Low Power Compression of EEG Signals Using JPEG2000

Garry Higgins, Brian Mc Ginley, Martin Glavin, Edward Jones
Bioelectronics Research Cluster, NCBES
National University of Ireland Galway
Galway, Ireland
g.higgins1@nuigalway.ie, brian.mcginley@nuigalway.ie, martin.glavin@nuigalway.ie, edward.jones@nuigalway.ie

Abstract— **This paper outlines a scheme for compressing EEG signals based on the JPEG2000 image compression algorithm. Such a scheme could be used to compress signals in an ambulatory system, where low-power operation is important to conserve battery life; therefore, a high compression ratio is desirable to reduce the amount of data that needs to be transmitted. The JPEG2000 specification makes use of the wavelet transform, which can be efficiently implemented in embedded systems. The standard was broken down to its core components and adapted for use on EEG signals with additional compression steps added. Variations on the components were tested to maximize compression ratio (CR) while maintaining a low percentage root-mean-squared difference (PRD) and minimize power requirements. Initial tests indicate that the algorithm performs well in relation to other EEG compression methods proposed in the literature.**

Keywords- EEG compression; Wavelets; JPEG2000

I. INTRODUCTION

Recent advances in health care have seen an increased focus on at-home care and monitoring of patients. Portable devices allow patients to be monitored at home on an out-patient basis, thus advancing the goal of providing ubiquitous and pervasive healthcare. This in turn, relieves pressure on over-burdened hospital systems, and allows the patient remain in an environment they are comfortable in. It also allows more comprehensive monitoring with patients involved in a variety of activities in their day-to-day lives. For a device to be truly portable, there is a minimum battery life that would be required of it so that the wearer would not need to constantly remain beside a power source. It is for this reason that one of the main factors in designing a portable health care device is ensuring power consumption is at a minimum.

Multichannel electroencephalogram (EEG) is a tool commonly used for measuring the electrical activity of the brain. The application of EEG to diagnose a variety of neurological conditions such as Epilepsy and Alzheimer's disease [1] has long been established. Diagnosis of these conditions however, often requires long-term monitoring of the patient's EEG activity. A portable device that monitors EEG activities at home, could allow patients remain at home in comfort and allow the data to be processed offline by a technician or classification tool. Wireless transmission of data allows for the possibility of near-constant remote monitoring of the patient by a clinical expert. Due to the nature of EEG signals however, even a short period of capture can result in large amounts of data being recorded. This can cause difficulties in transmitting the data, particularly if wireless transmission is being used to permit remote monitoring, as wireless communications can be a significant contributor to power consumption in a portable system [2,3]. Therefore, effective compression of the data is important to minimize the amount of information that needs to be transmitted wirelessly. A coexisting goal is that the compression itself needs to be carried out in an efficient manner so as not to unduly add to the power consumption of the device.

In comparison to other measures of biomedical electrical activity, such as ECG, there has been relatively little work done in the field of EEG compression. Of the work that has been done, most have focused on lossless compression, with only a comparative few having tested some form of lossy compression. Lossless compression maintains complete signal integrity in the decompressed signal but this limits the compression ratio (CR) that can be achieved. Lossy compression can achieve much higher CRs but results in a loss of some signal fidelity. Using a slightly lossy codec can achieve significantly greater compression, with minimum impact on the integrity of the signal.

This work proposes a scheme for lossy EEG compression, based on the JPEG2000 image compression standard, targeted at implementation on an ambulatory device. JPEG2000 was chosen due to its use of efficient compression methods and the choice of lossless or lossy compression, thus allowing a range of trade-offs between compression ratio, signal fidelity, and computational complexity. Work has already been done on low-powered implementations of this algorithm for portable hardware [4,5], thus indicating that efficient implementation of the core elements of the algorithm is feasible.

Section II of the paper describes the JPEG-2000 algorithm, in particular the wavelet transform and arithmetic coder used in the algorithm. Section III describes modifications made to the algorithms in order to increase EEG compression efficiency. Section IV details results of performance evaluation, while Section V presents conclusions.

