Wavelet Based Techniques for the Processing of Physiological Signals

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Abstract

In this paper we concentrate on the field of physiological signal processing and demonstrate how non-linear processing techniques, in particular wavelet transforms, can be applied to physiological signals. We have chosen also to focus upon two commonly used and studied physiological signals; namely the Electrocardiogram and Electroencephalogram. These physiological signals are commonly recorded in continuous monitoring conditions and require relatively high sampling rates to accurately record their high frequency components. This results in large volumes of data being acquired which presents problems for storage, retrieval and transmission of the electronic recordings.

1 INTRODUCTION

Patient monitoring via the internet is quickly becoming a reality with new technologies being created to allow patients to be continuously monitored from home [1]. This ease of access and low cost of the technology also implies that large numbers of patients will be able to be monitored by a single hospital system which would have to cope with enormous amounts of data being continuously collected and stored. Therefore a vital requirement of any such patient monitoring system would be the efficient storage of this data. This study investigates the compression, recognition and simulation of two of the most commonly used physiological signals, Electrocardiogram (ECG) and Electroencephalogram (EEG). ECG and EEG are recorded over extended periods of time at high sampling frequencies therefore requiring large databases for storage. A suitable compression algorithm will minimise the storage while not compromising the characteristics of the signals and the reduction in file size also means that speed retrieval and transmission of the recordings will be increased.

The compression of both ECG and EEG signals has been a topic of research for the past 20 years. In recent years new life has been given to the topic by the application of wavelet transforms to the problem. Wavelet processing of ECG and EEG signals has proven quite flexible and along with compression has been adapted to perform not only compression of the signals but feature detection [2] and classification [3]. Previously the ECG/EEG compression problem had been approached using classical direct data compression methods such as linear prediction and interpolation, these gave way to direct ECG and EEG data compression algorithms such as FAN, AZTEC, Turning Point, and peak picking which were variants on classical data compression modified specifically for the ECG signal [9].

Large amounts of data can also present problems to analyse and classify. The signals are frequently analysed via visual inspection by a cardiologist or electroencephalographer. This imposes considerable time constraints upon reviewers and how many patients they can assess within a given timeframe. Therefore automated recognition of the waveforms would be valuable in the scoring procedure. To do this an understanding of the signals must first be achieved.

A subset of physiological signals from the human body can be measured via surface electrodes. For example the ECG and EEG are indirect measurements of the electrical activity produced by the heart and brain respectively.

1.1 Electrocardiogram - ECG

The Electrocardiogram is a recording of the electrical activity in the heart. It is typically represented by 12 perspectives called leads that are recorded and derived from 10 electrodes placed around the torso and limbs of the patient. The ECG is comprised of several characteristic waveforms which represent the various stages of conduction of electrical activity through the myocardial tissue. This gives rise to a series of 6 potentials labelled with the letters P through U. Atrial depolarization is represented by the P wave, Ventricular depolarization by the QRS complex and repolarization of the ventricles by the T wave, the exact origin of the U wave is unknown. The ECG data used in this study was in MIT-BIH format, available from Physionet, sampled at 360Hz and also provided by the Griffith University School of Applied Psychology EEGLAB, which is sampled at 500Hz with a 16bit precision.

1.2 Electroencephalogram - EEG

The Electroencephalogram (EEG) measures the electrical potential between different locations on the scalp [4] or between cortical locations and a neutral reference. The electrical potential observed on the scalp is generated by population of neurons, and transmitted through the intervening tissue. As the signal is not taken directly from the brain, and brain activity itself is a low-power signal, the voltage measured at the various locations on the scalp is typically in the range of 1-300 μV [5].

