ECG Compression using wavelets

Master in Technology

in

Signal processing and Machine Learning

by

Soumyadeep Nandi & Nittala Aditya

(212SP016 & 212SP018)

Contents

Chapter 1

Introduction & Motivation

Electrocardiogram (ECG) is an efficient way of measuring activity of heart impulses over time. A graphical representation of voltage over time is presented in ECG by a process of Electrocardiography. ECG is one of the most common clinical cardiac tests used for screening and diagnosing heart diseases because every arrhythmia in ECG signals can be relevant to a heart disease [1]. It is a simple, reliable, risk-free, and inexpensive application for detecting cardiac abnormalities. The ECG signal for each heartbeat contain three main events: the P wave, the QRS complex, and the T wave. The sinoatrial node (SA) is the pacemaker of the heart and produces the P wave. The QRS wave is produced by the atrioventricular node (AV). The P wave in an ECG complex indicates atrial depolarization [2]. The QRS is responsible for ventricular depolarization and the T wave is ventricular repolarization. The amplitude and interval of P-QRS-T segment determine the function of heart.

The ECG signal is recorded by applying electrodes to various locations on the body surface and connecting them to a recording apparatus. For early detection of cardiovascular diseases (CVDs) or patients in intensive coronary care unit, or in long-term (24–48 hours) wearable monitoring tasks (Holter) require long term monitoring of ECG signals. Holter monitoring usually requires continuous 12 or 24-hours ambulatory recording. For good diagnostic quality, each ECG lead should be sampled at a rate of 300 -500 Hz with 12 bits resolution. The information rate is thus approximately 13–22 Mbits/hour/lead. The monitoring device must have a memory capacity of about 100–200 Mbytes for a3-lead recording. Memory costs may render such a solid-state device. Effective storage of such huge date is merely possible. As a result, compression of ECG data became a prominent issue of research in biomedical signal processing.

There are certain amounts of sample points in ECG signal which are redundant and replaceable. ECG data compression is achieved by elimination of such redundant data sample points. ECG compression were introduced to achieve good compression ratio with preserving the relevant signal information. Different ECG data compression algorithm has been developed and these algorithms were classified into three categories dedicated techniques such as AZTEC, FAN, CORTES, and turning point [3]. These techniques were based on the detection and elimination of redundancies on direct analysis of the original signal, and gives minimum distortion.

ECG data compression can also be achieved through transform-based techniques. In this compression is achieved based on spectral and energy distribution of the signal. There are many transform methods such as Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) etc.., due to which, there is drastically changed in the field of data compression. FFT is a discrete Fourier transform (DFT) algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N\log_2 N$ DFT is used in Fourier analysis of a signal in frequency domain[4-7]. The discrete cosine transform is widely exploited for data compression such as speech compression, image compression and ECG compression. DCT is calculated using the FFT algorithm as it is DFT. However, DCT gives the more weight to low-pass coefficients to high-pass coefficients. DCT gives nearly optimal performance in the typical signal having high correlations in adjacent samples [8-9].

Discrete Wavelet Transform (DWT) in recent years, has emerged as powerful and robust tool for analysing and extracting information from non-stationary signal such as speech signal and ECG signal due to the time varying nature of these signals. Non-stationary signals are characterized by numerous abrupt changes, transitory drifts, and trends. Wavelet has localization feature along with its time-frequency resolution properties which makes it suitable for analysing non-stationary signals such as speech and electrocardiogram (ECG) signals [10-11]. This project, presents a comparative analysis of ECG compression using Haar wavelet function and Huffman encoding. The algorithm of ECG compression is performing in three stages: (i) DWT decomposition, (ii) Threshold & Quantization, (iii) Entropy encoding.

The motivation of this algorithm is to solve the problem of storing or wirelessly transmitting ECG data, which tends to have a high sampling rate of 250-500 Hz with 12bit resolution which requires huge memory. By compressing the signal, more data can be stored or wirelessly transferred using less power without significant loss or no loss of information.

