P3 - Poster Session

EEG-Eye Blink Detection System for Brain Computer Interface

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Abstract. Brain-Computer Interface (BCI) has been focusing on the development of communication tools for patients with motor disabilities. ElectroEncephaloGraphy (EEG) is commonly used in order to acquire brain electrical activity and mental states.

Toward an application of brain computer interface, the aim of this paper is to detect eye blink signals from EEG signals. It develops the acquisition using BioRadio portable device and describes the methods used to pre-process these signals, and to classify the eye blinking signals using the Probabilistic Neural Network as a binary classifier. The results obtained are promising in order to be included in a neurorehabilitation application.

1 Introduction

The Neural-prosthesis is to read information out of the brain and/or give biofeedback information into the Brain and to the nervous system in order to help the severely paralyzed patients. The problem is that there are millions of people who are unable to move or to communicate. These individuals need an alternative way to communicate that does not rely on peripheral nerves and muscles. Brain Computer Interface (BCI) allows that the brain activity could be used as a communication tool in order to improve the quality of life of different patients.

Almost all of the BCIs studies are based on the Electroencephalography, EEG, recorded non invasively from the scalp [1][2].

Different physiological information can be extracted from the EEG such as alertness states, sleep stages or simply eye blinks. There are two types of Eye Blinks: the reflexive Eye Blink and the intentional Eye Blink. The reflexive eye blink is the simplest response and does not require the involvement of cortical structures. In contrast, intentional eye blink involves multiple areas of the cerebral

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cortex; the objective in this paper is to detect this intentional eye blink through the EEG signals.

2 Methodology

2.1 *BCI Architecture*

Fig.1 presents the brain computer architecture of the system developed. This paper will present the acquisition protocol of the EEG, the preprocessing and Classification of the signal by a classifier.

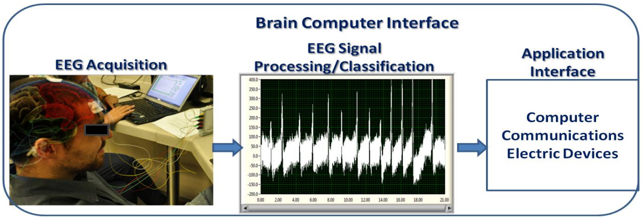

Fig. 1 BCI Architecture

2.2 *EEG Signal Acquisition*

The EEG signals were acquired in the Biomedical Department Laboratory-Holy Spirit University using BioRadio Pac from CleveLabs Laboratory [5]. The BioRadio is a wireless biomedical monitor.

Based on the 10-20 electrode positioning system, seven gold cup electrodes are placed at locations O1, O2, Fp1, and Fp2 to measure EEG, on each mastoid as references, and at FpZ (middle of the forehead) for the ground. The mastoid 乳突 processes (A1 and A2) are the bony structures behind the ears. A1 and A2 are used as the references since over the bony structures there is no electrical activity in this region.

During the experiment, 4 channels (Fp1-A1, Fp2-A2, O1-A1 and O1-A2) were saving the data while the user was intentionally provoking an eye blink. The EEG Data was acquired from different subjects (4 subjects). During one to two minutes of session duration, the subject was asked to blink an eye each sec (self-paced

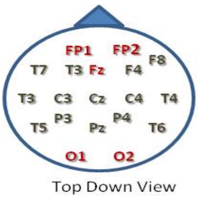

Fig. 2 Seven electrodes position -Eye Blink Detection

intentionally eye blink). The EEG signals are acquired at 480 Hz sampling frequency.

2.3 EEG Signal Preprocessing

EEG signals are recorded from the four channels. Channels 1 and 2 present two similar signals in terms of frequency and amplitude of the signals and can be used in order to detect an intentional left or right eye blink. Previous studies have shown that the eye blinks power spectrum in concentrated in the ranges of 0.5-3 Hz and 8–13 Hz. The signal was filtered using 6^{th} order Butterworth Band Pass filter between 0.5 Hz and 20 Hz. The signal is then detrended then normalized.

2.4 Feature Extraction

The signal is segmented into windows with 480 samples each (one second duration) using the Boxcar window.

After the observation of the filtered EEG signal we notice that the eye-blink signal can be detected by its positive and negative peak occurrences. The vector features taken from the signal were the maximum amplitude, minimum amplitude, in each sample window and the kurtosis of the present sample, kurtosis of the previous and kurtosis of the next sample. K is the kurtosis: 峰度

$$K = E((\frac{x-\mu}{\sigma})^4) \tag{1}$$

Where E is the expectation, μ is the mean of the realizations and σ is the standard deviation. The eye blink signals are characterized by high value of Kurtosis coefficient.