1.3 Wavelet Transform

In this study the wavelet transform is used to compress and perform recognition on the physiological data. The Wavelet Transform (WT) is a very powerful time-frequency analysis method, because it provides excellent control of time frequency trade-off compared to traditional techniques such as the Short Time Fourier Transform (STFT) [6], [7], [8]. The Fourier Transform gives a representation of all the frequencies present in a signal, for the entire duration of the signal being analysed however, the temporal resolution is fixed by the selected frequency resolution. The Wavelet Transform is similar to the Fourier Transform in that it gives a representation of all the frequencies present in a signal; however it also shows at what times in the signal the frequency was present [6] and indicates that this varies across the frequency spectrum. A wavelet is defined in time as a small, narrow band, multi frequency waveform, the wavelet is said to be supported for the interval in which the majority of the energy of the wavelet is contained. If the entire wavelet energy is contained within that interval the wavelet is said to be compactly supported, this property also allows for the perfect reconstruction of a decomposed signal, which will be discussed in more detail later.

1.4 Mother Wavelet

The Mother Wavelet is the initial characteristic wavelet type and shape from which the wavelet family or basis set is derived. The set of wavelets used to represent the original signals (also known as basis functions), "$g_{a,b}(t)$" is defined by Eq. 1.

$$g_{a,b}(t) = \frac{1}{\sqrt{a}} g\left(\frac{t-b}{a}\right)$$

Eq. 1 Derivation of basis functions from mother wavelet

The scaling factor "a" dilates or compresses each basis function, hence focusing on a particular bandwidth with a centre frequency related to the scaling factor. The translation factor "b" shifts each function in time. The power of the mother wavelet is maintained throughout the basis set by the normalization factor; "$1/\sqrt{a}$". The basis set is then used to perform wavelet transformation, as can be seen in Eq. 2 and is shown in figure 3 of [6].

$$c_{a,b} = \int_{-\infty}^{+\infty} E(t) g_{a,b}^{*}(t) dt,$$

Eq. 2 Continuous Wavelet Transform of E(t)

In Eq. 2 "$c_{a,b}$" represents the continuous wavelet coefficients and "$E(t)$" is the temporal signal being transformed. The choice of Mother Wavelet for the transformation of the physiological signals is based upon the characteristic shape of the signals.

$$E(t) = k \int_{-\infty}^{+\infty} \int_{0}^{+\infty} \frac{c_{a,b}}{a^2} g_{a,b}(t) da.db$$

Eq. 3 Reconstruction of Signal E(t)

The choice of mother wavelet can have dramatic effects on the results achieved as will be shown later for the case of the processing of the EEG.

1.5 Discrete Wavelet Transform DWT

The Discrete Wavelet Transform (DWT) is similar to CWT in that it generates coefficients based on the correlation between the wavelet of certain scales and the original signal. However, DWT uses orthogonal wavelets, such that a signal can be represented by a number of wavelet coefficients generated by distinct scales [6], respecting the number of degrees of freedom in the sampled signal. The mother wavelet is used as the original scale of the wavelet, with each level of decomposition representing a doubling of the scale. DWT also requires a companion function called a scaling function, which is "a combination of mother wavelets from all DWT scales larger than the scale of the first detail function" (Samar et al., 1999, page 23) [6].

2 REVIEW

To ensure that this study was not simply repeating work previously completed by other studies, an extensive review of applicable techniques for compression, recognition and simulation was undertaken.

2.1 Compression

In general ECG compression techniques may be classified as one of three types [9]; significant feature extraction, linear predictive coding or orthogonal transform. It is in the latter of these three that the wavelet based transform methods fall. Typical results for linear prediction and significant feature extraction methods range between Compression ratios of 2.0/2.5 (Turning Point/DPCM Linear Prediction) – 10 (AZTEC) with NRMSE values of 5.3% and 28.0% respectively. Several Orthogonal transform based ECG compression algorithms are compared in Table 1. The methods discussed in [10] & [11] are for all intensive purposes the same with the only difference being the number of bits allocated to the ECG recording.

The algorithms discussed in [12] make use of standard image processing methods and transforms in this case a 2 dimensional discrete cosine transform. The method from [13] is our won which makes use of a biorthogonal wavelet transform, zero-run length coding and recursive splitting Huffman Coding [20]. The advantage of the wavelet transform over the discrete cosine transform is its superior resolution at lower frequency levels which enables further dimensionality reduction but eliminating extraneous low frequency components which might not be resolved by the DCT. The advantageous properties of recursive Huffman coding over standard Huffman coding are discussed later.