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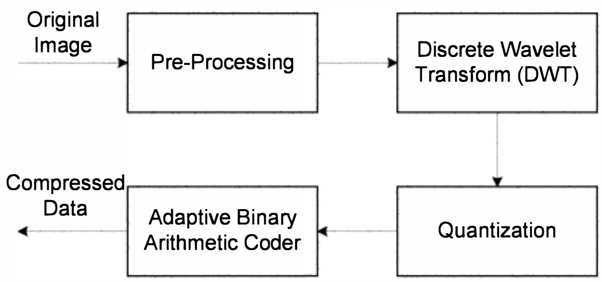

Figure 2: Core components of JPEG2000 Part 1

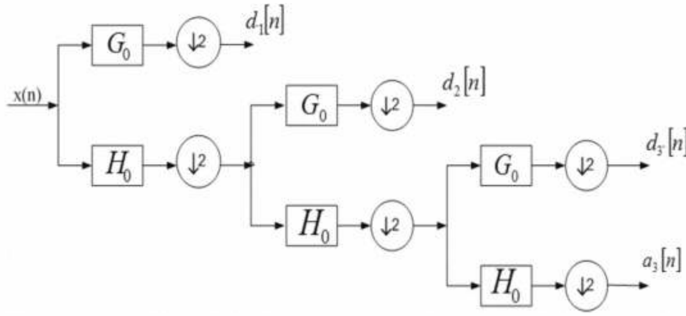

Figure 1: DWT of signal x(n)

II. JPEG2000

JPEG2000 is a compression algorithm designed for both lossless and lossy compression of image files. JPEG2000 Part 1 was ratified by the Joint Photographic Experts Group in 2000 [6]. It was designed to replace the older JPEG file format with more advanced features such as superior low bit-rate performance, lossless and lossy compression and good error resilience [7]. Part 1 contains the specifications for the core image coding system. These core components include, Discrete Wavelet Transform (DWT), quantisation and an Arithmetic Coder (AC) (Fig. 1).

Asides from the image specific changes in the Pre-Processing stages and Quantisation stages, the main areas of change are in the use of the DWT and AC.

The DWT replaces the Discrete Cosine Transform (DCT) of the original JPEG format. While DCT performs well at low compression ratios, it deteriorates quickly as compression ratios increases above 30:1. DWT meanwhile, has a much more gradual degradation [8]. The JPEG2000 Part 1 standard includes two types of DWT. The first is the Le Gall 5/3 integer-to-integer DWT. This DWT is used for lossless compression of images due to its fixed-point implementation. This allows faster transforms with a true lossless reconstruction, at the expensive of some loss in CR. A floating-point version of the CDF 9/7 DWT is used for lossy image compression to achieve a higher CR. This DWT has already achieved wide-spread use in a variety of fields such as compression of FBI finger prints and also for biomedical signal compression applications [9]

The Adaptive Binary Arithmetic Coder replaces the Huffman coder as the entropy coder for the compression standard. The AC can perform near optimal entropy coding on a given data set [10] and does not encounter the limitations of Huffman when probabilities approach one [11]. The adaptive arithmetic coder allows the message to be coded with no prior knowledge of the probability distribution function (PDF) of the message by either the encoder or the decoder.

A. *Wavelets*

The wavelet transform (WT) decomposes a signal into a set of basis functions known as wavelets [13-15]. The initial wavelet, also known as the mother wavelet, is used to construct the other wavelets by means of dilation and shifting:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

where a is the scaling parameter, b is the shifting parameter, and ψ (t) is the mother wavelet. Wavelets can be stretched or compressed to obtain low and high-frequency basis functions to analyse a signal at different resolutions.

The DWT is used to perform a fast computation of the WT of a discrete signal. It is normally computed quite efficiently with a recursive set of low and high pass filters. After the signals are filtered, they are downsampled by a factor of 2. The transformation is applied recursively on the low-pass series until the desired number of iterations is reached (Fig. 2). The high pass filter, G_0, produces detail information, d[n], while the low pass filter, H_0, produces approximations, a[n].

For the inverse DWT, the transform operates in the opposite way. Each subband is interpolated by a factor of 2 by inserting zeros between samples and filtering each resulting sequence by the corresponding low or high-pass synthesis filter bank. Finally the filtered sequences are added together to form an approximation to the original sequence.

The complexity of the DWT depends on a number of factors such as the filter size, the use of floating point or fixed-point arithmetic, and the method used to compute the wavelet coefficients. In general the DWT is more complex than transforms such as the direct cosine transform (DCT). The use of fixed point filters instead of floating point filters reduces complexity of the operation and allows for truly lossless compression, because there are no approximations in the forward or inverse transform operation. However, integer implementations also reduce the CR achievable by the transform.

