag{2}$$

where: $\{p_1,..., p_n\}$ is the set of probabilities of occurrence of all symbols from the source alphabet. Entropy gives the smallest number of bits needed, on average, to represent one symbol. Any algorithm that is able to code source symbols with close to E bits for one symbol is considered as an entropy encoder. The most popular entropy encoders are Huffman and arithmetic. A detailed description of popular entropy encoders can be found in many available textbooks e.g. [5, 6].

The compression ratio CR is defined as original file size divided by compressed file size. The original file size was evaluated as $16N$, were 16 stands for the number of bits for one sample of the input signal x (i.e. AD converter resolution) and N is the length of the input signal frame. Compressed file size was estimated as EN, where E determines the average number of bits for one wavelet coefficient. The compression ratios presented in the next paragraph were computed as:

$$CR=\frac{16\,N}{EN}=\frac{16}{E}\,. \tag{3}$$

Definition (3) does not require implementation of an entropy encoder and thus numerical experiments are simplified and speeded up. It is known from data compression literature [5], [6] that CR computed from (3) can be closely approached by popular entropy encoders or even exceeded by the cost of consuming more computational power when context coding (i.e. source memory) is applied.

3. RESULTS

Compression results strongly depend on the content of the data. The more information the signal contains the lower the compression ratio. The information is always the measure of uncertainty (2). On the other hand, the signal that can be exactly described analytically contains no information. This observation leads to conclusion that for the ideal case if voltages and currents in power system were all pure sinusoids the compression ratio would go to infinity, as arbitrary long time recording could be represented by a mathematical formula. In a real world power system, voltages and especially currents are practically always distorted from a pure sinusoid thus they have a stochastic nature (even samples of pure 50 Hz sinusoid when subtracted from analytic expression $A\sin(2\pi\, 50t)$ will not result with zeros because of many reasons one of them being quantization noise). The typical most common distortions in power systems are: flicker, transients, harmonics, dips and interruptions and other [3].

3.1 Test signals

To avoid overoptimistic results the set of energetic test signals with different disturbances as shown in Fig. 4 was prepared. All test signals are real world field recordings. The last two rows in Fig. 4 show recordings taken from the IEEE database [4] (files *wave1*, *wave14a*, *wave3a*, *wave4*, *wave5*, *wave8*). Additionally the test signals were taken at different sampling frequencies what can be seen from the number of samples on the *OX* axis. Amplitude resolution in all cases is 16 bits.

