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EEG signal compression using Compressive Sensing and Wavelet Transform

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Abstract: Biomedical signals need to be digitally stored or transmitted with a large number of samples per second, and with a great number of bits per sample, in order to assure the required fidelity of the waveform for visual inspection. Therefore, the use of signal compression techniques is fundamental for cost reduction and technical feasibility of storage and transmission of biomedical signals. Compressive Sensing is an effective method to make data compressed for EEG signals with high compression ratio and good quality of reconstruction. Experimental results show that the wavelet transform compression method performs much better based on Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

Keywords: Compressive Sensing (CS), Wavelet Transform, Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE).

I. INTRODUCTION

Electroencephalography (EEG) is the technique of measuring electrical signals generated within the brain by placing electrodes on the scalp. The EEG signal produced provides a non-invasive, high time resolution, interface to the brain, and as such the EEG is a key diagnosis tool for conditions such as epilepsy, and it is frequently used in Brain-Computer Interfaces [1]. EEG compression is achieved by exploiting correlation (redundancy) in the source data. The compressibility of EEG depends on its amplitude distribution and its power spectrum. EEG is not usually considered sufficiently sparse in time or frequency domains for matching the recovery requirements of the clinical practice. However, filtered EEG show an amplitude distribution and a frequency spectrum largely concentrated in suitable ranges [2]. EEG compression schemes have achieved up to 65% data reduction with lossless compression [3], and up to 89% data reduction when lossy compression is employed [4].

Compressive sensing method is to make the signal transform into low dimensional measurement domain with under-sampling and it is also known as compressive sampling in the recent years [5–6]. Just as the bandwidth to the Nyquist-Shannon sampling theory, sparsity of the signal is the essential condition to Compressive Sensing [6]. The relevance of using compressive sensing in these signals is double: On one hand it has been previously reported in [7] that EEG signals meet the necessary requirements to ensure reconstruction after compression when projected in certain basis. Hence compressive sensing appears as a very attractive technique to reduce the power consumption and thus the size of future miniaturized EEG systems, which could be used in a variety of applications ranging from long term medical monitoring [8] to brain computer interfaces [9]. The concept of compressive sensing [10] is based on the fact that there is a difference between the rate of change of a signal and the rate of information in the signal. Traditional Nyquist sampling, putting the signal into the digital domain ready for wireless transmission, is based on the former. A conventional compression algorithm would then be applied to all of these samples taken to remove any redundancy present, giving a reduced number of bits that represent the signal. Compressive sensing [11] is a novel technique which suggests random acquisition of the non adaptive linear projection at lower than the Nyquist rate, which preserves signal structure. By using an optimization problem the signal is reconstructed.

Wavelet Transform (WT) is a powerful time-frequency signal analysis tool and it is used in a wide variety of applications including signal and image coding [12]. Wavelet Transform and Subband Coding (SBC) are closely related to each other. In fact the fast implementation of Wavelet Transforms is carried out using Subband (SB) filter banks. Due to this reason Wavelet Transform based waveform coding methods are essentially similar to the SBC based methods.

Curvelet transform has undergone a major revision since its invention. The first generation curvelet transform is based on the concepts of ridgelet transform [13]. The curve singularities have been handled by smooth partitioning of the bandpass images. In each smooth partitioned block the curve singularities can be approximated to a line singularity. A ridgelet transform is applied on these small blocks, where ridgelets can deal the line singularities effectively. To avoid blocking artifacts, the smooth partitioning is done on overlapping blocks which results in redundancy, and the whole process involves subband decomposition using wavelet transform, smooth partitioning and ridgelet analysis on each block; this process consumes more time. The implementation of second generation curvelet transform is based on the Fourier transform and is faster, less complex, and less redundant.