The lifting scheme is an alternative method of computing wavelet coefficients. Proposed by Sweldens et al. [12], it has a number of advantages over traditional methods. It requires less computations and memory to calculate the coefficients so is better suited for ambulatory applications where efficient implementation is important. The inverse transform has the same complexity as the forward transform and no signal extension is required at the boundaries. It can also easily be expanded to use integer-to-integer WT for lossless compression.

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TABLE 1: PROBABILITIES AND RANGES FOR SYMBOLS a_n IN EXAMPLE:

Symbol	Probability	Range
a_1	0.5	[0,0.5)
a_2	0.25	[0.5,0.75)
a_3	0.125	[0.75,0.875)
a_4	0.125	[0.875,1)

B. *Arithmetic Coding*

Arithmetic coding is an entropy encoding algorithm used for lossless data compression. It encodes the required data stream into a single fractional value between 0 and 1. Similar in operation to Huffman coding, the coder converts the symbols to be encoded into a form where the most frequently used symbols are encoded using the least number of bits and the most infrequently used symbols using the most. The basic ideas of arithmetic coding can be traced back to the 1960's with more efficient implementations of it appearing later [13].

Arithmetic coding reduces the symbols to be encoded to a single, unique binary fraction based on the probability distribution function (PDF) of the symbols. In order to understand its operation, take for example, a source [redacted] that generates symbols from an alphabet of size 4,

$$A = \{ a_1, a_2, a_3, a_4\}$$

These symbols have probabilities:

$$P(a_1) = 0.5 \text{ , } P(a_2) = 0.25 \text{ , } P(a_3) = 0.125 \text{ , } P(a_4) = 0.125$$

which all lie on the interval [0,1)

The encoder begins with the interval [0,1) which is divided up into ranges for each symbol based on the probability of them appearing, as seen in Table 1. When the first symbol is passed to the encoder, the encoder updates the total range to correspond to the range of the symbol being encoded. This range is again divided based on the probability of the symbols occurrence. The next symbol is passed to the encoder, which again updates the range depending on the symbol passed. This continues until all the symbols in the sequence are encoded (Fig. 3). Any number within the final range can be outputted as part of the encoded sequence.

To decode the message**,** the decoder accepts the fractional value as input and again compares it to the range values from the table. In this case it sees that the value falls between the lower and upper bound of a_1 and so an a_1 is outputted. It then must update the encoded value to remove the effects of the first symbol. A new range is calculated by taking the lower bound of the decoded symbol from the upper bound. The encoded value is then calculated by taking the lower bound of the first symbol from the initial encoded value and dividing by the upper bound. This process continues until all symbols are decoded. It should be noted that the decoder will continue to decode unless the length of the original signal is passed as an argument or a predetermined escape character is received.

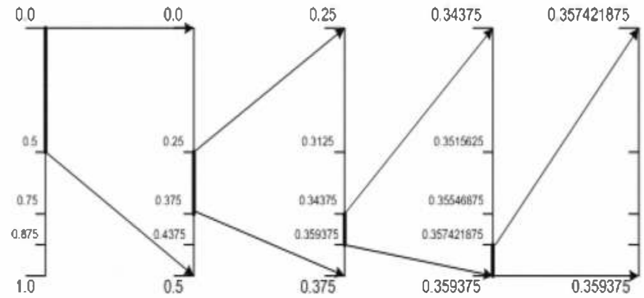

Figure 3: Example of arithmetic coder for encoding a four symbol long message

III. Algorithm Implementation and Enhancements

A number of modifications were made to the JPEG2000 algorithm for implementing an EEG compression algorithm. The EEG signal was processed in non-overlapping frames of size 1024. This window size was selected based on (a) preliminary tests of compressing varying sized signals and (b) previous findings in similar research [14].

While the JPEG2000 Part 1 specification allows use of a lossy and lossless WT, this research centred on the lossy CDF 9/7 WT. This allows us to maximise the attainable CR for the EEG signal with this algorithm with only a slight increase in computational requirements.

After the DWT has been performed, a new step was added, to threshold the resulting wavelet coefficients. All coefficients below this threshold are deemed to be not significant and set to zero. Zero values are efficiently encoded by the entropy coder and so the greater the number of zeros in the signal, the greater the compression that is achievable. The threshold level can be selected to allow different trade-offs between reconstruction error and compression ratio. The quantisation step is performed using standard uniform quantisation.