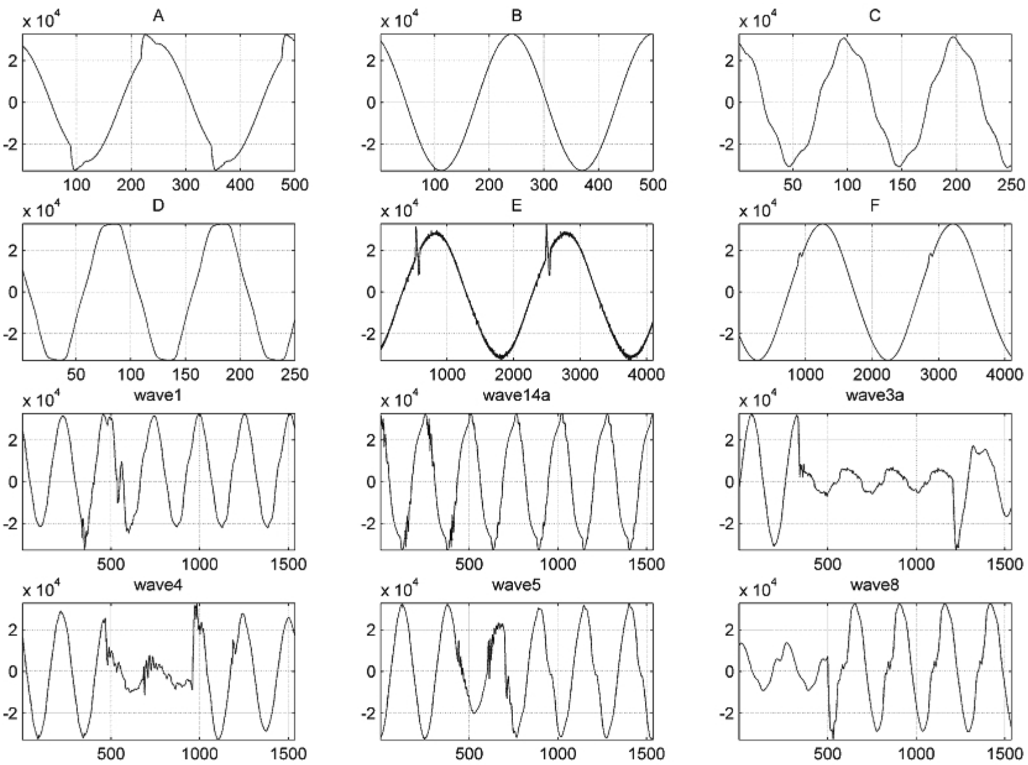

Fig. 4. The set of test signals, the *OX* axis shows the sample number.

3.2 Numerical experiments

The goal of the numerical experiments was to verify compression performance of the proposed algorithm from Fig. 1 for different possible LWT and Q configurations for selected test signals.

The proposed compression algorithm has the following parameters, the considered values are given in brackets: input data frame length (512, 1024, 2048 and 4096 samples except signals from [4] where only 1536 samples were available), number of lifting decomposition stages (3, 4, 5 or 6), length of *P* and *U* filters (all 16 combinations for filters given in section 2.1 e.g. $P = [1]$ and $U = [1/2]$, $P = [1]$ and $U = [1/4, 1/4]$ etc.), scaling *Q* (29 values from 1/8192 to 1). For the above settings 12(signals) × 4(frame length) × 4(decomposition stage) × 16(lifting filters) × 29(quantization levels) = 89088 simulations were run from which 12 × 4 × 4 × 16 = 3072 compression curves each containing 29 points of different PRD (quality) versus CR (efficiency) dependencies are drawn in Fig. 5a. As seen from Fig. 5a the range of compression ratios for a reasonably small reconstruction error PRD < 1% reaches values above 300. The results obtained by the above brute force testing method are very reliable and easy for interpretation. By carefully study of compression curves from Fig. 5a the best configuration of the compression algorithm can be selected for the given class of test signals.

a) b)

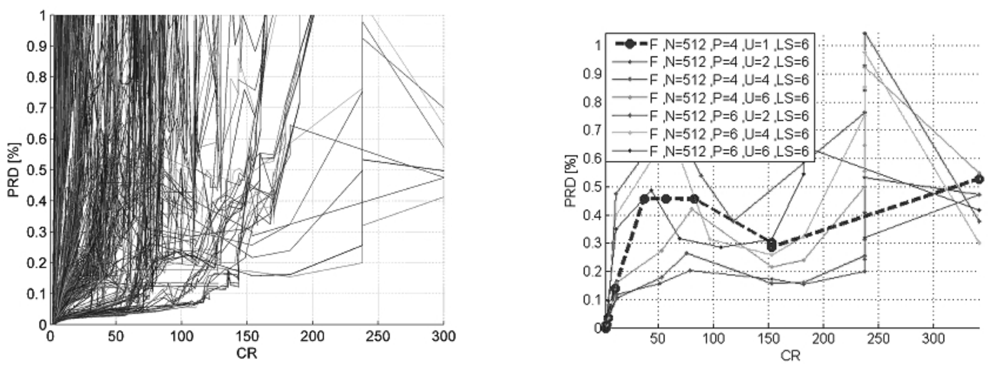

Fig. 5. a) Compression results for all configurations in brute force testing method (3072 curves), b) Best compression results selected for signal *F* (see Fig. 4) in the legend the length of the frame *N*, length of *P* and *U* filters and the number of lifting decomposition stages *LS* are given.

