DOI:10.21276/sjeat.2016.1.4.10

Saudi Journal of Engineering and Technology
Scholars Middle East Publishers
Dubai, United Arab Emirates
Website: http://scholarsmepub.com/

ISSN 2415-6272 (Print)
ISSN 2415-6264 (Online)

Research Article

LabVIEW for EEG Signal Processing

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Abstract: In this paper, motor imagery EEG signals are preprocessed, using the state-of-the-art measurement and control software LabVIEW. Firstly, the elliptic filter is used for digital band-pass filtering. Then the soft-thresholding approach is adopted for wavelet denoising to enable programming with the BCI Competition 2005 dataset. The experimental results show that the method not only saves a lot of time in development and debugging, but also provides a good foundation for implementing a BCI system.
Keywords: Brain-computer interface, EEG, LabVIEW, Wavelet denoising.

INTRODUCTION

BCI, short for Brain-Computer Interface, does not rely on the physiological pathway comprising peripheral nerves and muscles. It is a brand new communication and control method to detect consciousness through EEG signals [1, 2]. A general-purpose BCI system consists mainly of three parts, i.e. EEG signal acquisition, data processing, and peripherals and interfaces. Data processing as the core part involves preprocessing, feature extraction and classification etc. Preprocessing as the process to remove noise from EEG signals is essential to the implementation of the BCI system.

In this paper, EEG signals are preprocessed, using the state-of-the-art measurement and control software LabVIEW for filtering and denoising to enable programming with the BCI Competition 2005 dataset and provide a good foundation for implementing a BCI system.

LABVIEW IN EEG SIGNAL PROCESSING APPLICATIONS

Today, commonly used software development tools such as VB and VC require complex code compiling, which can be a problem for BCI designers who are not familiar with software development. LabVIEW from National Instruments (NI) is the answer to this problem. LabVIEW, short for Laboratory Virtual Instrument Engineering Workbench, is a visual system-design platform and development environment. It uses the graphical language "G" for programming with the minimum code compiling efforts needed. Instead, a virtual instrument is built by using a virtual front panel and a block diagram. The G language simplified the programming, reducing time and effort for developers. Widely used in industry, academia and research laboratories, LabVIEW has become a standard tool for data acquisition and instrument control [3, 4].

LabVIEW-based EEG signal filtering

The EEG data used in this paper are the bipolar EEG recordings from the BCI Competition III - Dataset IIIb, i.e. motor imagery with two classes (left hand and right hand), measured over the electrodes placed at positions C3, C4 and CZ with 0.5-30Hz EEG channels, 125Hz sampling rate, and 8s testing time.

LabVIEW offers a wide range of filters, such as Butterworth filters, Chebyshev filters, elliptic filters and so on. In this paper, the original EEG data is processed using an 8-30Hz digital band-pass filter, i.e. 8-30Hz cutoff frequency, 0.5dB attenuation, and 50dB stop-band attenuation. The LABVIEW filter module is shown in Figure 1.

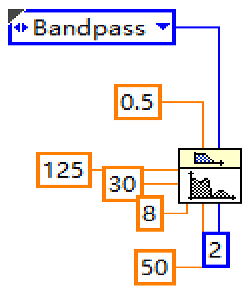

Fig-1: Elliptic filter module

Wavelet denoising Methods

Wavelet-based denoising of signals is a technique using wavelet transform to remove noise from a signal by projecting the desired part and the noise in the original signal onto the different orthogonal bands. The most common wavelet based denoising methods [5-8] are the decomposition and reconstruction method, Wavelet Transform Modulus Maxima and thresholding methods etc.

Decomposition and reconstruction

According to the fast algorithm of the orthogonal wavelet transform [9],

$$c_{j,k} = \sum_n c_{j-1,n} h_{n-2k}, k = 0,1,2\cdots N-1 \quad (1)$$

$$d_{j,k} = \sum_n c_{j-1,n} g_{n-2k}, k = 0,1,2\cdots N-1 \quad (2)$$

where $c_{j,k}$ is the coefficient of scale; $d_{j,k}$ is the wavelet coefficient; h and g are the orthogonal filter coefficients; j is the number of levels in decomposition; N is the number of discrete sampling points.

The reconstruction formula for wavelet transform is:

$$c_{j-1,n} = \sum_k c_{j,k} h_{n-2k} + \sum_k d_{j,k} g_{n-2k} \quad (3)$$

The decomposition and reconstruction method is based on a multiresolution analysis, decomposing the desired part and the noise in the original signal onto the different orthogonal bands to remove the noise and retain the desired signal. Then, the original signal can be reconstructed after noise reduction.