1.1 Objectives

1. To apply discrete wavelet transform (DWT) on Electrocardiogram (ECG) signal.

2. To design a Huffman encoder and decoder.

3. To compressing the ECG signal, so that more data can be stored or wirelessly transferred using less power.

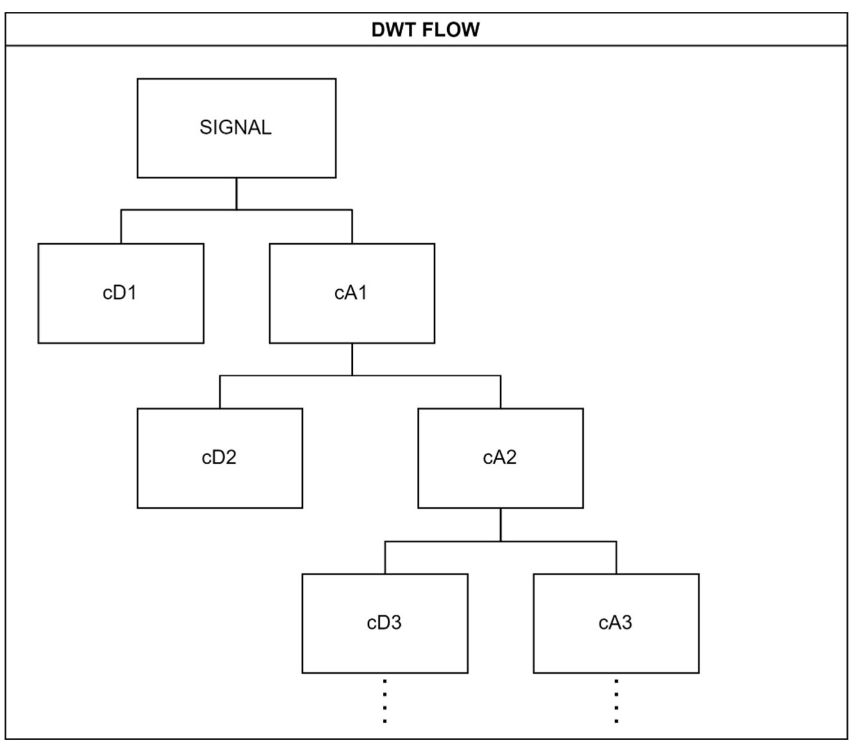
4. To achieve a low information rate, while preserving the relevant diagnostic information in the reconstructed signal.

Chapter 2

Work Done

2.1 Algorithm

2.1.1 DWT



The input signal is improved by removing the dc-offset using the detrend function. After that we have applied DWT to the ECG signal with 5 levels of decomposition using 'haar' wavelet. The output of scaling function is input of next level of decomposition, known as approximation coefficients. The approximation coefficients (cA_n) are low-pass filter coefficients and high-pass filter coefficient are detail coefficients (cD_n) of any decomposed signal.

2.1.2 Thresholding

Many of the wavelet coefficients are very close to zero while just a handful of coefficients represent most of the total energy. For representing the coefficients more efficiently, thresholding is done for each decomposed wavelet.

The threshold for each decomposition is calculated by using the following algorithm.

1) Calculate the total energy E in the wavelet coefficients X.

$$E = \text{Sum}(X^2)$$

2) Calculate the desired retained energy E' in the thresholded coefficients

$E = 0.999\ E$

3) Form the sequence Xs[k] by sorting the magnitudes of the wavelet coefficients in Descending order.

4) Use the following pseudocode to find the desired threshold

```
set energy = 0
set k = 0
  while energy < E'
  k = k + 1
  energy = energy +(Xs[k]²)
  end
thresh = Xs[k]
```

After thresholding, a binary map array is created that indicates whether any given value in the thresholded coefficients array is either zero or nonzero. If the coefficient was set to zero, the value in the binary map at the index of the zeroed coefficient is zero. Otherwise, the value in the binary map at the index of the coefficient is one.

$$[1, 0.6, -0.07, -0.05, 2]$$

$$\Big\downarrow \ \text{Thresholding}$$

$$[1, 0.6, 0, 0, 2]$$

$$\Big\downarrow \ \text{Binary - Map}$$

$$[1, 1, 0, 0, 1]$$

2.1.3 Quantizing

Step 1: Scaling

Before the wavelet coefficients can be quantized, they need to be scaled to the [0,1] range. To do this, each of the decomposition levels is shifted by the minimum value, and then divided by the maximum value.