The highest compression ratios were obtained for signal *F* and are depicted in Fig. 5b. Signal *F* was produced in the laboratory by an Agilent generator as a pure sinusoid with added transient distortion and recorded with a sampling frequency of 100 kHz after a low-pass circuit [23]. This is an almost ideal case of a signal without any harmonic distortion. The exact results of reconstruction errors for signal *F* are depicted in Fig. 6. As seen from Fig. 6a CR reaches the value of 341.33 for the part of the signal without distortions. The CR for the second frame of signal *F* with a transient event around sample number 900 is significantly lower and equals

54.17. Figures 6c, d depict results for signal *F* with length of the frame *N* equal to 2049 and 4096 samples. A conclusion can be drawn that it is advantageous to use a shorter frame length when compressing waves with transient distortions, as CR for frames with transients is lower and transients possess short duration times. The short length of the frame is also beneficial from the implementation point of view as it requires less hardware. Figure 7 depicts compression results for signal *E*. Signal *E* was generated in the same configuration as *F* but recorded after a high-pass circuit thus showing a significant amount of noise which occupies the whole spectrum. It can be seen from Fig. 7 that the reconstruction error is evenly distributed along the time axis. The zoom on the original and reconstructed signal in Fig. 7b shows that after lossy compression the signal was smoothed (denoised). The analysis of signals *E* and *F* illustrates additional functionalities of the proposed compression algorithm which are event (transient) detection (Fig. 6c, d) and signal smoothing (Fig. 7b). Both features are the results of applying wavelet transform in the compression algorithm.

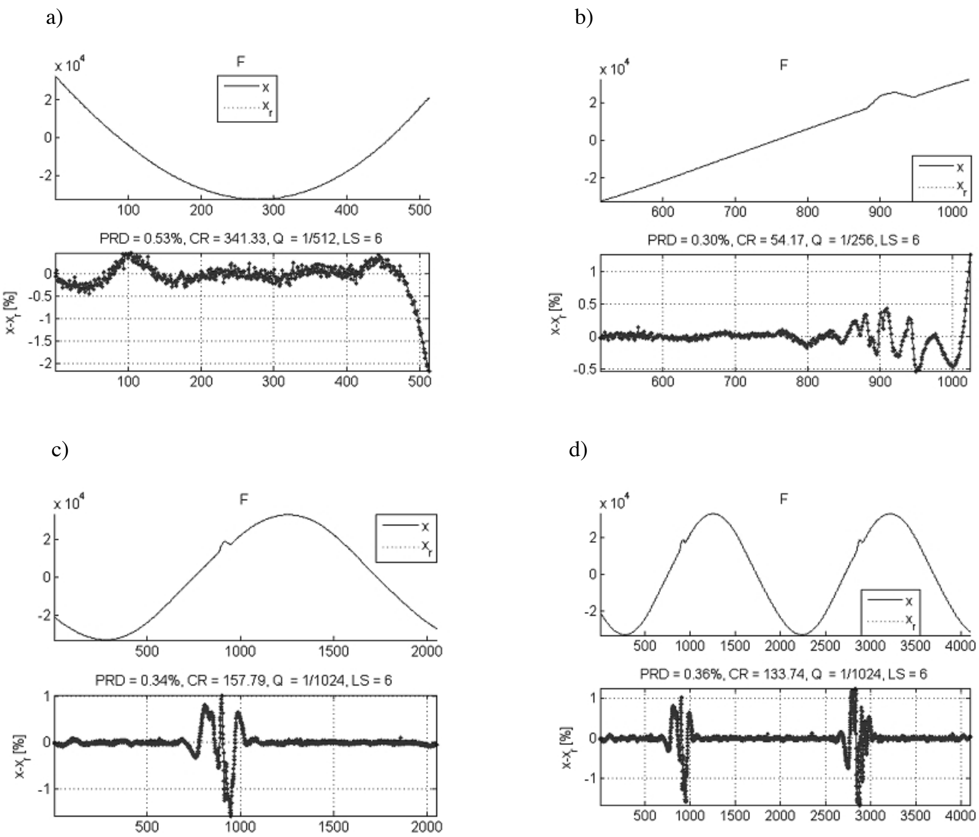

Fig. 6. Best compression results obtained for test signal *F* from Fig. 4, P = [-1/16, 9/16, 9/16, -1/16], U = [1/2], a) N = 512 first frame, b) N = 512 second frame, c) N = 2048, d) N = 4096. The compression results are given in lower subplot titles. In all cases signals x and x_r (upper subplots) and their difference (lower subplots) are shown.

The spectrum of signal *F* consists practically of 50 Hz frequency only. Thus during compression detail wavelet coefficients equal to zero (no information) and can be efficiently entropy encoded. The spectrum of signal *E* consists of 50 Hz frequency and wide-band noise, thus during compression detail wavelet coefficients are not equal to zero but posses some small values (some information) that cannot be entropy encoded as efficiently as in case of signal *F* and resultant CR is lower.

