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# Trade-offs of EEG data reduction on wearable device

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## Introduction

Electroencephalogram (EEG) has been proved as a noninvasive and reliable way for collecting a person's brain wave data which can be used in numerous areas such as epilepsy diagnosis [1], brain-computer interface (BCI), etc.

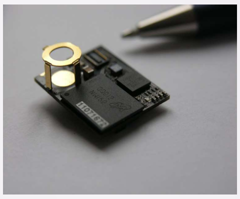

Figure 1. A wearable EEG recorder with a 4-channel input designed by Advanced Computer Architecture Group in University of York

Wearable EEG recorder has drawn a lot of attention in recent years since it saves much more time and money for researchers comparing to traditional data collecting equipment. A wearable EEG recorder can be as small as a 10p coin (Figure 1) so that the object of recording will not even notice it. Such device is preferable to be able to transmit the data via wireless transceiver to achieve the real–time monitoring and data analysis. However, wireless transmission apparently shortens device's running time because of the extra power consumed by the transceiver. The most obvious way to extend running time is to compress the EEG data before transmission, and with less data to be transmitted, the overall power consumption will be largely reduced (Figure 3).

Figure 2. Current solution of reading in the EEG data, a docking station.

Meanwhile, adding on a data compressor to the device also increases the complexity of the system, and compression unit itself is one of the contributors to recorder's power consumption, so exploring a best set of trade-offs between compression ratio (CR) and the power consumption of compressing the data will be helpful to solve all these problems, and that is the purpose of doing this research.

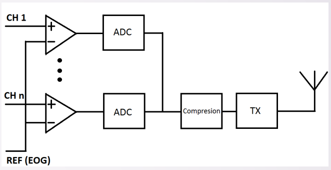


Figure 3. A simplified architecture of wearable EEG recorder

## Experiments

Several compression method candidates have been simulated so far including most well–known lossless Huffman coding [2], a lossy encoding technique called Discrete Wavelet Transform (DWT) [3], as well as a lossless log2 sub-band algorithm we designed which will be introduced in detail below.

Currently, EEG signals are usually quantized to no more than 16 bits in most experiments, and take this resolution as an example, in log2 sub-band algorithm scheme, we first compare the first 4 bits from 16 bits of the current sample with the same part in previous sample, and if they are identical, next 4 bits will be further compared, and the transceiver only transmits the bits that are different from previous sample. A flag of 2 bits is introduced to indicate how many nibbles are transmitted in a sample (Figure 4), which can be used to decompress the data.

The dataset used for simulation come from an EEG experiment taken in University Hospital of Bonn [4], and the sampling rate of data is 173.61 Hz, and are quantized into 10 bits for the simulation.

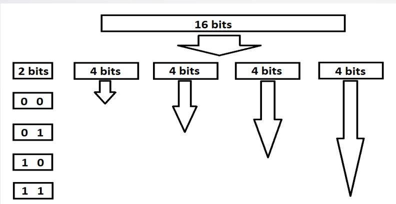


Figure 4. '00' indicates that 4 nibbles of this sample are transmitted, '01' indicates 3, '10' indicates 2, and '11' indicates 1 nibble.

## Results

The CR is defined as

$$CR=\frac{size\ of\ compressed\ data}{size\ of\ original\ data}$$

The data set for testing the Huffman coding is divided into 2 subsets, and each contains 10 files with 4096 data samples in every file. One subset is used to generate the Huffman tree (dictionary) so that the other subset can be encoded based on the previous dictionary. The result of log2 sub-band algorithm will also shown in the Figure 5.

According to [5], the DC-bias of EEG signal degrades the inter-channel decorrelation performance, and it

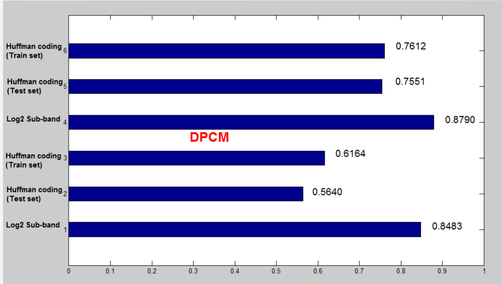


Figure 5. Compression Ratio of presented techniques

can be simply removed by using the differential pulse-code modulation (DPCM) which calculates the difference between adjacent samples. The performance of Huffman coding and log2 sub-band algorithm are both increased after applying DPCM (Figure 5).

As for DWT, it expresses a signal as a weighted sum of basis functions, and these basis are derived from dilated and translated versions of a function which is called mother wavelet [6]. So the original signal can be defined with coefficients of the set of basis functions, and this process causes some loss of the original signals, but as long as a optimal mother wavelet is chosen, the discrepancies between original and reconstructed signals are still acceptable. One file with 4096 data samples is used for simulation, and the mother wavelet applied are Haar (Figure 6), Daubechies 10 (Figure 7), and Coiflet (Figure 8) [3]. The reconstructed signal is recovered with 50 percent coefficients of original signal, so the CR is 0.5 in this case, and as they are shown in the figures, using Haar as mother wavelet gives worst reconstruction quality, and the results of using Daubechies 10 and Coiflet are close.

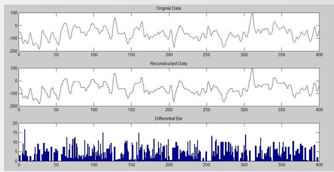

Figure 6. Reconstructed with Harr, and from top to bottom are original signal, reconstructed signal and differentials

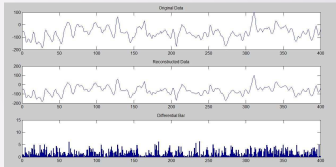

Figure 7. Reconstructed with Daubechies 10

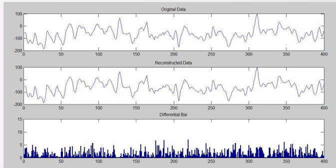

Figure 8. Reconstructed with Coiflet

## Conclusions

For a simplified wearable EEG recorder, which is only consisted with amplifiers, ADCs, and the transceiver, and power consumption of DSPs and the processor are neglected, the overall power consumption of the recorder can be given as

$$P_{sys}=P_{Amp}+P_{ADC}+P_{Comp}+CR*P_{Tx}$$

Where $P_{Amp}$ and $P_{ADC}$ are the power consumption of amplifiers and ADCs, and $P_{Tx}$ and $P_{Comp}$ are the power consumption of transceiver and doing data compression. Then the power reduction is

$$(1-CR)*P_{Tx}$$

By implementing a popular off-the-shelf GFSK transceiver nRF24L01 [7](TX power consumption is 23 mW), the power saving for using Huffman coding is at least 5.5mW, 11.5mW for using DWT, and 3.45mW for using log2 sub-band algorithm. As a result, these are power budgets for future hardware implementation of data compression techniques, and any technique requires lower power than its saving is considered as a proper method which leads to a longer working time of wearable EEG recorder. Furthermore, possible data compression techniques may also applicable to other biomedical data recorders as these signals have many similarities.

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