Step 2: Minimum Number of Bits (N) for Quantization

First the value of N is set to 8 , then the PRD (Percentage root mean square difference) of the reconstructed signal is calculated with the corresponding value of N. N is then decreased by 1 and this loop continues until the threshold of PRD (0.4) is met.

PRD = Norm(original signal – Reconstructed signal)/Norm(original signal)

After this Quantization is done where each wavelet coefficient is multiplied by 2^(N) – 1 and rounded to nearest possible integer.

2.1.3 Huffman Compression

The non-zero wavelet coefficients are combined in a single list, which is then encoded using Huffman encoding. We create a Probability map using heap data structure for the wavelet coefficients and assigning unique code based on the probability of each coefficient. Most frequently occurring coefficient gets smaller code and less frequently occurring coefficient gets larger code.

2.1.4 Reconstruction

Decoding of combined compressed wavelet coefficients is done based on the probability map and unique code for each coefficient. Then the decoded wavelet coefficients are remapped to their original state. After this Inverse DWT is applied on decoded wavelet coefficients using the waverec function.

Chapter 3

Results

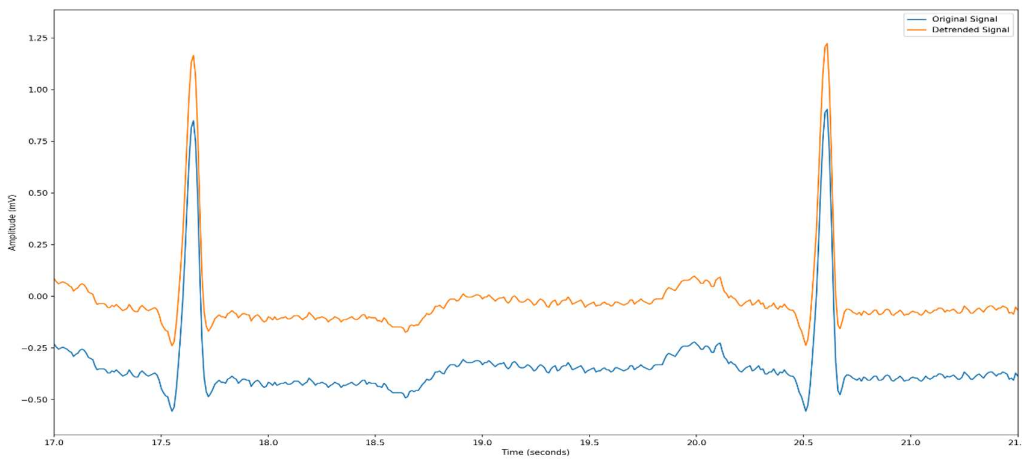


Figure 1 : Original Signal and Detrend Signal

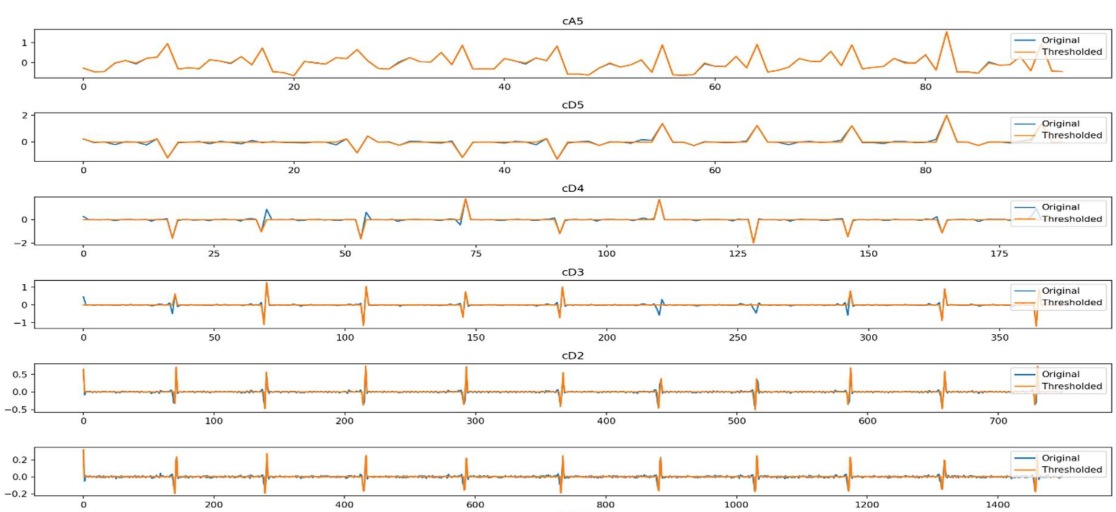