WTMM

The wavelet theory shows that the way modulus maxima magnitudes change with the change of the scale is determined by the associated Lipschitz exponent at the point of discontinuity [10]. Lipschitz exponent is defined as:

$$\left|x(t_0+h) - p_n(t_0+h)\right| \le A\left|h\right|^{\alpha}, n < \alpha < n+1 \quad (4)$$

and the Lipschitz exponent for $x(t)$ at t_0 is α, where h is a sufficient small amount and $p_n(t)$ are polynomials of degree n over $x(t_0)$. Extend the definition of Lipschitz exponent to an interval $[a,b]$, when any two points t_0 and t_0+h in the interval $[a,b]$ satisfies the equation (1), $x(t)$ is called the average Lipschitz exponent α for $x(t)$ in the interval.

Assume the wavelet function $\psi(t)$, when t is the in the interval $[a,b]$ and the wavelet transform of the arbitrary function $f(t)$ satisfies

$$\left|W_a f(t)\right| \le k a^{\alpha} \quad (5)$$

or

$$\log\left|W_a f(t)\right| \le \log k + \alpha \log a \quad (6)$$

then the average Lipschitz exponent is α for $f(t)$ in the interval $[a,b]$, where is k a constant. If $a = 2^j$, the equation (6) is transformed into

$$\log_2\left|W_{2^j} f(t)\right| \le \log_2 k + j\alpha \quad (7)$$

In the equation (7), $j\alpha$ connects the scale parameter j of wavelet transform with the Lipschitz exponent α, describing how modulus maxima changes with the change of scale; for the general signal, when α>0, modulus maxima increases with the increase of scale; for the white noise, when α<0, modulus maxima decreases with the increase of scale. Therefore, we can achieve signal denoising by removing a maxima point from the modulus maxima image when its magnitude decreases with the increase of scale and then reconstructing the original signal in accordance with the denoised modulus maxima image.

The thresholding methods

The concept of wavelet denoising by thresholding originally came from Donoho. Assume a finite-length signal with noise superimposed is $y_i = x_i + z_i$ ($i = 1,2\cdots N$) . Here are the steps to recover the original signal x_i from the signal y_i:

1.A discrete wavelet transform is applied to the signal y_i . The number of levels in wavelet decomposition and the basis of wavelets are selected properly to obtain the wavelet coefficient;

2.Hard thresholding or soft thresholding of the wavelet coefficients, as shown in equations (8) and (9);

Hard thresholding

$$\hat{X} = T_h(Y,t) = \begin{cases} Y, \left|Y\right| \ge t \\ 0, \left|Y\right| \langle 0 \end{cases} \quad (8)$$

Soft thresholding

$$\hat{X} = T_s(Y,t) = \begin{cases} \mathrm{sgn}(Y)(\left|Y\right| - t), \left|Y\right| \ge t \\ 0, \left|Y\right| \langle 0 \end{cases} \quad (9)$$

where $\hat{X}$ represents the estimation of X from Y .

3.Inverse transform is applied to the thresholded wavelet coefficient to obtain the recovered original signal x_i free of noise.

Among the above-mentioned methods for wavelet denoising, the thresholding method is the most used. In general, when soft thresholding is applied, the estimated signal is as smooth as the original signal, which is different from the hard thresholding methods that may lead to oscillation of the reconstructed signal. EEG signals are non-linear, non-stationary and mixed with a lot of noise. Therefore, soft thresholding is used for EEG signal denoising here.

LabVIEW-based wavelet denoising method for EEG signals

The LabVIEW-based denoising method is as follows: The denoising parameters are set for the original EEG signals with noise to pass the parameters to the corresponding functions for analysis and processing before the final results are shown. In this paper, Daubechies 4 wavelets (db4) are decomposed into four levels. The diagrams are shown in Fig. 2 and Fig. 3.