The Arithmetic Coder implemented was based on Sayood's work [15]. A variation on the coder was used whereby a static PDF is used by the encoder and decoder. This PDF is based on the average PDF of a large number of sample signals. The motivation for this was to give greater efficiency of implementation, at the expense of a slight decrease in CR. Alternative methods for adaptive coding require the encoder to continually update symbol ranges, as symbols are encountered and encoded. This mechanism adds a level of complexity that is not desirable in a low-power algorithm.

IV. Experimental Evaluation

For the testing of this algorithm, EEG data from the Epilepsy Centre of the University Hospital of Freiburg was used [16]. This database includes 24 hours of seizure and non-seizure data for 20+ patients.

During the algorithm's evaluation, two parameters were used. Firstly, the quality of the reconstructed signal is tested by comparing its similarity to the original input signal, and expressing the difference as Percentage Root-mean squared Distortion (PRD), defined as follows:

$$PRD = \left(\frac{\|x - \hat{x}\|}{\|x\|}\right) \tag{2}$$

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where x and $\hat{x}$ are the original and reconstructed signals, respectively, and || || represents the Euclidean or norm. Secondly, to check the efficiency of the compression, the Compression Ratio for each window was calculated as

$$CR = \frac{L.r}{\hat{b}} \tag{3}$$

where L is the length of the input signal in samples, r is the resolution of each sample and $\hat{b}$ is the number of bits of the compressed signal. We wish to achieve the best trade-off between PRD and CR. Initial tests have been carried out with a selection of data from four different patients, two of which contain seizure data and two containing non-seizure data. It was observed that variations in the quantisation level and threshold level had the greatest impact on signal CR and PRD and that wavelet levels above 8 did not provide a significant advantage. Three tests were carried out:

- The Threshold level was set to zero and varying quantisation levels were tested. The PRD and CR of each quantisation level were recorded.
- The Quantisation level was fixed at a midpoint and the threshold levels were varied. Again the resulting PRD and CR were recorded.
- Varying threshold and quantisation levels were used to try to achieve maximum CR.

Figure 4 plots the compression ratio (CR) as a function of Percentage RMS Distortion (PRD) for all three cases. It can be seen from the graph that the use of both quantisation and thresholding results in far greater compression ratio for a given PRD value, than either of the other two approaches individually. This increase in CR can be achieved at a very small cost in computational complexity.

V. CONCLUSIONS AND FUTURE WORK

While initial results are promising, complete testing of the algorithm must be performed before conclusive results are determined. In particular, a larger data set needs to be analysed. While we see a gain in the use of quantisation and thresholding, further testing will reveal what levels of each produce the optimum results. Analysis of the power usage of the algorithm will also be completed, as initial testing has focused on achieving the highest CR. It has already been established by other researchers [6-8] that the main elements of JPEG-2000 can be efficiently implemented, while the addition of thresholding proposed here will not add significantly to the computational complexity.

Expert clinical analysis of the decompressed EEG signal in relation to the original signal is desirable to ensure that signal integrity is maintained. Similarly, it is proposed to test the algorithm in conjunction with established automated diagnosis algorithms to ensure detection rates are maintained.

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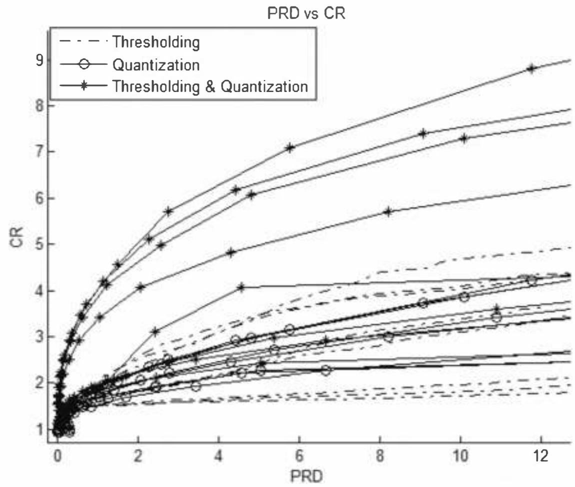

Figure 4: PRD vs. CR for three test cases

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