Figure 2 Original and Threshold decomposition levels

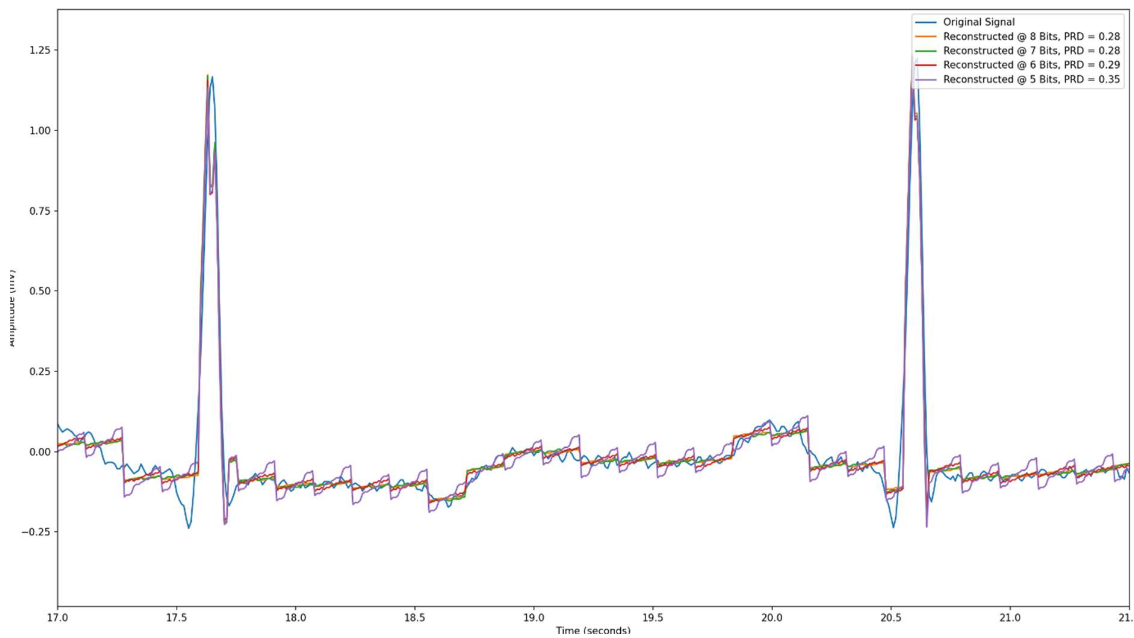


Figure 3 reconstructed signals with PRD levels

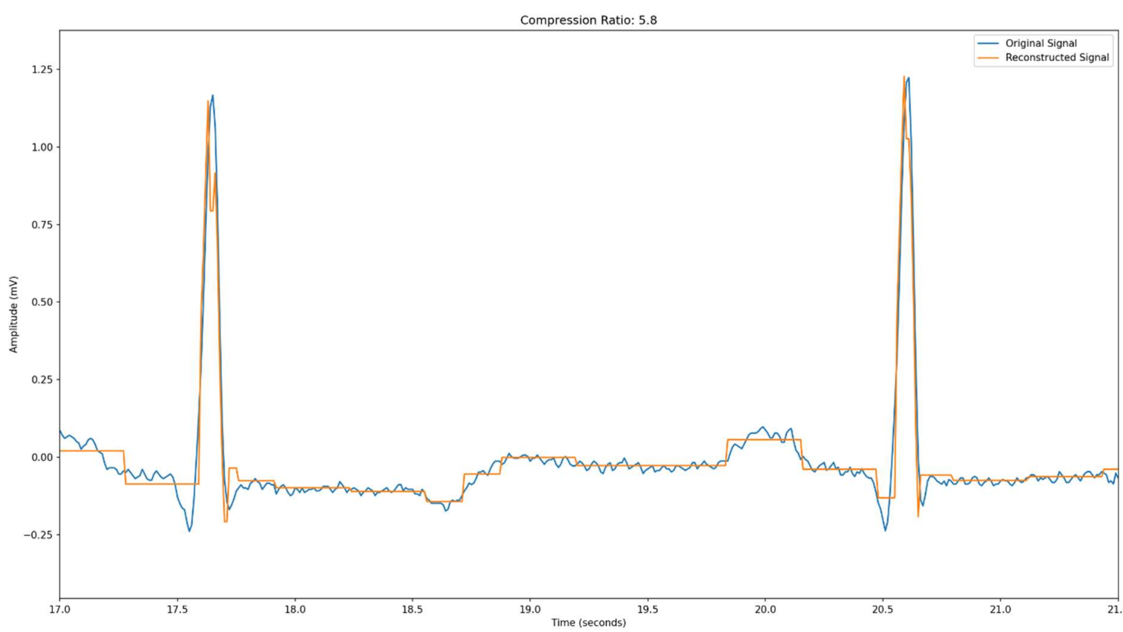


Figure 4 Original and Reconstructed Signal

Wavelet	Compression Ratio(CR)	PRD
Haar	6.0	0.343
Bior4.4	2.3	0.340
db5	2.2	0.342
db2	4.8	0.343
coif1	4.1	0.353

Figure 5 Comparison using other wavelets

Chapter 4

Conclusion

- In this project an effective method for compressing ECG signals using haar Wavelet has been performed. This was tested on the MIT-BIH database.
- We have successfully encoded and decoded wavelet coefficients using Huffman-Coding.
- We have compared the performance of haar wavelet with other wavelets.
- Performance parameters are compression ratio and PRD.

Chapter 5

References

1. A Review Paper on Analysis of Electrocardiograph (ECG) Signal for the Detection of Arrhythmia Abnormalities. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering. Joshi, Anand & Tomar, Arun & Tomar, Mangesh. (2014).

2. ECG Signal Filtering Approach for Detection of P, QRS, T Waves and Complexes in Short Single-Lead Recording. Yeldos & Kremlev, Artem & Margun, A.. (2019)

3.Ole-Aase, S., Nygaard, R., Husoy, J.H.: A comparative study of some novel ECG data compression technique. In: NORSIG 1998, pp. 273–276 (1998)