EEG compression has been performed in many instances, however primarily for ambulatory monitoring, not long-term storage of sleep signals. Several different techniques have been used to compress EEG data, with varying levels of compression ratio (CR) as can be seen in Table 2.

Table 1 Orthogonal Transform based compression methods (review section)

Compression Technique	CR	Sampling Frequency	Precision	NRMSE %
Wavelet Based Transform [10]	14	500	8	4.85
Wavelet Based Transform [11]	16.8	500	7	5.25
Cut and Align Beats approach [12]	12	360	12	7.03
As above	24	“”	“”	18.14
2D Transforms [12]	12	“”	“”	6.16
As above	24	“”	“”	10.08
As above	48	“”	“”	15.78
Biorthogonal Wavelet Based Transform with recursive Huffman coding [13]	21.42	500	8	2.94
As Above for 14 MIT-BIH files.	24.56	360	12	3.56

The lossless techniques allow perfect reconstruction of the signal after compression, whereas lossy techniques will give better compression at the expense of the signal integrity. It is apparent that lossless encoding will give lower compression ratios than lossy encoding, as more information is retained, however generally, the main limit for the lossy compression of a signal is the amount of error that can be tolerated.

Table 2: Compression techniques applied to EEG data

	Technique	**CR**
Lossless	Commercial Arithmetic Coders	2.5 - 3.8
Lossy	DWT [14]	8
	Iterative Function System w GA [15]	6.8-13.7
	AR prediction [16]	2.3-3.3

The Discrete Wavelet Transform (DWT) was implemented for EEG compression, as this study required the signal to have only the same sleep stage classification after compression as before, not a set limit of error. This meant that compression could be improved by removing the frequencies that are not needed for sleep stage classification (generally frequencies above 32Hz), which is simple using DWT denoising.

2.2 Recognition

Automated analysis of physiological signals is also of great necessity in a continuous patient monitoring environment.

Most analysis of the ECG occurs with relation to the QRS complex as it is the most characteristic and easily identifiable wave in the ECG. QRS complex detectors can be described as either syntactic or non-syntactic. Syntactic detectors require an analysis of the entire data record from which an average beat template is derived. These methods can be slow and are susceptible to noise and changes in beat morphology. Non-syntactic methods do not generate average beat models but rely on heuristic criteria to identify the QRS; they also employ some form of preprocessing transformation or paradigm. Approaches to QRS by software algorithms were well summarized in [17] which compares the preprocessing stages of many QRS detection algorithms. The categories of algorithms include:

- Signal derivative and Digital Filter approaches
- Wavelet Based Algorithms
- Neural Network Approaches
- Additional Approaches; which covers many varied approaches to the QRS detection problem including Hidden Markov models, Matched Filters and Genetic Algorithms.

Once the QRS complexes have been identified then specific beat classification can be performed. The variety, number and means of classifying cardiac arrhythmia would require a much more in depth discussion then can be afforded here.

Table 3 Comparison of QRS detection methods

System	**False +**	**False -**	**False Detection**
Wavelet Based [18]	0.056%	<0.001%	0.152%
Syntactic Template [19]	0%	0.577%	0.577%

Detection of the position each beat within an ECG recording can be of great diagnostic benefit by providing an accurate measure of the heart rate and providing a beat to beat comparison. Accurate detection is complicated by anomalous changes in the morphology of the ECG and changes in heart rate. These two factors are particularly difficult for the syntactic detection methods to deal with.

3 Solution

3.1 Compression

The nature of continuous monitoring means that a lot of data is collected quite quickly, therefore the compression algorithm has to be quick enough to work within a real-time system (compresses data faster than it is collected). From Figure 1 it can be seen that the majority of the ECG's energy is concentrated in the lower frequency levels therefore faithful reproduction of these levels is of upmost importance. However it should not be forgotten that diagnostically important information is still contained in the higher frequency component such that they can not be discounted altogether. The wavelet transform provides an excellent platform to address these concerns. The compression method discussed in [13] is our own and works as follows:

1. The signal is blocked into smaller segments.
2. The blocks are decomposed using a biorthogonal wavelet transform.
3. The individual transform levels are normalized and a hard threshold is applied to them.
4. The transform levels are zero-run length encoded.
5. Each level is assigned a specific quantization precision and is quantized.
6. Finally a recursive splitting Huffman Coder [20] is applied to the quantized coefficients.

