Selection of Optimal wavelet for lossless EEG compression for real-time applications

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Abstract

This paper discusses a wavelet based, lossless compression scheme for Electroencephalogram (EEG) signals. For any wavelet based compression scheme, selection of wavelet base is very important task for obtaining effective signal compression. Here, emphasis is given for selection of wavelet basis and number of decomposition levels. The proposed EEG compression algorithm comprises of a preprocessing step involving computation of the difference signal of EEG time series, followed by integer lifting wavelet transform and set partitioning in hierarchical trees (SPIHT) as a wavelet encoder. The optimal wavelet base is chosen based on the compression ratio (CR) as well as time taken for encoding the wavelet coefficients by SPIHT coder. The algorithm is tested with normal and abnormal multi-channel electroencephalogram data of 8 minutes duration. The optimal wavelet base and decomposition level is presented based on the experimental results.

Key Words: compression, electroencephalogram, lifting scheme, SPIHT, wavelet transform.

1. INTRODUCTION

Electroencephalogram (EEG) signal is a record of electrical activity of the brain, is widely used in sleep studies, diagnose brain disorders and brain research. As per international standard for EEG measurement, a 10-20 electrode system (21 electrodes) is employed for EEG signal acquisition. A large number of electrode arrays are employed in Brain Computer Interface (BCI), where more localized information is needed. Due to the use of large electrode arrays and prolonged recording, enormous amount of EEG data is generated. Hence an efficient compression algorithm is needed either for storage or transmission.

A wavelet based compression algorithm, relies on appropriate wavelet base and decomposition level for achieving higher compression performance. The experimental results for image coding using integer to integer lifting scheme by Calderbank et al, 1998 shows that, no wavelet consistently perform for all kinds of images. Selection of mother wavelet based on the image to be compressed, increased the compression ratio (Kharate et al, 2007). Hence, a search for suitable wavelet base for EEG compression is of immense interest and enables one to achieve higher compression performance.

Among the lossy and lossless compression techniques, lossless compression is the legal way to store medical information in many countries. Hence, lossless compression technique is generally preferred and always of interest for the compression of biomedical signals. Integer to Integer lifting wavelet transform (Calderbank et al, 1998), best suits for 'lossless compression, which preserves the integer nature and represents the signal at multiple resolutions. Set Partitioning in Hierarchical Trees (SPIHT) is a wavelet encoder that transforms the wavelet coefficients to an embedded bitstream (Said and Pearlman, 1997). A compression algorithm of this kind is addressed by (Sun et al, 2002). A detailed analysis on the wavelets to be used, the number of decomposition levels to be chosen, the encoding delay encountered during compression process and its effects on the lossless compression performance is not well addressed so far.

Antoniol et al, 1997 presented a survey of EEG lossless compression algorithms using predictive coding, transform coding, vector quantization together with entropy encoding. The scheme proposed
here, explores the choice of appropriate wavelet from the available wavelet base and number of
decomposition level for lossless EEG signal compression.

2. LIFTING SCHEME

Wavelets are defined as translates and dilates of one fixed function, which can be used to analyze
and represent general functions. Lifting scheme is a method to build and realize wavelets. Lifting
relies on exploiting the spatial domain correlation to build wavelets. Lifting, when used to build
translation and dilation invariant wavelets, will get reduced to ladder structures (factoring
algorithms). Wavelets that can be realized using filter banks can be decomposed into lifting steps.
The filter bank, being written in polyphase form can be factored into elementary matrices using
lifting. The lifting scheme allows us to construct and implement certain biorthogonal wavelets
(Calderbank et al, 1998; Daubuchies and sweldens, 1998)

A simplified form of lifting scheme is given in Figure. 1. The signal is split up into odd and even
samples known as lazy wavelet, which is followed by prediction (P) and update(U) operators. P and
U can also be visualized as a low pass and high pass filter respectively. $s_{0,i}$ represents the signal,
and $d_{1,i}$ represents the approximate and detail coefficients after first level of decomposition.

Lifting, can also be used to realize highly non-linear operations. Every wavelet or subband
transform can be obtained as the Lazy wavelet followed by a finite number of primal and dual lifting
steps and a scaling (Calderbank et al; 1998). The inverse transform, is obtained by flipping the signs
and reversing the steps.

![Fig. 1. Forward and inverse wavelet transform using lifting](image)

3. SET PARTITIONING IN HIERARCHICAL TREES ALGORITHM (SPIHT)

Set Partitioning in Hierarchical Trees (SPIHT) coding was developed by Said and Pearlman; 1996
and it achieved a notable success in the field of image coding. It takes wavelet coefficients as input
and generates an embedded bit-stream, by which the transmission can be stopped at any instant to
reconstruct the signal. It relies on the self-similarity among different temporal layers for achieving
compression.