II. SIGNAL COMPRESSION

Signal compression is the process where the redundant information contained in the signal is detected and eliminated. The aim of any biomedical signal compression scheme is to minimize the storage space without losing any clinically significant information, which can be achieved by eliminating redundancies in the signal, in a reasonable manner. The purpose of compression is three-fold:1) to reduce the volume of data to be transmitted, 2) to reduce the bandwidth required for transmission, 3) to reduce the storage requirements. Fig 1 shows the block diagram of data compression.

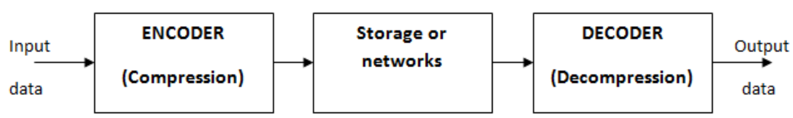

Fig.1: General Data Compression Scheme

The purpose of any signal compression technique is the reduction of the amount of bits used to represent a signal. This must be accomplished while preserving the morphological characteristics of the waveform. Signal compression techniques are commonly classified in two categories: lossless and lossy compression.

The design of data compression schemes involves trade-offs among various factors, including the degree of compression, the amount of distortion introduced, and the computational resources required to compress and uncompress the data.

A. Lossless compression

In lossless data compression, the integrity of the data is preserved. The original data and the data after compression and decompression are exactly the same because, in these methods, the compression and decompression algorithms are exact inverses of each other: no part of the data is lost in the process. Redundant data is removed in compression and added during decompression.

B. Lossy compression

Our eyes and ears cannot distinguish subtle changes. In such cases, we can use a lossy data compression method. In lossy compression, a controlled amount of distortion is allowed. The reconstructed signal is allowed to differ from the original signal. Lossy signal compression techniques show higher compression gains than lossless ones. Apart from obtaining good compression ratios with imperceptible degradation of signal quality, data reduction techniques should also hold low computational costs; particularly if they are going to be implemented on portable devices. Fig 2 shows the schematic of lossless and lossy compression.

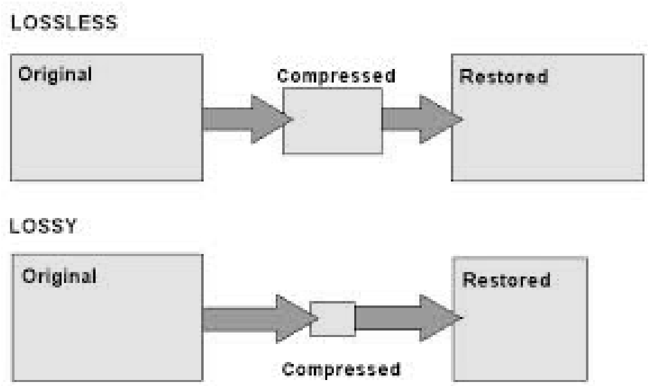

Fig.2: Lossless and Lossy compression

EEG signals have non-stationary behaviour; it means the behaviour through the time is changing every time window. For this reason, the pre-processing, processing, and analysis should be different of the deterministic and stationary signals. EEG signals can be compressed in the following domains: time domain, frequency domain and time-frequency domain.

Time-domain EEG compression

Generally, most of the techniques proposed in the literature devoted to EEG compression are mainly prediction based. This can be explained by the fact that the EEG is a low-frequency signal, which is characterized by a high temporal correlation. Some of these techniques are in fact a direct application of classical digital signal processing methods. These include Linear Prediction Coding (LPC), Markovian Prediction, Adaptive Linear Prediction and Neural Network Prediction based methods. On the other hand, some approaches include the information related to the long-term temporal correlation of the samples. In fact, if we analyze the correlation function of an EEG segment, we will note that spaced samples present a non-neglected correlation that should be taken into account during processing. This information might be integrated into various dedicated codecs. Finally, we can also evoke the techniques which consist of correcting the errors of the prediction using information intrinsic to the EEG.

