Mathematical model for event related potential signals

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Abstract. In the Neuroscience, Brain Computer-Interfaces (BCI) are pathways of communication between brain and external devices. But the problem with interface of external device and the brain is; very small potential difference generated because of the brain activities. Accurately sensing those signals and then understanding those signals related to a particular activity i.e. Event Related Potential (ERP) is still the challenge; as it also contains too much of noise.

Here we have created a mathematical model for specifically eye blink event. The coefficient of correlation between original EEG signal and the model is 0.9. With the help of this mathematical model we will be able to classify whether the signal is related to left eye blink or not. For our experiment, we used non-invasive type of sensor) electroencephalography (EEG) device (NeuroSky headset) to generate ERP.

Keywords: BCI, ERP, non-invasive sensor, EEG.

1. Introduction

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. EEG signals measure the electrical signals from brain through the BCI, and deliver the information related to mental activities. Although EEG signals are unique, they are weak, non-stationary and contain a lot of noise. Therefore it is difficult to process EEG signals. For a successful brain computer interface system for EEG signal analysis, there are four major tasks to process, including pre-processing, feature extraction, feature selection and classification. This paper mainly deals with feature extraction for classification of EEG signals. The aim of this paper is to transform the acquired EEG signals to prepare a mathematical model for the acquired signal and make its use for feature applications like classification.

2. Literature Review

Brain computer interfaces (BCI) are a relatively new technology that takes advantage of the innate computing power of the brain. Developing BCIs have, up until recently, been thought of as science fiction. Ever since the first discovery of electroencephalography (EEG) by Berger, scientists have been trying to decode signals from the brain [1], [2].

A BCI traditionally consists of four main parts; a sensing device, an amplifier, a filter, and a control system. The sensing device consists of a cap with electrodes placed to the International 10-20 standard [3], [4].The amplifier can be one of numerous biological amplifiers on the market [5]. The filter and control system applied to the brain signals is the focus of BCI research.

The first proposed application of a BCI was for use in therapeutics and for mental disorder classifications [6], [7]. Modern BCI research focuses on patients with amyotrophic lateral sclerosis (ALS), also known as “locked-in” syndrome [8], [9], [10], [11], [12]. BCI research has also expanded to include systems that healthy individuals can utilize to expand normal human capabilities [13], [14].

3. Statistical Method

The mathematical model for EEG signal is supposed to be linear combination of sinusoidal signals with different frequencies. And it also includes exponential term too.

The variation in these sinusoidal signal frequencies and their phase causes the change in shape of the final signal. With three sinusoidal signal terms and one exponential term we obtain the signal with closer match in the actual signal. The mathematical model we prepared here is,

$$\mathrm{Y(t, f, \phi, d, p)} = -e^{-t^{p}} * \left\{ \prod_{i=1}^{3} \sin\left(\left(\frac{2\pi f i t}{d i} \right) + \phi i \right) \right\} * Constant$$

Here the EEG model signal Y depends on the f frequency, ф the phase, d and pare constant values.

4. Result and Conclusion

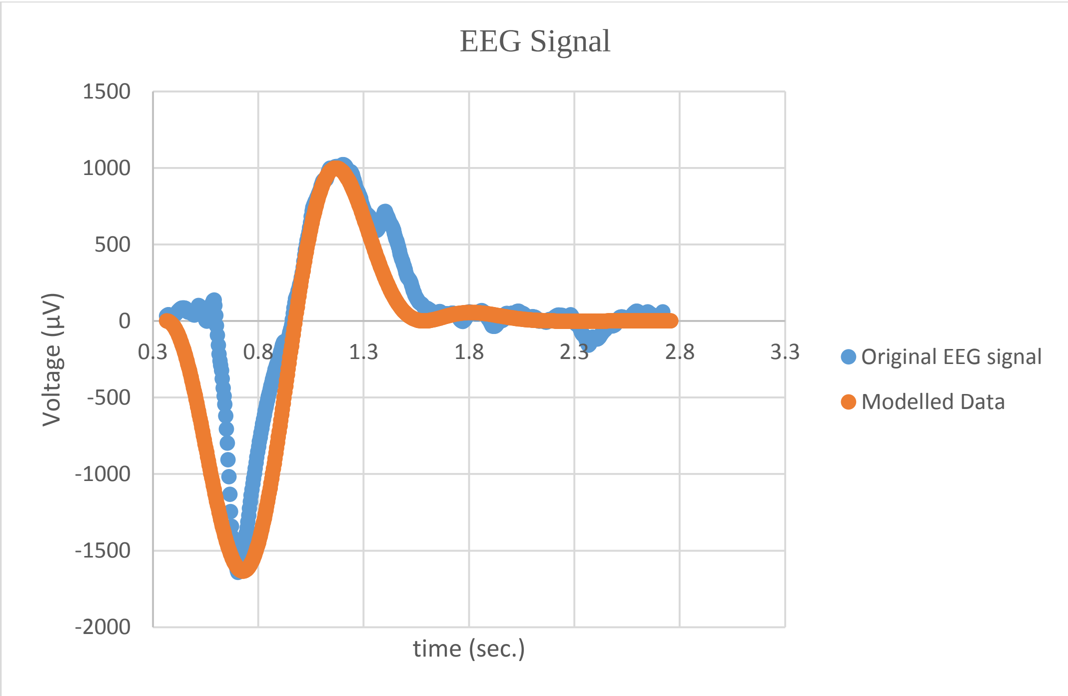

Fig.1. Plot of Original EEG signal and the modelled signal

As we can see the modelled signal closely matches the original EEG signal, the coefficient of correlation comes out to be 0.9.

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