Wavelet based algorithm to denoise EEG signals

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Abstract. Denoisning EEG signals is a major concern, as it contains important information regarding our human brain. EEG signals contains various types of noise of different frequencies, these frequencies disturbs the actual EEG signal which is recorded at a particular time of respective human activity. In this paper we have developed an algorithm which will denoise an EEG signal with the help of a particular threshold frequency. This algorithm is divided into two parts, in first part the EEG signal is prepared with the help of scaling and its co-efficient values are stored with the help of sampling. Furthermore, in the second part the sampled coefficients are transferred to high and low pass filter and by iterative level function of the filter the coefficients are reduced, because of a threshold frequency. Thus, by this noise present in the abrupt changes of the EEG signal gets removed.

Keywords: EEG Wavelet, Denoising algorithm, Low pass filter.

1 Introduction

Over a small period of time, the record of unstructured brain's electrical activity is known as Electroencephalography (EEG) signal [9]. Electric is the only semantics within the nervous system. By altering the flow of electrical currents across membranes of human brain [1], they process information and placing electrodes on the scalp, the electric and magnetic fields generated from the currents can be recorded. Amplification of potentials between different electrodes takes place, to get recorded as the Electroencephalogram (EEG). Therefore, by this EEG signal recording gives us comprehensive knowledge about inclusive movement of the millions of neurons [4].

In Neuroscience, one of the major problem focus on the statistical analysis of electrical recordings of the brain activity by an Electroencephalogram. The complexity of identification of cerebral signals can be generated as they have several origins. Therefore, noise removal is of utmost requirement to make interpretation and representation of data easier and recuperate the signal that equals the brain which functions perfectly [5].

Electroencephalography (EEG) is used by brain-computer interfaces (BCI) and neurofeedback (NFB) and, as it satisfy great temporal resolution and therefore, has grown into a largely used skill for real time brain monitoring applications. As EEG signals are disposed to artifacts, denoising could be regarded as a crucial step that enables adequate subsequent data processing and interpretations [7].

2 Proposed Work

Firstly let us evaluate what a wavelet is, the gradually varying trends or oscillations interspersed with transients which demonstrate in the world of data or signals. The information which are provided by these abrupt changes are often most stimulating part of the data in a perceptual manner, as widely held of them contains noise. The Fourier Transform is a powerful tool for data analysis, but the abrupt changes are not efficiently demonstrated by it. The reason for that is, the fourier transform represents data as a sum of sine waves which are not localized in time or space, these sine waves oscillate forever. Thus, we need a new class of functions that could be recognised as well localized in domain of frequency and time, which bring us to the focus of wavelets. A wavelet could be defined as rapidly decaying wave like oscillation that has zero mean. A wavelet will only exist for finite duration and are not like sinusoids which tends to infinity.

2.1 Part 1 (Scaling and shifting of EEG wavelet)

The part 1 of algorithm includes concepts of scaling and sampling which will satisfy the initial requirement of the algorithm.

2.1.1 Scaling

Assume a signal $\psi(t)$, scaling refers to the, "process of stretching or shrinking the signal in time" which can be expressed using below equation,

$\psi\left(\frac{t}{s}\right) s > 0$ ---------- (eq. 1)

In eq. 1, S is a scaling factor which refers to a positive value and resembles in what depth a signal is scaled in time.

The scale Factor is inversely proportional to frequency, this can be showed in eq. 2

$Feq \propto \frac{1}{s}$ ------------ (eq. 2)

For example,

When a sine wave is scaled by two then its unique frequency is reduced by half or by an octave. For a particular wavelet, relationship between the scale and the frequency is reciprocal with a constant of proportionality. The constant of proportionality in eq. 2 is called the centre frequency of the wavelet. The reason behind this is "unlike the sine wave the wavelet has a band pass characteristic in the frequency domain" [10].

$Feq = \frac{Cf}{s\delta t}$ -------------- (eq. 3)

In eq. 3, using the following equation, equivalent frequency could be defined.

Where,
Cf = Center frequency of the Wavelet
s = wavelet scale
δt = Sampling interval.

Thus, scaling by factor 2 of a wavelet, the reduction in equivalent frequency is by an octave.

A greater scale factor fallouts a stretched wavelet which results to a lower frequency. A lesser scale factor fallouts a shrunken wavelet which results to a high frequency. To capture the slowly varying changes in a particular signal, a stretched wavelets is used and to capture the abrupt changes in a particular signal, compressed wavelet is used.

