Essential Processes for Electroencephalography

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***Abstract*—Electroencephalography (EEG) is important for studying brain activities and detecting brain disorders. This paper presents an overview of essential processes for EEG signal processing, including data acquisition, preprocessing, feature extraction, and classification.**

Keywords—Electroencephalography, Wavelet transform

I. Introduction

Human brain is the most important organ which consists of billion neurons. These neurons create small electrical signals to communicate between brain and body. The electroencephalography (EEG) signal [1] is non-invasive electrical signals from the scalp of the brain. EEG signals can be used to detect brain activity disorders such as Alzheimer's disease, Epilepsy, sleep disorder, etc. The EEG signals are collected from multiple channels, which record all brain activity signals. To detect a disorder or an activity of the brain, the EEG signals are eliminated any interference and then are transformed to the appropriate frequency range by means of the following essential processes: data acquisition, preprocessing, feature extraction, and classification as shown in Fig. 1.

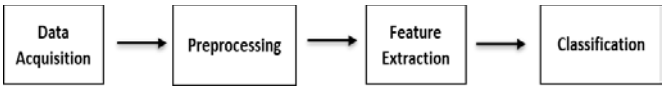

Fig. 1. EEG signal processing for classification

II. Data acquisition

To collect brain activity signals, it requires the specific device and the understanding of the proper use of it.

A. EEG Device

Nowadays, EEG signals can be collected by a small headset device which is portable and easy to use. The EEG device has 4 main components – electrodes, conductive gels, amplifiers, and analog to digital converter. There are many neuroheadset devices from many companies, such as Mind-Wave from NeuroSky, Muse from InteraXon, and EPOC from Emotiv.

B. 10-20 System

Each part of the brain controls different functions of the body. For example, the left frontal lobe of the brain is responsible for speech and language [1]. Therefore, the loca-tions of the electrodes are important for collecting the acti-vity of the brain.

The electrodes are used to conduct the electrical signals from the scalp of the brain. The 10-20 System is a method to describe the position of the electrodes. The '10' and '20' refer to the distance between adjacent electrodes that are either 10% or 20% from front to back or right to left of the skull [2]. Each electrode placement is represented by the letters (F-Frontal, T-Temporal, C-Center, P-Parietal, O-Occipital, z-midline region) and the digits (odd number-left brain, even number-right brain) which indicate the position of the brain lobe as shown in Fig. 2.

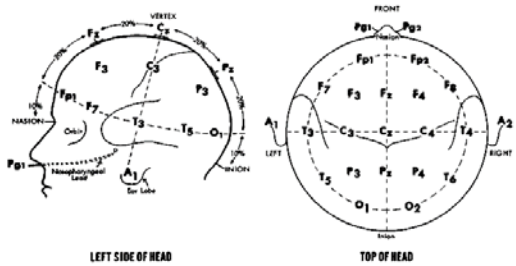

Fig. 2. 10-20 System for locating the electrodes

III. Preprocessing

Preprocessing is a procedure for eliminating the unnecessary information and noise.

According to [1], most of EEG signals are in range 0.1–100 Hz. EEG data filtering depends on frequency band of each brain activity. For example, the muscles movement and eyes movement require 2.5 ~ 25 Hz bandpass filter.

IV. Feature extraction

Feature extraction is one of the most important parts of all processes. The better feature extraction gives the better result of classification. There are many options for feature extraction such as Fourier transform and wavelet transform. Fourier transform such as Short Time Fourier transform cannot work for the multi-resolution signals, while wavelet transform can.

Wavelet transform is one of the most popular methods for EEG signal feature extraction. There are two forms of wavelet transform for feature extraction: continuous wavelet transform (CWT) and discrete wavelet transform (DWT) [3].

A. Continous Wavelet Transform

Continuous wavelet transform of an analog signal f is expressed as

$$C_{b,a} = \left(W_{\psi} f\right)(b,a) = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t)\, \overline{\psi\left(\frac{t-b}{a}\right)}\, dt \qquad (1)$$

where $C_{b,a}$ is the wavelet coefficient, $\psi(t)$ is the basic wavelet or also called mother wavelet, b is the translation of $\psi(t)$, and a is the dilation or scale factor of $\psi(t)$.