Frequency-domain EEG compression

The compression of the EEG in the frequency domain did not come from classical techniques such as Karhunen-Loève Transform (KLT) or the Discrete Cosine Transform (DCT). The EEG signal is dominated by low frequencies, mainly lower than 20 Hz. In fact, it is considered that the main energy is located around the alpha rhythm (between 8 Hz and 13 Hz).

Time-frequency domain EEG compression

Among the time-frequency techniques, the wavelet transform has been commonly used to compress the EEG. In this technique, the signal is segmented and decomposed using Wavelet Packets. The coefficients are coded afterwards. Other algorithms such as the well known EZW (Embedded Zerotree Wavelet) have also been successfully applied to compress the EEG signal.

III.COMPRESSIVE SENSING

Compressive sensing is a useful tool for eliminating the inefficiencies caused by traditional signal processing algorithms, because 1) it offers simpler hardware implementation for encoder, as it transforms its computational burden from encoder to decoder, 2) no need to encode the location of the largest coefficients in the wavelet domain, 3) its ability to reconstruct the signal from significantly fewer data samples compared to conventional Nyquist sampling theory.

Compressed Sensing is about acquiring and recovering a sparse signal in the most efficient way possible with the help of an incoherent projecting basis.

1. The signal needs to be sparse
2. The technique acquires as few samples as possible
3. Later, the original sparse signal can be recovered
4. This done with the help of an incoherent projecting basis

IV. WAVELET TRANSFORM BASED COMPRESSION

For biomedical signals, most of the statistical characteristics are non-stationary. In particular, the analysis of biomedical signals should exhibit good resolution in both time domain and frequency domain. Several time-frequency analysis methods such as the Short-Time Fourier Transform (STFT), Wigner-Ville Distribution Function (WDF), Hilbert-Huang Transform (HHT), etc were proposed to represent the signals in both time and frequency domains at the same time. The problem with the STFT is that using a large window size may improve frequency resolution, but the assumption of stationary within the window may be compromised; whereas using a small window leads to poor frequency resolution. WDF offers high clarity in both time and frequency domains, but suffers from cross-term problem. For most biomedical signals, WDF is not suitable either because they have multiple components or because their phase terms are higher than second order.

An alternative way to analyze the non-stationary biomedical signals is the wavelet transform, which has variable time-frequency resolution over the time-frequency plane. The analysis phase of the wavelet transform decomposes a signal into elementary building blocks or frequency bands that are localized in both space (time) and frequency (scale). This differentiates a wavelet transform from a Fourier transform. The window size (scale) used in wavelet transform is chosen to be short at high frequencies and long at low frequencies (to pick up all the abrupt changes), providing good time resolution at high frequency and good frequency resolution at low frequencies. Because of this localization property, wavelets are very good in isolating singularities and irregular structures in signals. The main advantage of wavelet transform over other time-frequency analysis is little storage space. The dimension and size of the output signal is about the same as the input signal, which gives wavelet transform very powerful potential in image processing. Because of the above reasons, the wavelet transform has become a popular technique in feature detection, noise reduction, signal compression, and image and video processing.

Wavelet Transform (WT) is a powerful time-frequency signal analysis tool and it is used in a wide variety of applications including signal and image coding. “The wavelet transform is a tool that cuts up data, functions or operators into different frequency components, and then studies each component with a resolution matched to its scale”.

The goal of using the DWT in the compression of EEG signals is the possibility of choosing the signal's coefficients with a significant energy and discards the others that have a very low percentage of energy. This is possible because in every level of decomposition, the energy of different frequencies and time position is related to a specific coefficient.
The technique includes three important stages: the decomposition of the signal; the identification of low energy coefficients and its rejection (thresholding); and finally, the reconstruction of the new coefficients. It is shown below:

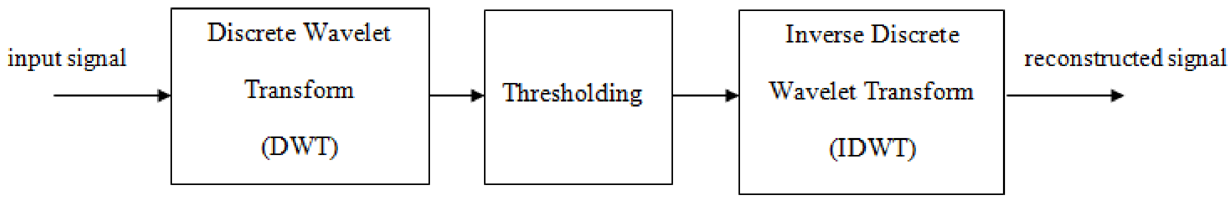

Figure 3: Wavelet Transform based compression

The DWT is both "complete" and has "zero redundancy", which means that all the signal information is contained in the resulting transform and none is duplicated between transform coefficients. By converting the signal into its DWT coefficients and then removing all except those containing the most pertinent signal information, the resulting transform is much smaller in size, which provides a good way of compressing a signal. Performing an inverse transform on the remaining components recreates a signal that very nearly matches the original. This is the basis of compression algorithms that can be applied to EEG signals.

DWT is commonly used in compression algorithms due to its ability to represent signals in both the time and frequency domain. The DWT decomposes a signal into a set of basis functions known as wavelets. The initial wavelet, also known as the mother wavelet(c), is used to construct the other wavelets by means of dilation and shifting. Dilation is achieved by multiplying the function's time orientation n by a scaling factor 2^m, where mϵZ. Shifting in time is done by kϵZ. Therefore, the wavelet decomposition is defined by

$$x(n) = \sum_m \sum_k c_{m,k} (\psi(2^m n - k)), \quad m, k \in Z \tag{1}$$

where the scale m relates to the wavelet's dilation. Basis functions associated with large scales extract low-frequency information from the signal, while small scales extract high-frequency or fine- detail components.
The DWT coefficients cm,k are defined as the inner product of the original signal and the selected basis functions:

$$c_{m,k} = < x(n), \psi_{m,k}(n) > \tag{2}$$

These coefficients provide an alternative representation of the original signal, giving good localisation of the signal's energy components from both a time and frequency perspective.
The wavelet transform of a signal e(t) can be calculated efficiently and the signal can be reconstructed from the transform coefficients under some necessary and sufficient conditions given by Daubechies. Since relatively few wavelet coefficients capture most of the signal energy, it is possible to make a lossy reconstruction of the original signal by zeroing out all the coefficients in the wavelet expansion but the

largest ones before inverse transforming. The amount of energy concentrated in low frequency bands is a measure of signal's smoothness, and ultimately of good compressibility.

Wavelet analysis can be understood as a form of sub-band coding with quadrature mirror filters. The two basic wavelet processes are decomposition and reconstruction.

A. Wavelet Decomposition

Wavelet processing is based on the idea of sub-band decomposition and coding. Wavelet "families" are characterized by the low-pass and high-pass filters used for decomposition and perfect reconstruction of signals.

A single level decomposition puts a signal through two complementary low-pass and high-pass filters. The output of the low-pass filter gives the approximation (A) coefficients, while the high pass filter gives the detail (D) coefficients.

Wavelet transforms encode more information than other techniques like Fourier transforms. Time and frequency information is saved. In practical terms, the transformation is applied to many scales and sizes within the signal. This results in vectors that encode approximation and detail information. By separating the signals, it is easier to threshold and remove the redundant information. Thus the data can be compressed.

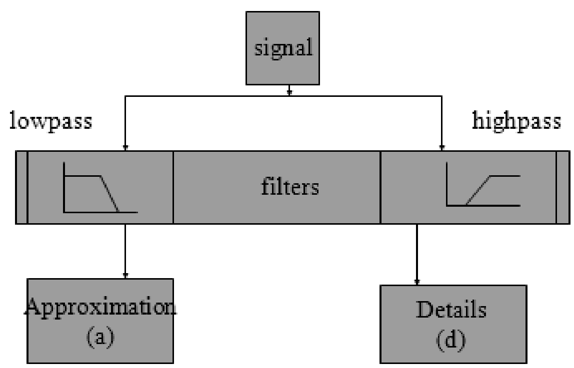

Fig 4: Wavelet Decomposition

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components. This is called the wavelet decomposition tree.