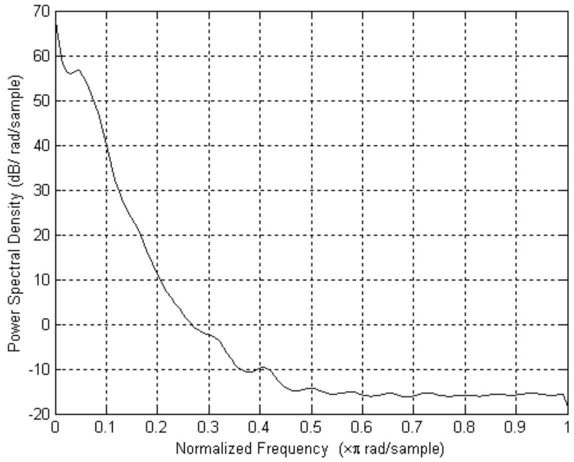

Figure 1 Power Spectral Density of an ECG

The EEG data processed was in European Data Format, available from Physionet, and was sampled at 100Hz. For sleep stage classification (using only EEG), the information needed is generally in the frequency range of 0.5-32Hz, so the data was filtered using finite impulse response techniques, to fit this range. If Wavelet Packet Transform had been used instead of DWT, filtering would have been performed as part of denoising. Sleep stage classification is often performed by analysing epochs of 30 seconds; the EEG data was therefore compressed in 30 second periods or windows, to allow precise extraction of the data of interest. After bandpass filtering and windowing the signal was transformed to generate the wavelet coefficients. The power of the discrete wavelet transform in compression is its characteristic of breaking up the signal into coefficients resembling discrete frequency bands. Frequencies that are characteristic of unwanted information can therefore be easily removed. This is called denoising, and uses thresholding to actually remove the coefficients. Thresholding was performed on ECG and EEG by zeroing out the coefficients in the unwanted frequency band less than a certain magnitude, and then performing Zero Run-Length Encoding (ZRLE) to reduce the amount of data.

Huffman encoding was performed on top of this reduced data set to improve the compression ratio again, without increasing the error of the compressed signal with respect to the recorded EEG signal. The entropic coding scheme employed was a Huffman coder using recursive splitting, developed by K. Skretting [20]. The Huffman coder made use of recursive splitting of the wavelet coefficients so that greater coding gain, and hence bit rate, could be achieved. This is due to the fact that the wavelet coefficients aren't independent of each other, they infact exhibit some correlation, and therefore can be split such that each new sequence of coefficients has statistically different information. This allows different Huffman coding schemes to be applied to each sequence which means that code symbol length is minimized. For further explanation it is recommended that the reader refer to the paper by Skretting, et al.

3.2 Recognition

The simplest approach to automated ECG analysis is to begin by identifying and locating each beat which would then allow for beat to beat analysis. The easiest characteristic to identify in each beat is the QRS complex, by locating the position of each QRS complex the R-R interval can also be calculated which means that we can assess basic heart rate. The next step is then to examine the associated waveforms of every beat. The relatively high frequency and energy content of the QRS complex means that it will be clearly visible in the first few levels of a DWT, by using a low order DWT we can highlight each QRS complex and correlate the information from each level to produce a robust means of locating the QRS. This is achieved by applying a frame square average to each level and then searching for the peaks which will correspond to the high energy QRS complexes. In addition to this a set of decision rules is used to improve the robustness of the detector to interferences such as movement artefact. These heuristics can be used once each beat is detected and can also improve the accuracy of the QRS detection. Typical rules include defining a timeframe in which only one QRS complex should occur. This timeframe can be adaptable to compensate for changes in heartrate. Other characteristics can then be searched for within the defined timeframe, these can include the P wave and T wave and various segments of the ECG.