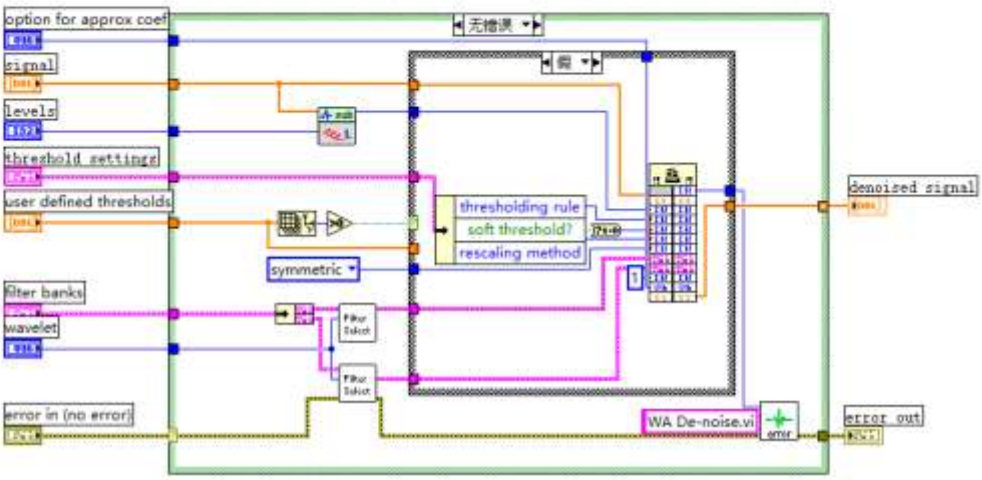

Fig-2: Block Diagram of Wavelet Denoising

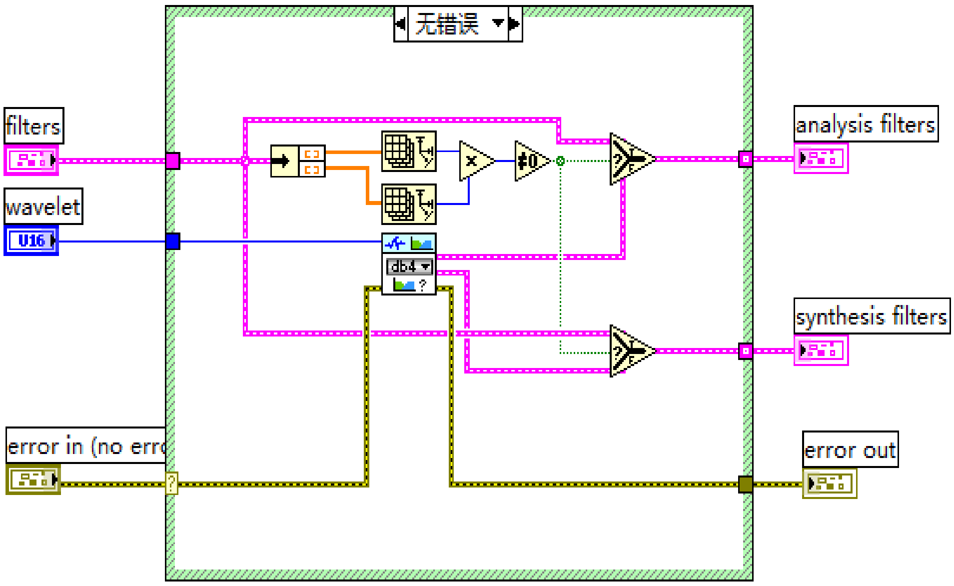

Fig-3: Block Diagram of Wavelet Selection Models in Wavelet Denoising

RESULT ANALYSIS

The result of applying the wavelet-based denoising method to EEG signals with noise is shown in Fig.4. As indicated, wavelet denoising has greatly reduced noise in the signals and the clear EEG signals are separated.

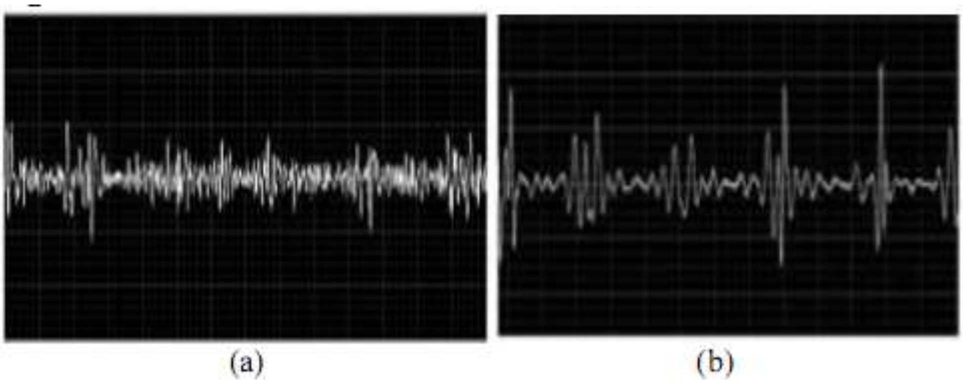

Fig-4: Comparison of EEG signals (a)before denoising (b)after denoising

CONCLUSION

BCI is one of the hot topics in research at home and abroad [11], involving disciplines such as neural engineering, computing and electronics. Although much progress has been made, some technical issued remained unsolved. In this paper, the state-of-the-art measurement and control software LabVIEW is used to create a friendly man-machine interface to analyze and process EEG signals. The results show that LabVIEW not only saves a lot of time in development and debugging, but also provides an easy-to-use, friendly graphical interface to facilitate the process of signal analysis and processing.

ACKNOWLEDGMENTS

The work is supported by Project of Shandong Province Higher Educational Science and Technology Program, China(Grant No. J13LN04)

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