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Pre-Processing of Multi-Channel EEG for Improved Compression Performance using SPIHT

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***Abstract*— A novel technique for Electroencephalogram (EEG) compression is proposed in this article. This technique makes use of the inter-channel redundancy present between different EEG channels of the same recording and the intra-channel redundancy between the different samples of a specific channel. It uses Discrete Wavelet Transform (DWT) and Set partitioning in hierarchical trees (SPIHT) in 2-D to code the EEG channels. Smoothness transforms are added in order to guarantee good performance of SPIHT in 2-D. Experimental results show that this technique is able to provide low distortion values for high compression ratios (CRs). In addition, performance results of this method do not vary a lot between different patients which proves the stability of the method when used with recordings of different characteristics.**

I. INTRODUCTION

Electroencephalography is the monitoring or recording of electrical activity in the brain. Recording techniques of EEG involve placing electrodes either inside the brain, over the cortex under the skull, or at certain locations over the scalp. Electroencephalography provides an insight on the human brain: it can detect abnormalities, diagnose mental disorders like dementia, epileptic seizures and psychiatric disorders. In addition, effects of the administered drugs on the changes in EEG waveforms can be observed. EEG is also used in telemedicine and brain computer interface (BCI).

Recording of EEG is done over several hours and along several channels. The number of channels can even exceed 256 for increased accuracy and reliability in diagnosis. Every sample of EEG might be important and cannot be disregarded. The recording can result in huge amounts of data to be stored and/or transmitted, which calls for efficient and low distortion compression techniques. Although lossless compression is more desired for medical signals, it was shown that higher compression rates can be achieved using lossy techniques.

Scalp recordings of EEG can be seen as the measure of the projection of the activity inside the brain on certain locations on the scalp. The same source of activity can have several projections on the scalp. For this reason, when reading different EEG channels, a lot of similarity and even superposition of the signals can be noticed. When aiming at compression of these EEG channels, looking at the signals in a spatial dimension, rather than just time dimension, can help capture more redundancy and similarities. Therefore, better compression can be achieved when combining all channels used in the recording.

As mentioned previously, visual correlation is highly visible both between several channels and in a single channel between different time segments. This correlation or redundancy should be exploited when building a compression algorithm. In compressing medical signals, it very important to maintain all relevant information contained in the signals for accurate medical diagnosis. Thus, an accurate reconstruction of the EEG signals is a very important factor, specially in tele-medicine where noise, jitter and delays, caused by the telecommunication technique used to transmit the signals, add further distortion to the compression. The suggested method aims at exploring these correlations in order to achieve better compression with low distortion using classic transforms and coding techniques.

The following paragraphs provide a literature review on the usage of Wavelet Transform (WT) and set partitioning in hierarchical trees (SPIHT) in compressing EEG signals. Afterwards, a novel method of applying these compression methods on EEG channels is suggested. The article ends with an analysis on the simulations' results and suggestions for improvement.

Cardenas-Barrera *et al.* use Wavelet Packet Transform (WPT) to segment and decompose the EEG Signals [1]. The compression algorithm is composed of the following sections: segmentation, transformation, thresholding of the low-relevance coefficients, quantization and Run-Length Coding (RLC). Calculating the proper thresholds is the main issue in this model, these values should preserve the signal's characteristics while keeping the distortion within acceptable limits. This compression algorithm is able to achieve a Compression Ratio (CR) of 9.06 with a Percent Root-mean squared distortion (PRD) of 5.3275. CR is defined as the ratio of the number of bits used to represent the original data to the number of bits required to code the compressed data. This method does not examine the mutual information that exists between the different channels of the same recording.

A 2-D compression technique that uses an integer lifting wavelet transform (ILWT) as the de-correlator, with SPIHT as the source coder is presented [2]. The 2-D algorithm is compared to the same one in 1-D that also uses ILWT with SPIHT and the 1-D case gave much higher distortion for the same bit rate and larger delays. 2-D SPIHT coding is suited for smooth natural images. However, EEG signals possess a non-stationarity characteristic. Thus, the 2-D matrix formu-

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lation of the channels is not as smooth as natural images and the compression performance deteriorates for certain segments. Smoothness transforms should be added to the 2-D EEG matrix to enhance the performance of SPIHT. Authors do not show how distortion varies at different CRs, however, bit planes are used to display the results of the compression.