4 RESULTS

4.1 Compression

As wavelets were used for both ECG and EEG compression, and are based on denoising, an intrinsically lossy technique, the amount of compression gained is determined by how much information is lost – that is, less data stored will give better compression. Due to this, the results are shown as compression vs. error, although the best compression is likely to be irrelevant due to a loss in signal characteristics of interest. Two parameters were used to evaluate the level of compression of the signal, and the error caused by compression, Compression Ratio (CR) and Normalised Root Mean Square Error (NRMSE) respectively.

4.1.1 Compression Ratio

The Compression ratio is defined as the ratio between the original file size and the compressed file size. A higher compression ratio indicates better compression.

4.1.2 Normalized Root Mean Squared Error

Normalized Root Mean Squared Error (NRMSE) indicates the error in the final signal as a percentage of deviation from the original signal, as can be seen in Eq 4. The NRMSE is the numerical evaluation of the error of the signal and is used in this paper to find the maximum compression ratio possible without loss of vital information from the signal. This ranges between 0% and 100%.

$$NRMSE\% = \sqrt{\frac{\sum_{i=1}^{n}[x_{org}(i) - x_{rec}(i)]^2}{\sum_{i=1}^{n} x_{org}^2(i)}} * 100\%$$

Eq. 4 Normalized Root Means Squared Error

4.2 Experimental results

The results of our compression algorithms and comparisons of them with other orthogonal transform based compression algorithms are shown below. In Figure 2 the effect of the order used in the DWT on the compression ratio achieved and the NRMSE suffered is shown, from these results the effect of changing the global threshold level was determined using standard 9th order DWT decomposition. Figure 3 shows the NRMSE and Compression Ratio achieved using our Wavelet Based compression algorithm and its performance as the threshold level of the wavelet transform was varied between 0.2 and 10% of each transform level's dynamic energy range, the hard thresholding method was used.

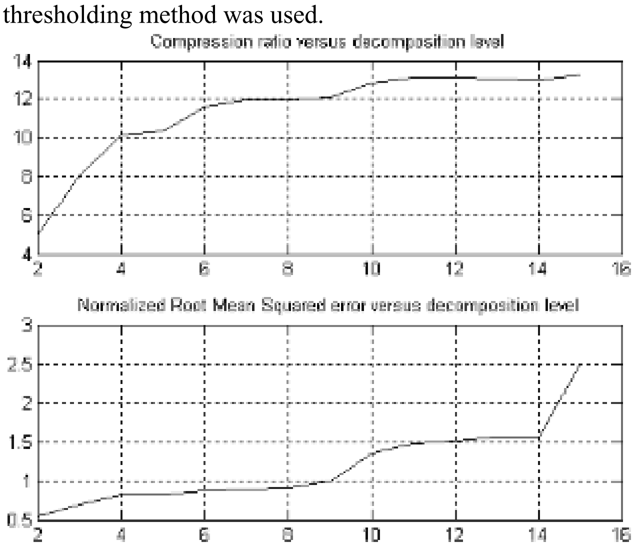

Figure 2 Compression Ratio and NRMSE vs. level of DWT decomposition for ECG data.

When wavelet based compression was applied to the EEG signals, it could be seen that again the error intrinsic in the signal was the limit for the compression ratio that could be achieved. All the results presented for EEG compression use wavelet techniques, and Huffman encoding. The wavelet used generated significantly different levels of error, with wavelets such as Biorthogonal 5.5 and Symlet 10 giving the best CR/NRMSE ratio, as can be seen in Table 4 below, while other wavelets such as Haar gave a much lower CR/NRMSE. It can be observed from Figure 4 that the wavelet chosen often has little effect on the NRMSE of the generated file, but can increase the CR substantially (each point refers to a different mother wavelet used in the algorithm). There are however several exceptions to this rule, with the NRMSE for most 1st order models of wavelets above 10%.