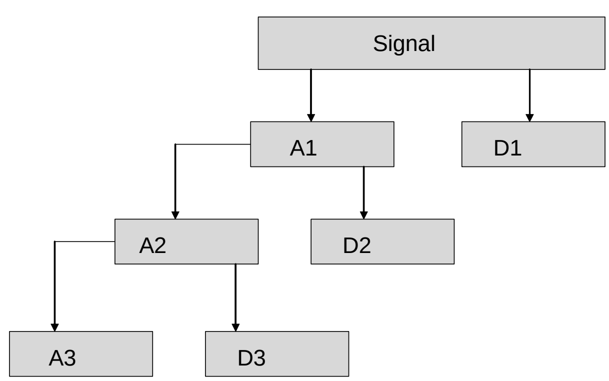

Fig 5: Wavelet Decomposition Tree

The signal can be recursively decomposed to get finer detail and more general approximation. This is called multi-level decomposition. A signal can be decomposed as many times as it can be divided in half. Thus, we only have one approximation signal at the end of the process.
The decomposition tree can be schematically described as:

B. Wavelet Reconstruction

The data can be decompressed using the Inverse Wavelet Transform. The approximation (A) and detail (D) coefficients can be used to reconstruct the signal perfectly when run through the mirror reconstruction filters of the wavelet family.

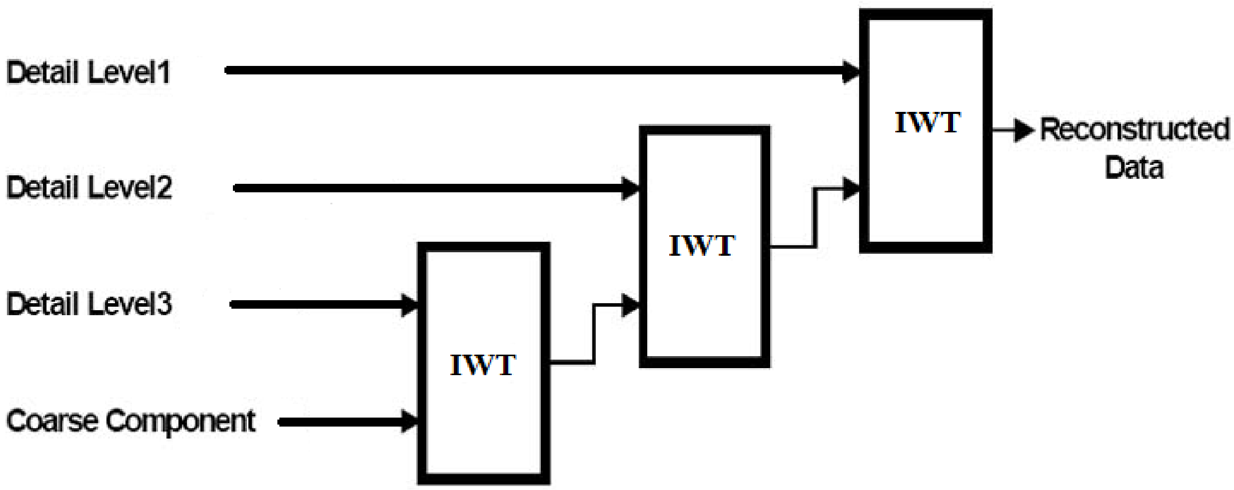

Fig 6: Wavelet Reconstruction

IV.PERFORMANCE EVALUATION

Depending on the nature of the application there are various criteria to measure the performance of a compression algorithm.