A high CR was also obtained for signal *B*. It was a voltage signal with slight harmonic distortion recorded with a sampling frequency of f_s = 12796 Hz. Harmonic distortion lasts during the whole recording time, thus as seen from Fig. 8a the reconstruction error is evenly distributed along the time axis.

Compression results for the rest of the test signals were comparable. Figure 8b shows average compression curves for different configurations. The averages were computed for test signals except the discussed above signals *B*, *E* and *F*. It is seen from Fig. 8b that for highly distorted waveforms (compare Fig. 4) one can expect CR in the range of 20 with PRD < 2%.

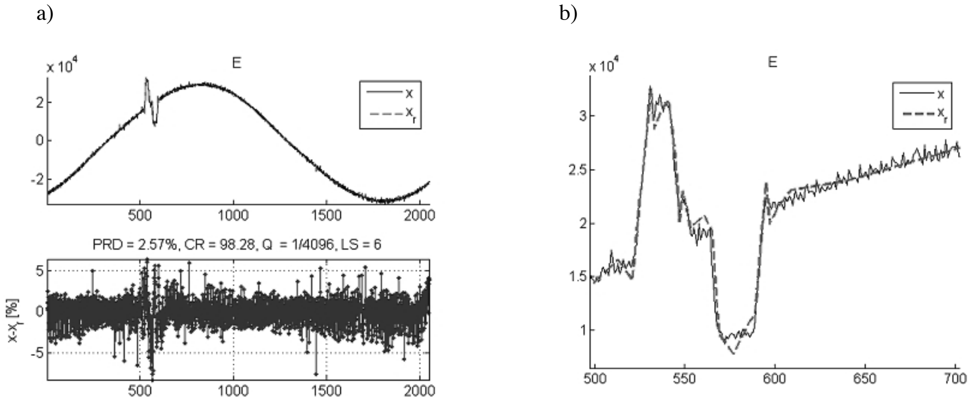

Fig. 7. Compression results for signal *E*: a) original signal *x*, reconstructed signal x_r and the difference between these signals, b) detailed view of the transient disturbance in original *x* and reconstructed x_r signals.

Figure 9 presents compression results for highly distorted sinusoidal signal *wave4* for two quantization levels. Compression ratios 19.79 and 31.43 were obtained with PRD 1.98 % and 4.75 % respectively. Subjective inspection of differences between original and reconstructed signals in Fig. 9 gives the impression of high compression quality even in the case of PRD = 4.75%.

a) b)

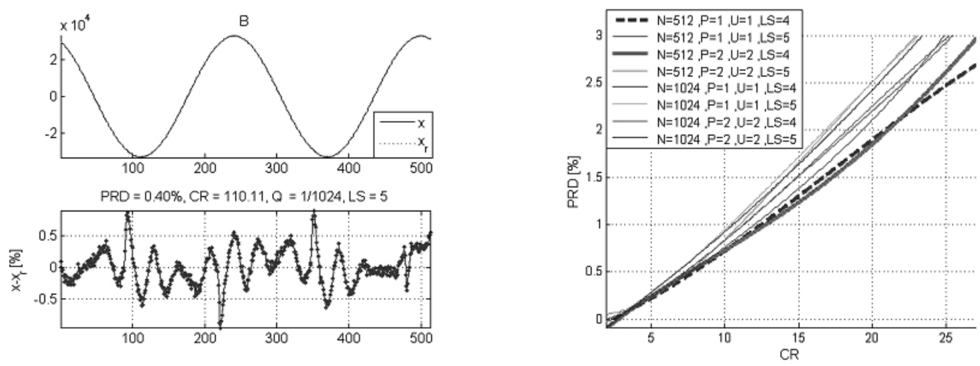

Fig. 8. a) Compression results for signal B. b) Averaged compression results for test signals (Fig. 4) except signals B, E and F.

a) b)