4. Jalaleddine, S.M.S., Hutchens, C.G., Strattan, R.D., Coberly, W.A.: ECG Data Compression Techniques-A Unified Approach. IEEE Transactions on Biomedical Engineering 37, 329–342 (1990)

5. Koski, A., Juhola, M.: Segmentation of digital signals on estimated compression ratio. IEEE Transactions on Biomedical Engineering 43, 928–938 (1996)

6. Mammen, C.P., Ramamurthi, B.: Vector quantization for compression of multichannel ECG. IEEE Transactions on Biomedical Engineering 37, 821–825 (1990)

7. Horspool, R. N., Windels, W. J.: An LZ approach to ECG compression, proceeding IEEE Symp. Computer-based Medical System, 71-76, 1994.

8.Batista, L.V., Melcher, E.U.M., Carvalho, L.C.: Compression of ECG signals by optimized quantization of discrete cosine transform coefficients. Medical Engineering & Physics 23, 127–134 (2001)

9. Allen, V.A., Belina, J.: ECG data compression using the discrete cosine transform (DCT). IEEE Proceedings, Computers in Cardiology, 687–690 (1992)

10.Rajoub, B.A.: An Efficient Coding Algorithm for the Compression of ECG Signals Using the Wavelet Transform. IEEE Transactions on Biomedical Engineering 49, 355–36(2002)

11. Mallat, S.G.: A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. IEEE Transaction on Pattern Analysis and Machine Intelligence 11 (July-1989)

12. Bashar A Rajoub : An Efficient Coding Algorithm for the Compression of ECG Signals Using the Wavelet Transform(May 2002)