- Mean Square Error(MSE)
- Peak Signal to Noise Ratio(PSNR)
- Compression Ratio (CR)

A. Mean Square Error

Mean Square Error is defined as follows:

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(x_n - y_n)^2 \tag{3}$$

where x_n,y_n and N are the input data sequence, reconstructed data sequence and length of the data sequence respectively.

B. Peak Signal to Noise Ratio

Peak Signal to Noise Ratio is defined as follows:

$$PSNR = 10\log_{10}\frac{x_{peak}^2}{\sigma_d^2} \qquad (4)$$

where σ_d^2 is the MSE.

C. Compression Ratio

Compression Ratio (CR) is the most important parameter in data compression algorithms. The amount of compression is measured by Compression Ratio. High Compression Ratio leads to a better response. It is the ratio between the number of bits before compression to that after compression.

$$CR = \frac{\textit{number of bits of original signal}}{\textit{number of bits of compressed signal}}. \qquad (5)$$

V.RESULTS

The simulation results obtained using MATLAB show that compressive sensing is an effective method to make data compressed for EEG signals with high compression ratio and good quality of reconstruction.

First of all, the EEG signal is compressed using Compressive Sensing. The sparse signal is thus obtained. The Discrete Wavelet Transform of the sparse signal is obtained. The wavelet used is the Daubechies wavelet. Afterwards, Inverse Discrete Wavelet Transform is used to reconstruct the coefficients. The simulation results are shown in Fig 4. Fig. 4(a) is the original EEG signal, and Fig. 4(b) shows the compressive sensed signal. Fig. 4(c) shows the reconstructed EEG signal.