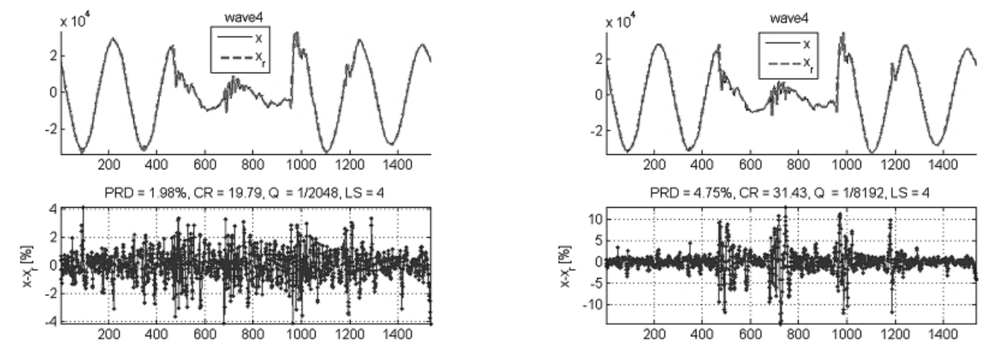

Fig. 9. Compression results for signal *wave4*; original signal x, reconstructed signal x_r and the difference between these signals is shown for: a) CR = 19.79, PRD = 1.98% and b) CR = 31.43, PRD = 4.75%.

4. CONCLUSIONS

Lifting based wavelet compression method for electric power system signals is proposed in the paper. Preliminary compression results in the form of plots showing the quality measured by PRD versus compression ratios are presented for a broad range of field recorded power system signals (some of them selected be IEEE experts). It was verified that for sinusoidal signals with slight distortion, a high compression ratio in the range of few hundred can be obtained while preserving high quality of lossy compression. For highly distorted sinusoidal waves, the worst case example, a compression ratio in the range of 20 was obtained with PRD not exceeding 2%, but such distortions are rare and if they appear only in a few frames of the signal they will be compressed with a lower ratio. Still the lowest compression ratios obtained are at least 2 times higher then those reported in [14–17].

Lifting wavelet transform that is used for data decorrelation can be additionally used for transient detection and signal smoothing (denoising). Thus the compression algorithm can be extended for signal analysis and enhancement, although for high vales of PRD signal of interest (i.e. disturbance) can be partially or even fully removed or changed, which is main drawback of all lossy compression algorithms. It is also possible for progressive quality based coding by employing the EZW algorithm [5, 6, 10, 13].

The advantages of LWT were highlighted in section 2.1. Implementation of LWT can be very efficient in integer arithmetic. Lifting scheme allows in-place computations (without the need of additional memory) and the coefficients of lifting filters are based on powers of two, thus multiplication can be done by bit shifts. It was shown that in most cases good results are obtained with the frame length equal to 512 samples with 4 or 6 (for a high sampling frequency) wavelet decomposition levels and short lifting filters of order 1 or 2.

Implementation of the entropy encoder depends of available computational power. Huffman coding is computationally cheap but requires a code table. The table can be designed as near optimal for a chosen class of signals, it can be updated during encoding or dynamic Huffman coding can be used. For coding of detail wavelet coefficients, zero counting algorithms can also be used, as most of them, especially after scaling have a value of zero. Compression ratios were evaluated on the base of Shannon entropy. One can expect higher compression ratios than those reported in the paper in case of implementation of additional encoding algorithms like context coding in the entropy encoder.

The paper proposes the compression method rather than a specific implementation, but the obtained general results guarantee good compression performance in systems for storing and transmitting power system signals. The proposed compression algorithm will be incorporated in a currently developed system for monitoring power signals based on a PC computer and DAQ (Data AcQuisition) board.

Straightforward reference to compression algorithms of power signals presented in literature is difficult for several reasons. The main obstacle is the lack of a widely accepted database of electric power system signals that could be used as a reference for testing the quality of proposed compression solutions. In most papers devoted to compression of power signals the authors choose different test signals containing various phenomena acquired with different sampling frequencies and resolutions or even ideal test signals artificially generated in MATLAB and thus their work can not be fairly confronted with others. In this paper the part of testing signals was purposely selected from the publicly accessible IEEE database to overcome the above-mentioned difficulties in comparing different compression methods.

REFERENCES

1. Phadke A.G., Thorp J. S.: "History And Applications of Phasor Measurements", *Power Systems Conference and Exposition*, Oct. 29 – Nov. 1 2006, pp. 331-335.