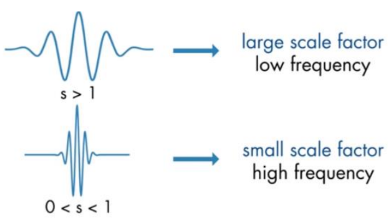

Fig. 1. Impact of scale factor on signal

Let, $\psi_{(t)}$ be an EEG signal which has frequency Fbw. Scaling has been performed on the EEG signal $\psi_{(t)}$. It completely depends on what activity a person is performing. As the frequency of brainwaves increases scale factor increase, and due to this the frequency decreases and we get the required scaled EEG signal.

$Fbw \propto s$ ------------------ (eq. 4)

In eq. 4, Fbw is frequency of brainwave and s is scale factor.

2.1.2 Sampling

Sampling of signal means dividing the signal into various discrete interval and storing the values of that interval such that the original signal can be generated from the discrete interval values which were stored.

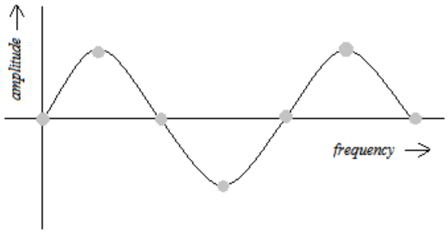

Fig. 2. Sampling of a wave

It can be possible that discrete interval values which were stored fails to generate original EEG signal, than this condition is known as aliasing.

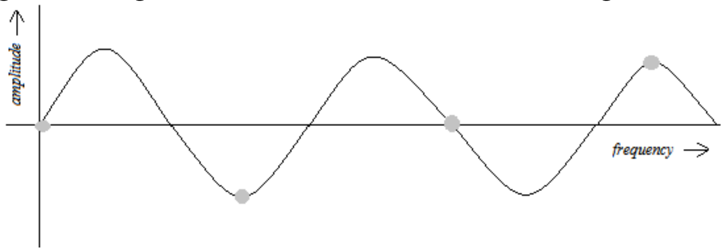

Fig. 3. Random sampling

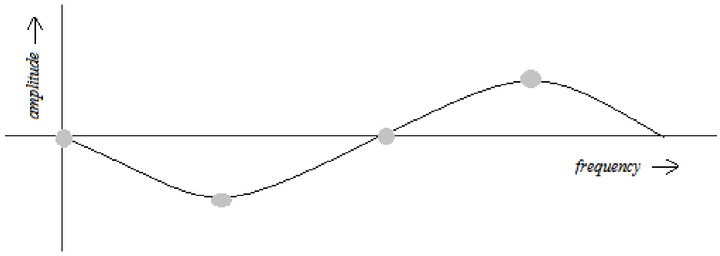

Fig. 4. Demonstration of aliasing

Aliasing can be removed when sampling rate is slightly greater than the maximum frequency present in the EEG signal.

$Sr > Fm + \in$ -------------- (eq. 5)

In eq. 5, Sr is the sampling rate and $Fm + \in$ is value slightly greater than maximum frequency Fm.

After performing scaling on a particular EEG signal with respect to its frequency, which helps to balance signal overall. Then after process of sampling is performed on the scaled EEG signal. The sampling factor for the EEG signal is decided with respect to its maximum frequency. Thus, with the help of these two steps the EEG signal is sampled and the discrete sampled interval values are stored which can be used to denoise the EEG signal or wavelet. Higher scales per octave is directly proportional to high level of discretization.

2.2 Part 2 (Wavelet Denoising)

2.2.1 Steps to denoise EEG signal

Step 1: Perform a multilevel wavelet decomposition to obtain the approximation and detail coefficients.
After scaling and sampling of EEG signal we get large number coefficients which contains noise. The filter (High pass filter and low pass filter) process these large number of coefficients as their inputs. The output coefficients of high pass filter are known as approximation level coefficients and output coefficients of low pass filter are known as detail level coefficients [6][8].

Given a signal S, the filtration of signal takes place with special high pass and low pass filter to yield high pass and low pass sub bands. Half of the samples are discarded after filtering, after eq. 5 is applied. For the next level of decomposition, the low pass sub bands LPF_1 is iteratively filtered by the same technique to yield narrower sub bands LPF_2 and HPF_2 and so on [3]. The number of coefficients becomes half iteratively, when the sub band level increases for the decomposition. Therefore, this technique will help you to internment signal of interest with large magnitude of initial coefficients with removing the coefficients which contain noise.