The principles of SPIHT are partial ordering of the transform coefficients by magnitude with set
partitioning sorting algorithm for an ordered bit-plane transmission. The SPIHT divides the subset
based on its temporal orientation trees. The same set-partitioning rule is shared by the encoder and
decoder, hence they have the same computational complexity. The number of branches in temporal
orientation trees is governed by the number of decomposition levels chosen. An increase in the
number of decomposition levels affects the compression ratio and coding delay. The relationship is
not explicit and depends on the data chosen for compression. Choosing a correct number of
decomposition levels will enhance the compression ratio and reduce coding delay.
4. COMPRESSION ALGORITHM

EEG is a random signal whose derivatives are close to zero. This fact can be utilized to introduce a simple preprocessing technique to improve the compression. Pre-processing reduces the dynamic range of the signal and removes the DC component, which usually decreases the temporal decorrelation performance. The compression algorithm is given in Figure 2.

The explanation of compression algorithm is follows,

1) EEG signal $x$ of block length $M$, is subjected to first difference to yield $y_d$,

$$y_d[i] = x[i+1] - x[i]; i = 1,...,M - 1$$

$Index = x[1]$

2) $y_d$ is subjected to lifting wavelet transform

3) The wavelet coefficients are encoded by SPIHT encoder until bit-plane 0.

4) The Index information from the pre-processing step is added to the header information of output bit-stream given by SPIHT coder.

The inverse follows immediately by removing the header from bitstream, followed by SPIHT decoder and inverse lifting transform to obtain the difference signal. The index value is then used to reconstruct the signal back. Index is inserted as first sample and then cumulatively summed up to get $x$ given by,

$$x[i] = \sum_{j=i}^{i} y_d[i]; i = 1,...,M$$

5. EXPERIMENTAL RESULTS

The compression algorithm is tested with both normal and abnormal EEG data. The data consists of sixteen channels of EEG sampled at a rate of 500Hz and digitized at a resolution of 16 bits. The duration of the record is around 8 minutes, but is split into blocks of size 2048 samples for convenience. Wavelet base which achieves maximum compression ratio and reduces the encoding delay is considered as the optimal one. Experiments were done by varying the wavelet base and the number of decomposition levels. In this work, lifting construction of daubechies(db), symlets(sym) and cohen-daubechies-feauveau(cdf) wavelets are taken for analysis, decomposition level is varied from 3 to 8. The compression ratio, can be calculated using the following formula,

$$CR = \frac{M \times N_x}{H + S}$$

where $M$ is the total number of samples, $N_x$ is the number of bits per sample, $H$ is the number of header bits and $S$ is the length of the bitstream from SPIHT coder. Encoding delay is the time taken by the SPIHT coder for converting the wavelet coefficients into bitstream, is calculated from the runtime of the program.

The experimental results were consolidated in two aspects. (i) The wavelet that is giving maximum compression ratio and less encoding delay is to be determined. The average values of the
compression ratio and delay, computed across decomposition levels and summarized as Compression ratio- Encoding delay plot for the wavelets taken for analysis, given in Figure 3. (ii) The decomposition level giving maximum compression ratio is to be selected. For selecting the decomposition level, average CR and delay is computed across all the wavelets and given in Table I.

The wavelets occupying the right-bottom corner in Figure 3, achieves higher compression ratio and reduces delay. Low delay corresponds to reduction in dynamic range of the wavelet coefficients; hence they can be used as good base for EEG signals. The compression performance is maximum for the wavelets having vanishing moments nearly 2 to 4. By referring to Table I, decomposition level of 6 & 7, which increases the CR and reduces the delay can be considered for lossless compression.

![Fig. 3. Compression ratio Vs Encoding delay: The values given here is the average of the values obtained for both the datasets. wavelets encircled achieve a higher Compression ratio & less encoding delay](image)

**TABLE I**

<table>
<thead>
<tr>
<th>Decomposition level</th>
<th>Parameters</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
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<tbody>
<tr>
<td>CR</td>
<td>1.904</td>
<td>1.906</td>
<td>2.021</td>
<td>2.038</td>
<td>2.044</td>
<td>2.046</td>
<td></td>
</tr>
<tr>
<td>Delay (s)</td>
<td>0.857</td>
<td>0.777</td>
<td>0.771</td>
<td><strong>0.762</strong></td>
<td><strong>0.758</strong></td>
<td>0.766</td>
<td></td>
</tr>
</tbody>
</table>

**6. CONCLUSION**

This paper addresses the issue of selection of wavelet base and decomposition level to achieve higher compression ratio and less encoding delay, thus explores the possibility of real-time applications. A further reduction in delay is expected as one optimizes the code. The maximum compression ratio that can be obtained from this technique is nearly 2.16. Biorthogonal wavelets with vanishing moments around 2 to 4, with a decomposition level of 6 & 7 can be considered as an attractive candidate for lossless EEG compression. A further improvement can be achieved by employing adaptive lifting transform and applying magnitude set representation for integers. Compression algorithm is chosen simple, primarily to bring out the relationship between the wavelet base and the signal taken for compression. Having clearly understood this relationship, sophisticated compression algorithms can be built delivering a higher compression performance.

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