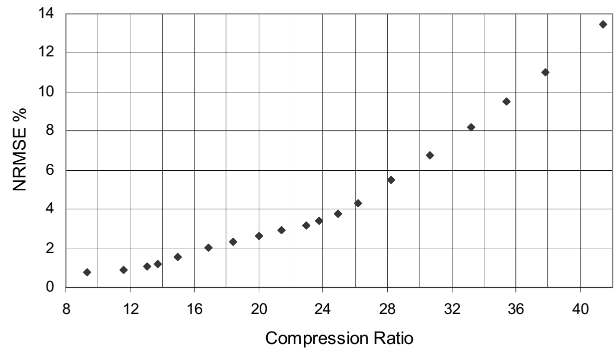

Figure 3 Compression Ratio vs NRMSE for ECG using Biorthogonal 2.8 with varying thresholds.

Wavelet Used	CR	NRMSE (%)	CR / NRMSE	Wavelet Used
Biorthogonal 5.5	7.9	4.9	1.7	Biorthogonal 5.5
Symlet 10	7.8	4.7	1.6	Symlet 10
Daubechies 10	7.8	4.7	1.6	Daubechies 10
Coiflet 5	7.5	4.7	1.6	Coiflet 5
Discrete Meyer	6.7	4.6	1.5	Discrete Meyer

Table 4: Effect of Mother Wavelet used on Compression Ratio and NRMSE for EEG compression

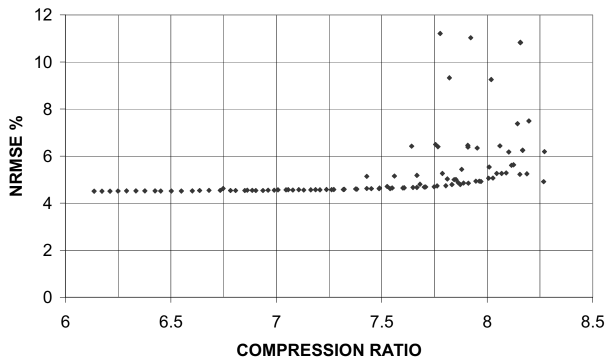

Figure 4: Effect of different types of wavelets on CR and NRMSE for EEG

The relationship between the error of the signal and the compression that can be achieved can be seen in. High compression ratios can be achieved easily by increasing the level of thresholding (retaining less information), and applying additional techniques, such as storing the wavelet coefficients as n-bit integers instead of floating point values, on top of the wavelet techniques. These techniques will however increase the error substantially. Lossless techniques such as Huffman encoding or arithmetic encoding may also be applied, and may increase the compression with no increase in error. Similar studies have achieved compression ratios and errors as shown in Table 5. It should be noted that this table is a composite of ECG and EEG parameters, and that the amount of compression possible on both of these is dependent primarily on the error. Because of this the results of all the techniques are presented for a similar level of error where available, as well as the maximum CR and error reported by those studies.

Technique	**ECG / EEG**	**CR with lowest NRMSE**	**Max. CR reported**	**NRMSE for Max. CR**
Entropic Coding (lossless)	ECG	2.6	2.6	2.6
Biorthogonal DWT with Recursive Huffman coding [13]	ECG	12.42 (NRMSE = 0.93)	41.38	13.49
2D Transforms [12]	ECG	12 (NRMSE =6.16)	48[1]	15.78

Table 5: Comparison of this study to compression results for similar studies

4.3 Recognition

As mentioned previously, the major constraint for EEG compression was for the compressed data to receive the same classification as the original data. A major reason for this is the development of an automated sleep stage classification program that will ultimately be able to score EEG data as well as, or more accurate than, current manual scoring following Reschtaffen and Kales criteria.

ECG compression has a smaller range of error that is suitable due to the wider range of anomalies that can be identified, however currently an automated QRS detection routine has been implemented successfully. The routine utilizes the DWT and signal averaging over several transform layers to improve the accuracy of the detector. Testing of this system on a selection of MIT-BIH recordings showed a 100% positive detection accuracy however a small percentage of false positives still occurred.