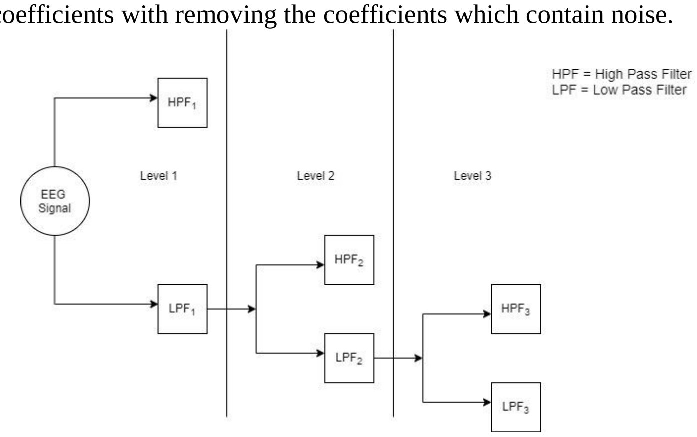

Fig. 5. Low pass & High pass sub bands

Most of the high frequency is caught by the first level detail coefficients of the signal, these coefficients comprise of noise exist in the signal. However abrupt changes in the signal are made up of high frequency component, which contains noise in it. But at times this abrupt changes also contains some useful information and you don't want to lose them, therefore a threshold value is set to filter out noise from the useful information.

Working of a low pass filter
Low pass filter kills all the coefficients which have frequency above threshold frequency Fc.

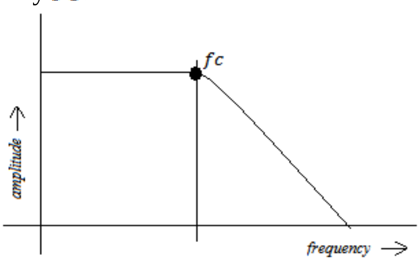

Fig. 6. Low pass filter graph

In the above amplitude-frequency graph, the frequency is increasing and after a certain fixed threshold frequency Fc, the frequency decreases.

(Circuit)

$Fc = \frac{1}{RC} rad/sec$
$Fc = \frac{1}{2\pi RC} Hz/sec$ ----------- (eq. 6)

With the help of eq. 6, we can calculate respective values of R and C in the given circuit.

As the signal is AC, therefore we will use impedance here.
$Zr = R$ --------- (eq. 7)

In eq. 6, Zr is AC resistance and R is normal resistance. Both are same as change in frequency does not change resistance of a circuit.

$Zc = \frac{1}{j\omega C}$ ---------- (eq. 8)

In eq. 7, Zc is AC capacitance and $j = \sqrt{-1}$. Here capacitance of a circuit changes with change in frequency.

Applying KVL,
$Vin - iR - i\frac{1}{j\omega C}$
$Vin = iR + i\frac{1}{j\omega C}$ ------- (eq. 9)

According to ohm's law,
$Vr = iR$
$Vc = Vout = i\frac{1}{j\omega C}$ ------- (eq. 10)

Substituting eq. 10 in eq. 9,
$Vin = iR + Vout$
$Vout\ .j\omega C = i$
$Vin = (Vout\ .j\omega C)R + Vout$
$Vin = Vout\ (j\omega CR + 1)$
$\frac{Vout}{Vin} = \frac{1}{1 + R\, j\omega C}$ ------- (eq. 11)

In eq. 11, $\frac{Vout}{Vin}$ is the transfer function which is used to transfer EEG signal coefficients to subsequent level of low pass filter.

Step 2: To analyse the detail coefficients and identify a suitable thresholding technique.

Most of the noise present in the signal are present in first level of detail coefficients as it internments the high frequency of the signal, as high frequency consist of various abrupt changes in the signal. The basic scope here is to hold sharp changes, which contains important information and get rid of noise. The other way to do this is by threshold, in which scaling of detail coefficients takes place [2].

By the universal threshold method,

$$Teq = \frac{Sqrt\ (2*\log(length(x)))*\ median(abs(D))}{0.6745}$$ -------------- (eq. 12)

In eq. 12, x is the signal, D is the set of first level detail coefficients and Teq is the required threshold. The value of Teq can be different for different level depending upon the requirement for denoising.

Step 3: Detail coefficients should be threshold and the signal should be reconstructed.

There are two types of thresholding techniques, difference in both the techniques is dealing of coefficients which are greater in magnitude than thresholding value.

1) Soft thresholding

In soft thresholding technique, the threshold value is subtracted from the coefficients which are greater in magnitude than threshold to shrink them to zero.

2) Hard thresholding

In hard thresholding, no alteration is performed if coefficients greater in magnitude than threshold.

Therefore, from above two thresholding techniques best technique is choose which fits the requirement to denoise the EEG wavelets from a particular threshold frequency.

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