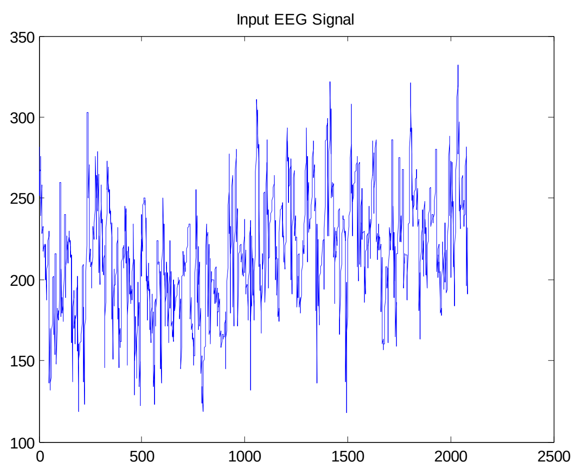

Fig. 4(a) Original EEG signal

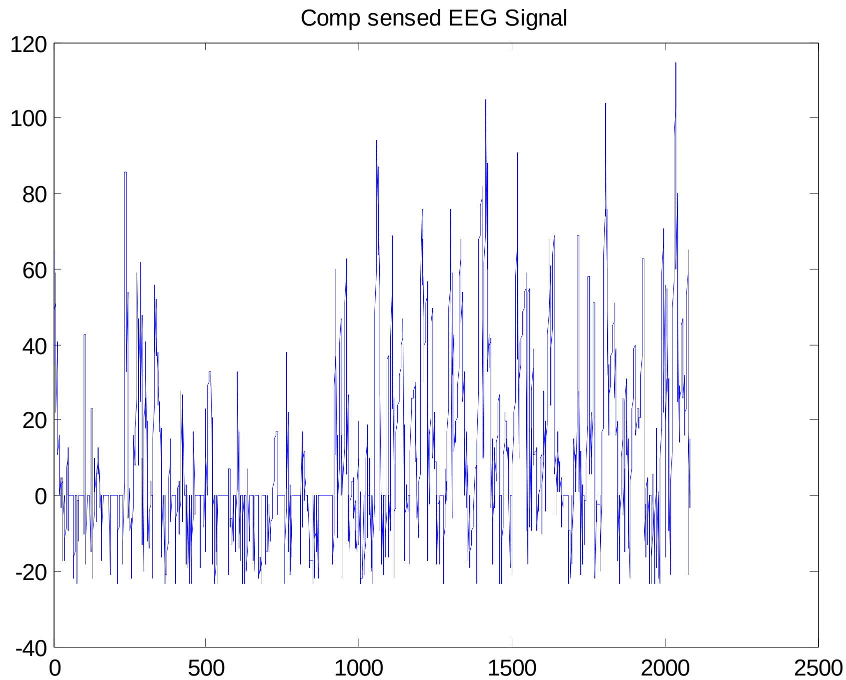

Fig. 4(b) Compressive sensed signal

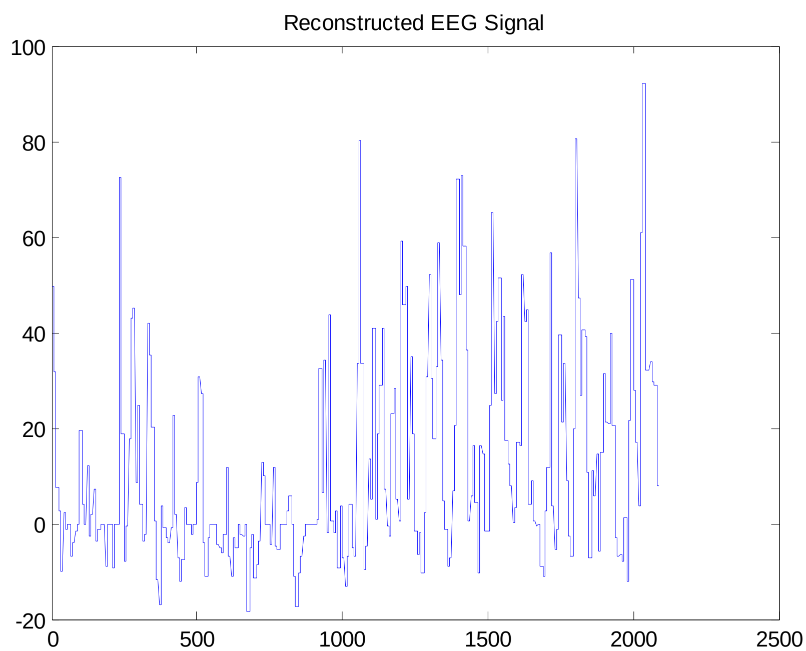

Fig. 4(c) Reconstructed signal

Table 1 shows the performance of wavelet transform compression method based on Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

Input signal	Compression Ratio	PSNR in	MSE
eeg_signal1 (awake)	14.95	35.45	18.53
eeg_signal2 (drowsy)	15.46	33.17	31.33
eeg_signal3 (sleep stage-1)	15.07	34.12	25.19
eeg_signal4 (sleep stage-2)	15.79	29.18	78.5
eeg_signal5 (deep sleep)	15.98	26.11	108.7
eeg_signal6 (REM sleep)	14.68	35.62	17.8

Table 1. Performance of wavelet transform method based on CR, PSNR and MSE

VI.CONCLUSION AND FUTURE WORK

EEG is not only a key diagnostic tool for neurologists, but it is growingly used in Brain-Computer Interfaces (BCI) applications. The traditional approach to EEG signal processing is to perform Nyquist sampling on the bandlimited version of the signal. Compressive Sensing is a useful tool for eliminating the inefficiencies caused by traditional signal processing algorithms. Compressive Sensing is an effective method to make data compressed for EEG signals with high compression ratio and good quality of reconstruction. Experimental results show that the wavelet transform compression method performs much better based on Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

The compressive sensing (CS) methodology can be used in EEG analysis for discriminating among different, possibly pathological, brain states. It can be used for diagnosing and controlling Alzheimer's disease patients. An interesting alternative to use the CS derived compression coefficients can be to use a set of connection weights extracted from a trained Spiking Neural Network. This approach can certainly be the object of further studies.

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