2.5 EEG Classification

RBF networks have been successfully employed in many real world tasks in which they have proved to be a valuable alternative to multilayer perceptron (MLPs). The function computed by a general RBF network is therefore of the form:

$$f(u,w) = \sum_{b=1}^{K} w_b s_b(u) \tag{2}$$

Where u the vector is applied to the input units and s_b denotes the radial basis function. The RBF network has three layers. The input layer composed of N components u_i (i=1..N) of the input vector, u, feed forward the hidden kernel layer composed of K basis functions whose outputs are linearly combined with the weights $w_b{}^K{}_{b=1}$ into the network output layer *f(u)*. The Gaussian Radial Basis Function is used.

$$f(u,w) = \sum_{b=1}^{K} \left(\frac{-\| u - m_b \|^2}{2\sigma_B^2}\right) \tag{3}$$

Where each hidden node b is parameterized by 2 quantities: a center m_b in input space, corresponding to the vector defined by the weights between the node and the input node, and a width σ_b. A sigmoid function is placed on the output neurons to give 0/1 output values. The method implemented using the MathWorks© Artificial Neural Networks ToolBox. 42 sample signals were randomly taken as a dataset for "training" the Neural Network; each sample with its own target vector.

3 Results

Fig.3 shows the brut EEG signal obtained at Channel I. Fig.4 shows the signal filtered, detrended and normalized.

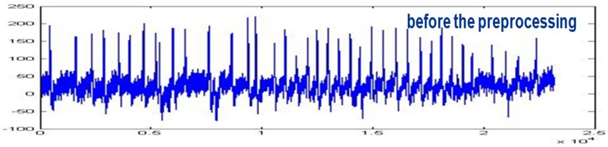

Fig. 3 Raw Noised EEG Signal (Fp1-A1)

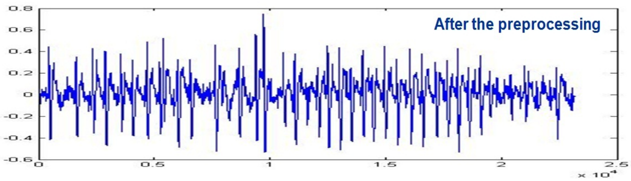

Fig. 4 Preprocessed Signal

Table 1 Comparison with Other Classifiers

Accuracy of classifiers	*Training(%)*	*Test(%)*
MLP-FFBP	96.687	71.6
MLP-CFBP	99.83	54.78
RBF Binary Classifier	100	75.375

Four datasets corresponding to the EEG signals of 4 subjects were used. Data was divided randomly into two groups: 70% for training and 30% for testing. The maximum accuracy obtained 81.25%, the average accuracy around 75.375 %. Multiple cross validation (repeated randomly) have been tested on the data. RBF is generally known for being very high accurate for most of the data sets [7]. We compared the results as shown in Table 1 with the two existing types of (MLP) entitled Feed Forward Back Propagation (FFBP) and Cascade Forward Back Propagation (CFBP) [3] already implemented on these types of signals using the same feature extraction method.

4 Conclusion

This paper presents a binary classification of eye blinking detected through the EEG signals. The binary classifier RBF presents an accuracy promising better compared to the other MLP networks. Eye blink detection can be integrated with other phenomenas such as motor imaginery in biofeedback and control applications in neurorehabilitation.

References

[1] Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M.: Brain–Computer Interfaces for Communication and Control. Clinical Neurophysiology 113, 767–791 (2002)

[2] Lotte, F.: Study of Electroencephalographic signal processing and classification techniques towards the use of Brain Computer Interfaces in Virtual Reality applications, PhD Thesis (2008)

[3] Chambayil, B., Singla, R., Jha, R.: EEG Eye Blink Classification using neural network. In: Proceedings of the World Congress on Engineering (2010)

[4] Sanei, S., Chambers, J.: EEG Signal Processing. Wiley, CRC Press, England (2009)

[5] BioRadioPacs, CleveLabs Laboratory

[6] MathWorks: Neural Network Systems, PNN ToolBox (2009)

[7] Baughman, D.R., Liu, Y.A.: Neural Networks in Bioprocessing and Chemical Engineering: with Disk., 1st edn. Academic Press, Inc. (1995)