EEG Compression in 3-D was applied by Dauwels et al. and tested on two types of data [3]. Methods like SVD (Singular Value Decomposition), Parafac and Tucker decompositions were tested on recordings of patients with mild cognitive impairment (MCI) and on EEG-Motor Mental Imagery datasets of the physiobank database [4]. Rate distortion curves show that Tucker and Parafac gave the best results in compression. However results vary a lot between the two different types of recording. Better results were found for the second dataset where the subject opens and closes his fist until a certain target disappears from a screen. When reading this data, peaks are observed every few seconds and on all channels. This data is very artificial and does not reflect the characteristics of EEG data types that are usually recorded over long periods of time like long-term monitoring of patients with epilepsy.

A recent article published in Electronic Letters studies the compression of EEG using 1-D SPIHT [5]. In this article, the computational complexity of the method is analysed. Their results show that 1-D SPIHT is able to achieve a CR of about 30 for a PRD of 30%. Testing was done on intra-cranial recordings of 21 patients suffering from epileptic seizures. However, when compressing EEG signals, results can vary a lot between different types of recordings. 1-D SPIHT is tested on scalp recordings in this article and the results are shown in section IV. Authors of this article do not show how the results are varying between the different patients. In addition, this algorithm compresses each channel alone and does not take into account the inter-channel redundancy that exists between the different channels. This redundancy is more present in intra-cranial electrodes that provide recordings at the same location but at different depths.

This article presents a lossy EEG compression scheme that applies image compression techniques on 2-D EEG matrices. Spatial correlation between different EEG channels is reduced using 2-D DWT and SPIHT. A method that adds smoothness to the EEG matrix is suggested. This is done to enhance the performance of SPIHT and achieve better performance in compression.

II. Methods

A. Discrete Wavelet Transform (DWT)

Wavelet Transforms provide multi-resolution, locality, and compression when combined with zero-tree coding techniques. Many compression algorithms use these transforms to decompose a signal and take advantage of the properties of these coefficients in energy compaction.

DWT gives the time-scale representation of a digital signal using digital filtering techniques. To find the DWT coefficients, the signal is passed through cascades of low and high pass filters implemented at the low frequency bands of each level, the high frequency bands are left unchanged. 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.

B. Set partitioning in hierarchical trees (SPIHT)

The Set-Partitioning in Hierarchical Trees (SPIHT) is a coding algorithm that exploits the relationships between the wavelet coefficients across the different scales at the same spatial location in the wavelet sub-bands [6], [7]. Exact bit usage control can be achieved using the SPIHT algorithm. A pre-specified bit-rate or quality requirement can be used as criterion to stop the encoding and decoding process at any instance [8]. SPIHT targets the coding of the position of significant wavelet coefficients and the coding of the position of zero-trees in the wavelet sub-bands. It was originally suggested for the compression of 2-D images, thus it exploits the basic characteristics of this type of data. More precisely, it exploits the following image characteristics [6]:

1) Most of the image's energy is located in the low frequency components and there is a decrease in variance as we move from the highest to the lowest levels of the frequency sub-band pyramid.
2) Spatial self-similarity is observed among the sub-bands, and the coefficients are likely to be better magnitude-ordered when going deeper in the frequency sub-band pyramid along the same spatial orientation.

Signal's smoothness can be measured by the amount of energy in the low frequency bands [9]. When working with 2-D matrices, one level of wavelet decomposition produces an approximate sub-band (low frequency (LF) band) and three high frequency (HF) bands. The matrix is considered smooth when more energy is concentrated in the LF band compared to HF bands.

III. Compression Scheme

SPIHT coding originally targets two dimensional images. In EEG, transferring the data into two-dimensional matrices can be accomplished either in one channel or in a multi-channel context. However, choosing the appropriate segment and matrix size and the optimal channel numbering in the multi-channel case can highly affect the performance of the compression.

The 2-D multi-channel matrix is formed by choosing the rows of the matrix as segments from different channels as follows:

$$\underline{\mathbf{EEG_i}} = \begin{bmatrix} \mathbf{s}_{i,1} \\ \mathbf{s}_{i,2} \\ \vdots \\ \mathbf{s}_{i,M} \end{bmatrix} \tag{1}$$

where $\mathbf{s}_{i,l}$ is the EEG segment of index i of channel at index 1 and M is equal to the number of channels used in the recording. Each EEG segment used in the matrix groups N consecutive time samples. Arrangements of the channels in the matrix affects the smoothness of the matrix and thus the performance of the compression.

