Classification of Functional Near-Infrared Spectroscope Signals for Brain Functional Cognition

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Abstract

Functional Near-Infrared Spectroscope (fNIRs) is one of the latest technologies which utilize light in the near-infrared range to determine brain activities. Near-infrared technology allows design of safe, portable, wearable, non-invasive and wireless qualities monitoring systems. This indicates that fNIRs signal monitoring of brain hemodynamics can be value in helping to understand brain tasks. In this paper, we present results of fNIRs signal analysis to show that there exist distinct patterns of hemodynamic responses which recognize brain tasks toward developing a Brain-Computer interface. We applied Higuchi's fractal dimension algorithms to analyse irregular and complex characteristics of fNIRs signals, and then Wavelets transform is used to analysis for preprocessing as signal filters and feature extractions and Neural networks is a module for cognition brain tasks. Throughout two experiments, we have demonstrated the feasibility of fNIRs analysis to recognize human brain activities.

Keywords: functional near infrared spectroscope (fNIRs), brain-computer interface (BCI), wavelets, neural networks, brain activity, neuroimaging

1 Introduction

In recent years, functional near-infrared spectroscopy (fNIRs) has been introduced as a new neuroimaging modality with which to conduct functional brain-imaging studies. fNIRs technology uses specific wavelengths of light, introduced at the scalp, to enable the noninvasive measurement of changes in the relative ratios of deoxygenated hemoglobin (deoxy-Hb) and oxygenated hemoglobin (oxy-Hb) during brain activity. Wireless fNIRs system consists of personal digital assistant (PDA) software controlling the sensor circuitry, reading, saving, and sending the data via a wireless network. This technology allows the design of portable, safe, affordable, noninvasive, and minimally intrusive monitoring systems [1].

For such advanced features, fNIRs signal processing really becomes an attractive field for computational science. In [3], M. Izzetoglu and et.al. investigated canceling motion artifact noise from fNISs signals by Wiener filter. The authors indicated that the noise including in fNIRs is an important limitation on the use of optical data in these applications. Motion artifact can cause the NIR detectors to shift and lose contact with the skin, exposing them to either ambient light or to light emitted directly from the NIR sources or reflected from the skin, rather than being reflected from tissue in regions of interest. Another noise can cause the blood to move toward (or away from) the area that is being monitored, increasing (or decreasing) the amount of oxygen, hence result in an increase (or decrease) in the measured data. Hence, canceling noise from fNIRs signals is one of necessary tasks in order to use fNIRs as a brain monitoring technology in its full potential to many real life application areas. In [4], M. Izzetoglu and el.al. presented statistical analysis of fNIRs signals for the purpose of cognitive state assessment while the user performs a complex task. The results indicated that the rate of change in blood oxygenation of fNIRs signals was significantly sensitive to task load changes and correlated fairly well with performance variables. In [5] [6], S. Fantini and et.al. describe a specific frequency-domain instrument for near-infrared spectroscopy and imaging of tissues proven that the hemodynamic changes monitored with NIR spectroscopy correlate with the activation state of the cortex in response to a stimulus. They investigated the possibility of combining phase and average intensity data in fNIRs frequency-domain imaging of the brain activation presenting different spatial/temporal features.

In this work, we consider fNIRs signals and analyze irregular and complex characteristics by Higuchi fractal dimension algorithms. This method was successfully applied for EEG bio-signal processing in [8], [9]. Fractal dimension values along period of time sever as meaningful characteristics of studied bio-signals. With obtained experiment results, fractal dimensions of fNIRs signals can not clearly indicate information of brain activities. Therefore, we proposes Wavelet-Neuron model to recognize brain activities through fNIRs signals.

Wavelet transform became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications. Wavelets processing play a role of extraction algorithm to draw features of fNIRs signals and to filter high frequency noises. Extracted features are inputs of neural networks to classify brain tasks. Neural networks are very powerful tools for pattern recognition. The neural network used wavelets coefficients as its inputs and brain activities are depicted by outputs. The paper is organized as follows: In section 2, the mathematics basic models are set up including Higuchi's fractal dimension algorithm, Wavelet transform, and Neural Network model. In section 3, fNIRs data acquisition is described including instruments and 2 experiments. Section 4 shows results and discussion. Section 5 is conclusion.

2 Methods

Higuchi's algorithm shown in [10] performs fractal dimension of a time series directly in the time domain. Its principle is based on a measure of length, L(k), of the curve that represents the considered time series while using a segment of k samples as a unit. If L(k) scales like

$$L(k) \approx k^{-D_f} \tag{1}$$

Fractal dimension, D_f, equals 1 for a simple curve and equals 2 for a curve which nearly fills out the whole plane. D_f measures complexity and irregular characteristics of time series signals.

From [11], the wavelets transform of a signal s is the family C(a,b), which depends on two indices a and b. C represents how closely correlated the wavelet is with this section of the signal. The higher C is, the more the similarity. More precisely, if the signal energy and the wavelet energy are equal to one, C may be interpreted as a correlation coefficient. The set to which a and b belong:

$$C(a,b) = \int_R s(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \tag{4}$$

Where:

$a=2^j$, $b=k.2^j$, $(j,k) \in Z^2$

ψ is wavelet functions

a is scale of wavelets functions

b is position of wavelets functions on the signal s.