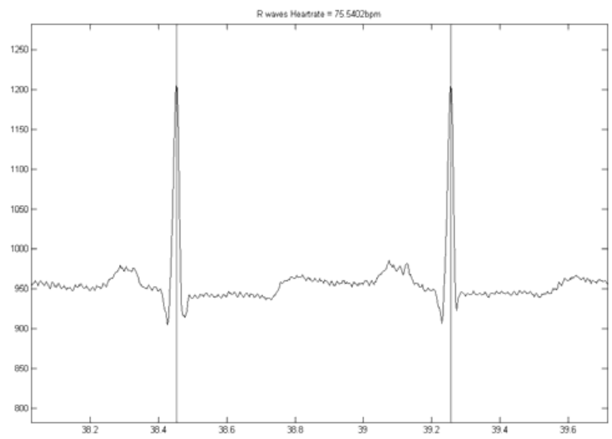

Figure 5 QRS detection via DWT for MIT-BIH 108

5 Discussion

5.1 Compression

The results for the compression investigated in this study indicate a higher level of compression than achieved in similar studies. This study has improved on results from other studies using the wavelet transform by implementing entropic coding techniques on top of the denoised wavelet coefficients.

5.1.1 ECG

As shown in the review section the Orthogonal transform approaches to ECG compression performed significantly better than the classical and direct methods. The comparison of orthogonal transform methods also showed that the Wavelet transform offered an advantage over the discrete cosine transform due to its superior low frequency resolution properties. The use of Huffman Coding with recursive splitting improved compression ratio and bitrate over the standard Huffman coders used in [10][11].

5.1.2 EEG

The main feature of wavelet-based EEG compression that this study has identified is the effect of using different mother wavelets. It is apparent from Figure 4 that the mother wavelet chosen can effect the level of compression and the amount of error present significantly - two different wavelets can give different amounts of compression for the same error. Additionally, the wavelet suitable for a particular application will depend on the amount of computational power available. For instance the higher order symlets are not suitable for real-time due to their complexity requiring over 30 times more time than the average. The wavelets used for the EEG component of this study were the pre-existing wavelets available in the Wavelet toolbox for MATLAB.

5.2 Recognition

Wavelet based recognitions techniques offer improved performance over syntactic methods in their robustness against noise and morphological changes in the QRS. The advantage that the syntactic method developed in [19] has is its low incidence of false positive detection. However

[1] A compression ratio of 96 was also reported in [12] however testing results were not complete.

with a thorough set of heuristics the Wavelet transform approach can be improved.

6 Conclusions

ECG and EEG compression are implemented in this study for the storage of data recorded by an automated sleep monitoring device that has been developed, and will allow long term storage of the ECG and EEG data generated by these techniques. As ECG and EEG have the highest sampling frequencies, the compression of this data is most crucial. However, due to the similarities between implementation for ECG and EEG, it is believed these techniques can be modified slightly for use with other physiological signals recorded such as EMG and EOG.

This study has also shown that it is likely that Wavelet based EEG compression is not as powerful as ECG compression. This is not unexpected as EEG is such a chaotic signal in comparison to the ECG which can be generally characterised by an appropriately shaped mother wavelet such as the biorthogonal wavelets. This characterisation means that the original signal can be efficiently represented in terms of time-frequency coefficients with minimal residual detail coefficients. As EEG for sleep studies are generally only interested in frequencies beneath 40Hz, the NRMSE may not be as suitable in determining the effective error present as a professional sleep scorer's opinion. For instance, if the NRMSE represents primarily higher frequency components of the EEG, which are not used for sleep monitoring purposes, the effective error of the compression technique will be much less than this value. The error that can be tolerated and therefore the maximum possible compression ratio will hence depend on the application.

The superior performance of the wavelet based methods over classical methods and their ease of implementation make them ideal for clinical applications. The flexibility of the discrete wavelet transform is highlighted by its ability to be the basis of compression and recognition algorithms for physiological signals. This gives rise to the possibility of amalgamating both processes so that, in the case of the ECG, beat recognition data could be stored with the compressed data. This would significantly improve analysis by aiding the reviewer as well as reducing the time for retrieval and transmission.