CWT uses Scalogram plots to represent the continuous variation of translation and dilation factors of EEG signals by using its colors. Fig. 3 is an example of Scalogram.

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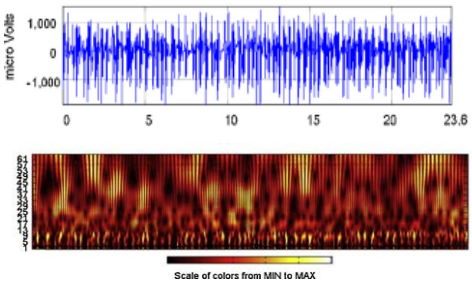

Fig. 3. Example of CWT Scalogram of Epileptic.

Discrete wavelet transform decomposes a raw EEG signal into detail coefficients and approximation coefficient are expressed as

$$C_{b,a} = \left(W_{\psi} f\right)\left(\frac{k}{2^j}, \frac{1}{2^j}\right) \qquad (2)$$

In order to calculate $W_{\psi} f(b,a)$, dyadic value $b = k/2^j$ and value $a = 2^{-j}$. This method can also call "dyadic wavelet transform".

If wavelet decomposition goes through the 5th level, the original signal (S) is decomposed into five detail coefficients (D1-D5) and one approximation coefficient (A5) as shown in Fig. 4.

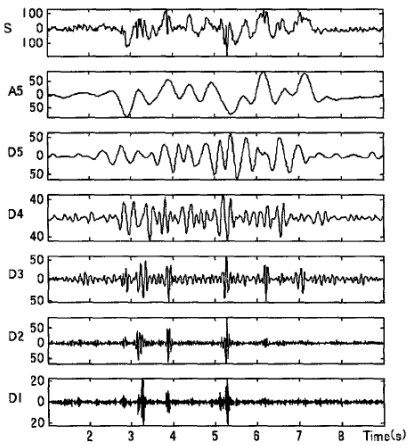

Fig. 4. 5th level of wavelet decomposition

With a comparison between CWT and DWT in [4], wavelet transform is often used more than other methods. For wavelet transform, DWT is often used more than CWT for researches in Epileptic seizure detection. From 81 researches, 40 papers selected DWT, 21 papers selected CWT for their researches, and remainders selected others methods.

V. CLASSIFICATION

Classification is essential process for detecting brain activities or brain disorders. Each classifier typically has different behaviors and provides different results. There is a study on a comparison of several classifiers in [5] such as linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), kernel fisher discriminant (KFD), support vector machine (SVM), multilayer perceptron (MLP), learning vector quantization (LVQ), neural network, k-nearest-neighbor (k-NN), and decision tree (DT) with dataset III and IV in BCI competition 2003. Dataset III and IV are for motor imagery signals and finger movement signals, respectively. Almost of results from the same dataset and feature extraction have nearly accuracy with the fixed time window (fixed starting point and length of time) and each classifier has the best result with different temporal filtering. The result shows that the optimal starting point of time window is between 550–560 for dataset III and 43–46 for dataset IV. The authors suggest that linear classifiers are the first choice because of its simplicity but they seem to be more sensitive with different temporal filter.

The performance of classifiers [6] can be measured by accuracy, sensitivity, and specificity. In this review, *TP*, *TN*, *FP*, and *FN* refer to true positive, true negative, false positive, and false negative, respectively.

Accuracy is the rate of positive and negative outcomes are correctly calculated.

$$Accuracy\ (\%) = \frac{TP + TN}{TN + TP + FN + FP} * 100 \qquad (3)$$

Sensitivity is the rate of positive outcomes correctly calculated.

$$Sensitivity\ (\%) = \frac{TP}{TP + FN} * 100 \qquad (4)$$

Specificity is the rate of negative outcomes correctly calculated.

$$Specificity\ (\%) = \frac{TN}{TN + FP} * 100 \qquad (5)$$

VI. CONCLUSION

This paper reviews about the essential processes for EEG signals. Data acquisition is the process of collecting raw EEG data. Preprocessing is the procedure to eliminate noise and filtering the unwanted data. Feature extraction is the process of transforming signals to the appropriate form for classification. In this review, we pay attention to wavelet transform because of its popularity and providing the multi-resolution signals. Classification is the process to classify the brain activities or disorders.

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