2. IEC 61000-4-7, Electromagnetic Compatibility (EMC) – Part 4: *Testing and Measurement Techniques Section 7: General Guide on Harmonics and Interharmonics Measurements and Instrumentation, for Power Supply Systems and Equipment Connected Thereto*, IEC, Geneva, Switzerland, 2002.
3. *IEEE Recommended Practice for Monitoring Electric Power Quality*, IEEE Std 1159-1995, June 14, 1995.
4. http://grouper.ieee.org/groups/1159/2/testwave.html
5. Salomon D.: *Data Compression: The Complete Reference*, 3rd Edition, Springer, 2004.
6. Tinku A., Ping-Sing T.: *JPEG2000 Standard for Image Compression Concepts, Algorithms and VLSI Architectures*, Wiley & Sons, 2005.
7. Daubechies I.: *Ten Lectures on Wavelets*, SIAM, Philadelphia, Pennsylvania, 1992.
8. Mallat S.: *A wavelet tour of signal processing*, Academic Press 1998.
9. Coifman R. R., Wickerhauser M. V.: "Entropy-based algorithms for best basis selection", *IEEE Trans. on Inf. Theory* 1992, vol. 38, no. 2, pp. 713-718.
10. Zhitao L., Dong Y. K., Pearlman W. A.: "Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm", *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, July 2000, pp. 849-856.
11. Duda K., Turcza P., Zieliński T. P.: "Lossless ECG Compression with Lifting Wavelet Transform". *IEEE Instrumentation and Measurement Technology Conference*, Budapest, Hungary, May 21-23, 2001.
12. Duda K.: "Lossless ECG Compression with Adaptive Lifting Wavelet Transform", *International Workshop on Spectral Methods and Multirate Signal Proc*. 16.06.2001 – 18.06.2001 Pula, Croatia.
13. Duda K.: "Lossless ECG Compression with SPIHT", *International Conference on Signals and Electronic Systems* 2001, Łódź, 18-21 September 2001, pp.187-192.
14. Santoso S., Powers E. J., Grady W. M.: "Power Quality Disturbance Data Compression Using Wavelet Transform Methods", *IEEE Transactions on Power Delivery*, July 1997, vol. 12, no. 3, pp. 1250-1257.
15. Litter T. B., Morrow D. J.: "Wavelets for the Analysis and Compression of Power System Disturbances", *IEEE Transactions on Power Delivery*, April 1999, vol. 14, no. 2, pp. 358-364.
16. Hamid E. F., Kawasaki Z. I.: "Wavelet-Based Data Compression of Power System Disturbances Using Minimum Description Length Criterion", *IEEE Transactions on Power Delivery*, July 2002, vol. 17, no. 2, pp. 460-466.
17. Panda G., Dash P. K., Pradhan A. K., Meher S. K.: "Data Compression of Power Quality Events Using Slantlet Transform", *IEEE Transactions on Power Delivery*, July 2002, vol. 17, no. 2, pp. 662-667.
18. Daubechies I., Sweldens W.: "Factoring Wavelet Transforms into Lifting Schemes", *The J. of Fourier Analysis and Applications*, vol. 4, pp. 247-269, 1998.
19. Calderbank A. R., Daubechies I., Sweldens W., Yeo B. L.: *Wavelet transforms that map integers to integers*, Technical report, Department of Mathematics, Princeton University 1996.
20. Duda K.: "Computing interpolating predictors without boundary effect for wavelet lifting transform", *ICSES'2000 – International Conference on Signals and Electronic Systems,* 17-20 October 2000, Ustroń, Poland.
21. Zieliński T. P., Stępień J., Duda K.: "Filter design for adaptive lifting schemas", *X European Signal Processing Conference*, 4-8 September 2000, Tampere, Finland.
22. Duda K.: "Integer Fast Fourier Transform – Implementation and application", *EUSIPCO 2004, XII European Signal Processing Conference*, 6-10 September 2004, Vienna, Austria.
23. Duda K, Bień A.: "Digital measurement of transient disturbances in electric power network with analog integration – experimental research", *PAK 10 bis*, pp. 143-146, XVI MiSSP: Krynica, 17–21 Sept. 2006. (in Polish).