The algorithm first computes the correlation coefficient of each row of the matrix with all other rows. To build the smooth EEG matrix, the first row is kept as the first EEG channel used in the recording, then each adjacent row is chosen as the highest correlated row among all other rows in the matrix. When doing this, in most matrices, the last rows are the channels that are close to the reference. This is due to the fact that there is least amount of activity in this region.

This method of choosing the rows of the matrix guarantees that each two adjacent rows are highly correlated. To achieve more smoothness, the first $P+1$ rows are selected. The value P is chosen as the highest value that is smaller than M and divisible by 2^k, with k equal to the number of levels used in the DWT. From these $P+1$ rows or channels, the channel that has the highest correlation coefficient with all other P channels, Ref, is selected. The values of its samples are subtracted from each channel of the P-by-N matrix. This results in added smoothness to the 2-D EEG matrix. DWT is then applied on this P-by-N matrix. However, high correlation is still present within the blocks of the DWT coefficients of the same sub-band, which is common when compressing naturally smooth images [10]. To reduce this, a de-correlation block, that involves simply applying Discrete Cosine Transform (DCT), was added after DWT [10]. SPIHT coding is then performed on the transformed DWT coefficients.

The reference channel and the other least correlated channels are coded using 1-D DWT and SPIHT. The indices of the channels showing the chosen arrangement in the matrix, and the index of the highest correlated row, Ref, are sent as overhead with SPIHT output. This coding scheme is repeated for every block of $M \times N$ samples in the recording.

IV. Results and Discussions

In the scalp recordings done at the EEG lab at the Montreal Neurological Institute (MNI) that are used in this paper, 29 electrodes are used with a sampling frequency of 200 Hz. The montage used is referential with the reference located on the center of the scalp, known as FC_z in the International 10-20 System [11, p.139].

The performance parameter used to analyse the results is the percent-root mean square distortion (PRD):

$$PRD_{i,l}(\%) = \sqrt{\frac{\sum_n^N (s_{i,l}[n] - \hat{s}_{i,l}[n])^2}{\sum_n^N s_{i,l}[n]^2}} \times 100 \qquad (2)$$

where $s_{i,l}[n]$ is the EEG sample n of segment at index i and channel at index l, and $\hat{\mathbf{s}}_{i,l}$ is the reconstructed EEG segment after compression. Thus PRD is calculated for each EEG channel, l, and segment i, then the mean over all segments and channels is calculated to reflect the PRD at a certain CR.

In the testing, M is equal to 29, resulting in P equal to 24 for a DWT number of levels, k, equal to 3. Values of k equal to 2, 3 and 4 were tested and 3 was chosen because it guarantees that the least correlated channels coded using 1-D SPIHT are the four channels closest to the reference. It gave better performance than the other values. For choosing the appropriate wavelet in the DWT, it is suggested that Biorthogonal 4.4 wavelet has a more established popularity in compressing 2-D images [12], [13]. The compression method re-arranges the 2-D matrix in order to achieve more smoothness. The transformed EEG matrices have almost similar properties as natural images. For this reason, in our testing, biorthogonal 4.4 proved to be better than the classic Haar wavelet.

Fig. 1 shows the PRD results for different compression ratios of 1-D SPIHT and 2-D SPIHT. 1-D SPIHT was used with segment length N equal to 1024, which gave the best results compared to other values like 128, 256 and 512. The size of the EEG channel segments used in the 2-D SPIHT method is equal to 256. A 5 level DWT with biorthogonal 4.4 wavelet, was performed prior to SPIHT coding in the 1-D case. This plot highlights the fact that 2-D SPIHT is able to achieve higher compression ratios for the same PRD percentage. This is due to the fact that in the one dimensional case, the correlation between the channels still exists after compression. Thus, redundant information is still being sent. In addition, when applying SPIHT in 2-D, the entropy of the output is close to 0.5. Whereas, for 1-D SPIHT, the entropy is close to 1. For this reason, a Run-Length coding (RLC) block was added to 2-D SPIHT output and there was a relevant decrease in the total number of bits required for coding a specific matrix.

1-D SPIHT is shown to achieve a CR of about 30 for a PRD of 30% when tested on intra-cranial recordings of patients with epilepsy [5]. However, when testing on the scalp recordings obtained from MNI, results are different and the proposed method is able to achieve better compression performance. This highlights the fact that EEG recordings differ a lot between different types of recording methods and different patients.