References

[1] D. James, et al., "Internet Based ECG Medical Information System", Australasian Physical & Engineering Sciences in Medicine, Vol 26, No. 1, 2003

[2] S. Kadambe, T. Murray, G. F. Boudreaux-Bartels, "Wavelet Transform-Based QRS Complex Detector" IEEE Transactions on Biomedical Engineering, Vol 46 No 7 July 1999

[3] A Prochazka, M Storek, "Wavelet Transform use for signal classification by self organizing neural networks", Artificial Neural Networks, 26-28 June 1995, Conference Publication No. 409, IEE 1995.

[4] M. Browne, "Wavelet Methods for Analysis of Event-Related Potentials", Griffith University, October 2001

[5] H-J Park et al., "Automated Detection and Elimination of Periodic ECG Artifacts in EEG Using the Energy Interval Histogram Method", IEEE Transactions on Biomedical Engineering, Vol. 49, Issue. 12, December 2002

[6] Samar et al. "Wavelet Analysis of Neuroelectric Waveforms A Conceptual Tutorial", Brain and Language 66, pp 7-60, 1999

[7] J. Raz et al., "A Wavelet Packet Model of Evoked Potentials", Brain and Language Vol. 66, pp 61-88 (1999)

[8] V. Samar, "Multiresolution Analysis of Event-Related Potentials by Wavelet Decomposition", Brain and Cognition, Vol. 27, pp398-438, 1995

[9] S. Jalaleddine, C.G. Hutchens, R.D Strattan, W.A. Coberly, "ECG Data Compression Techniques – A Unified Approach", *IEEE Transactions on Biomedical Engineering,* Vol. 37, NO.4, April, 1990, pp 329-343

[10] I. Provazník, J. Kozumplík, "Wavelet-Based Compression of ECG signals", Department of Biomedical Engineering, Faculty of Electrical Engineering and Computer Science, Technical University of Brno, Czech Republic

[11] I. Provazník[1], J. Kozumplík[1], J. Bardonová[12], M. Nováková[2], Z. Nováková[2], "Wavelet Transforms in ECG Signal Processing", [1] Department of Biomedical Engineering, Brno University of Technology, [2] Institute of Physiology, Masaryk University Brno, Euro Conference, 2000

[12] H. Lee, K.M. Buckley, "ECG Data Compression Using Cut and Align Beats Approach and 2-D Transforms", *IEEE Trans On Biomed Eng*., Vol 46, No. 5 May 1999

[13] A.Diery, "Digital Electrocardiogram Processing Techniques and Applications", Thesis, School of Microelectronic Engineering, Griffith University, 2002

[14] A. Folkers et al., "Realtime bioelectrical data acquisition and processing from 128 channels utilizing the wavelet-transformation", Neurocomputing, Vol. 52-54, June 2003, pp247-254

[15] S. Cerutti, et al., Non-linear algorithms for processing biological signals, Computer Methods and Programs in Biomedicine, Volume 51, Issues 1-2, October 1996, Pages 51-73

[16] N. Memon, "Context-based lossless and near-lossless compression of EEG signals", IEEE Transactions on Information Technology in Biomedicine, Volume: 3 Issue: 3 , Sep 1999 pp231-238

[17] B.U. Köhler, C. Hennig, R. Orglmeister, "The Principles of Software QRS Detection", IEEE Engineering in Medicine and Biology, 0739-5175/02, January/February, pp 42-57, 2002

[18] C.Li, C. Zheng, C. Tai, "Detection of ECG Characteristic Points Using Wavelet Transforms", pp 21-28, IEEE transactions on Biomedical Engineering, Vol 42, No1, Jan, 1995.

[19] T.R.H. Cutmore, "Matlab QRS detection for the electrocardiogram using a template approach", Unpublished algorithm, School of Applied Psychology, Griffith University, (2002)

[20] K. Skretting, J. H. Husøy, and S. O. Aase: "Improved Huffman coding using recursive splitting," in Proc. of Norwegian Signal Proc. Symp., Oslo, pp. 92-95, September 1999. Available at http://www.ux.his.no/~karlsk/proj99/