The proposed method is compared to Tucker and Parafac tensor decompositions applied on 3-D EEG tensors [3]. The size of the tensor used in these two methods is equal to 29-by-16-by-16. Thus the same EEG segment used in 2-D SPIHT of size N equal to 256 is arranged in 2-D as 16-by-16 as explained in the article [3]. The third dimension in these two methods is the EEG channel number. Testing was done on 9 patients over a period of one hour for each patient. Fig. 3 shows the PRD results with the 25 and 75 percentiles to highlight how the PRD values are varying between the patients. The proposed method gave better performance results than Tucker and Parafac. However for CRs higher than 18.5, the performance of the new method and Parafac are almost the same. A 7% PRD is suggested to be the maximum allowed loss for preserving clinically relevant information [1], [5]. For this PRD value, Parafac is able to achieve a CR of around 2, while the proposed method can achieve a CR of around 5. The methods were also tested for N equal to $1{,}024$, resulting in 29-by-32-by-32 tensors, but the same improvement in performance was noticed. The only difference in the results is all three PRD lines drop by almost 3%.

For compression ratios below 20, the PRD results vary

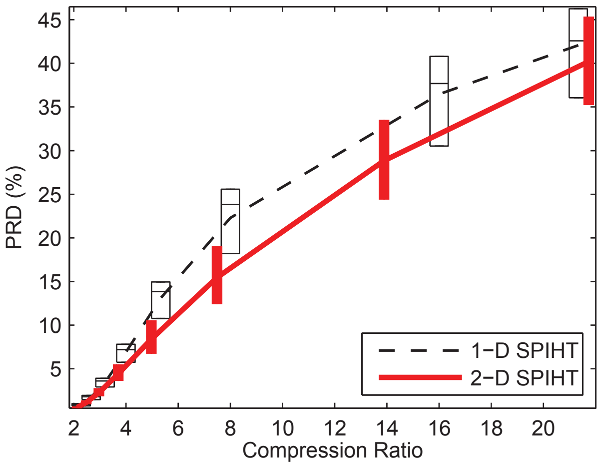

Fig. 1. Percent-root mean square distortion comparison between 2-D and 1-D SPIHT.

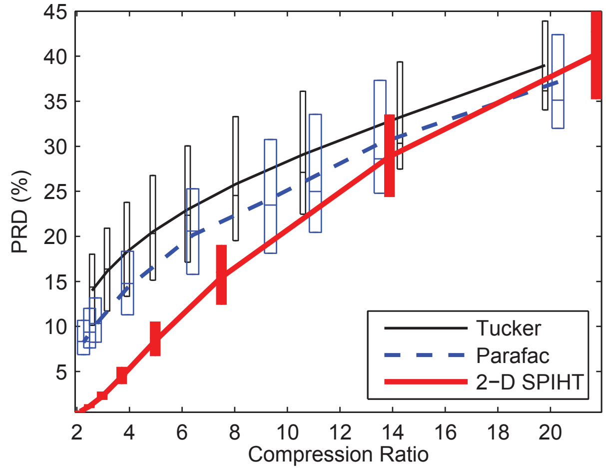

Fig. 2. Percent-root mean square distortion comparison between Tucker [3], Parafac [3] and the proposed method. The boxes extend from the 25th percentile to the 75th percentile.

much less between patients for the proposed method than for Parafac and Tucker. This variance is negligible for CRs below 7. This criterion is very important in EEG compression since the characteristics of the recordings vary a lot between different patients.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

Looking at the EEG channels in 2-D enables us to make use of the redundancy found between the channels and between the samples of the same channel. The proposed algorithm is able to achieve low variance between patients and low distortion compared to other compression methods like 1-D SPIHT, Tucker and Parafac. For PRD values lower than 30%, the proposed algorithm achieves higher compression ratios. Above this value, distortion can be regarded as high which is to be avoided when dealing with biomedical signals with important diagnostic information.

B. Future Works

EEG recordings vary a lot between both different types of recordings and different patients of the same type of recordings. Thus, finding an algorithm that has stable performance is a challenge. In addition, the compression scheme should still preserve important diagnosis information. It would be important to test abnormality detection systems, like epileptic seizure detection, on both the original data and the compressed output to further analyse the performance of the compression algorithm. In addition, the performance of the compression should be tested on different types of recordings like invasive intra-cranial EEGs.

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