The main aim of this paper is recognition and classification fNIRs signals corresponding to brain activities. After testing for non-linear in fNIRs signal by Higuchi fractal dimension and feature extracting by wavelet transforms, neural networks are very powerful tools for classification or pattern recognition shown in [11]. Informative features are extracted from the coefficients computed with the wavelets transform and used as inputs for classification.

As usual, the back propagation training is based on the minimization of the following quadratic cost function:

$$E = \frac{1}{2}\sum_{n=1}^{N}(y_n - d_n)^2 \tag{12}$$

Where:

N is number of patterns.

yn is output of network

dn is desired output.

3 fNIRs data acquisition

We used a multichannel fNIRs instrument, OMM-3000 from Shimadzu Corporation, Japan, for acquiring oxygenated hemoglobin and deoxygenated hemoglobin concentration changes. The system operated at three different wavelengths of 780 nm, 805 nm and 830 nm, emitting an average power of 3 mW.mm−2. The illuminator and detector optodes were placed on the scalp. The detector optodes were fixed at a distance of 3 cm from the illuminator optodes. The optodes were arranged above the hemisphere on the subject's head.

Near-infrared rays leave each illuminator, pass through the skull and the brain tissue of the cortex and are received by the detector optodes. The photomultiplier cycles through all the illuminator–detector pairings to acquire data at every sampling period. The data were digitized by the 16-bit analog to digital converter.

Because oxygenated and deoxygenated hemoglobin have characteristic optical properties in the visible and near-infrared light range, the change in concentration of these molecules during neurovascular coupling can be measured using optical methods By measuring absorption changes at two (or more) wavelengths, one of which is more sensitive to oxy-Hb, the other to deoxy-Hb, changes in the relative concentrations of these chromophores can be calculated. Using these principles, researchers have demonstrated that it is possible to assess brain activity through the intact skull in adult humans

The fNIRs instrument was capable of storing the raw signals for each of channels, one of which consists of the intensity values of 3 wavelengths, as well as the derived values of oxygenated hemoglobin [Ox-Hb], deoxygenated hemoglobin [Deox-Hb] and total hemoglobin [total-Hb]= [Ox-Hb] + [Deox-Hb] concentration changes for all time points in an output file in a pre-specified format. Under the view of recognition brain activities, we chose the total hemoglobin [total-Hb] concentration changes to analysis its functions.

In this work, we investigate 2 tests to recognition brain activities. Test 1 is implemented with a 32 year old male doing three tasks, as follow:

Task 1: controlling physical motion of right arm,

Task 2: imaging the motion of right arm,

Task 3: relaxing.

Each of tasks is measured during 3 minutes, by 7 channels, and sampling frequency 18Hz.

Test 2 is implemented with a 28 year old male with mission imaging numerical push on a calculator. Each of imaging tasks corresponding to a number is measured during 1 minute, by 17 channels, and sampling frequency 10Hz.

4. Results and Discussion

The first test acquired 3275 points, in which each 100 point is enough to calculate fractal dimension, D_f, called window index runing along the signals. Computing results are shown in Fig. 1.

Fig. 1 shown that fractal dimension mostly more over than 1.9 indicating high degree of complexity of fNIRs signals as well as complexity of brain dynamics generating the given bio-signals. However these results can not demonstrate difference in each task of human brain activities. Therefore, we use model combining

Wavelet Transform and Neural Networks to recognizing brain activities.

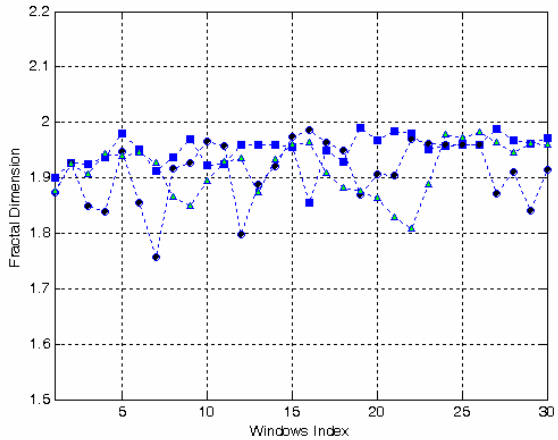

Fig. 1. Fractal dimension of three fNIRs channels of 3 tasks of the first test corresponding to circle-point line, square-point line, and triangle-point line

In the first test, Wavelet mother is chosen discrete approximation of Meyer wavelet. Level of decomposition is 3. SNR_{gain} are calculated for each channel and shown in Table 1.

Table 1. Signal to noise ratio *(SNR)* gain of 7 channels and 3 tasks.

Total-Hb	Ch-1	Ch-2	Ch-3	Ch-4	Ch-5	Ch-6	Ch-7
Task 1	2.70	2.57	3.12	2.89	0.25	1.26	0.88
Task 2	4.70	1.15	5.26	2.28	0.70	0.75	1.12
Task 3	3.00	2.23	3.57	2.99	0.30	1.42	0.91

From Table 1, *SNG-gain* average is calcutated as SNR_{gain}-average = 2.10

Multilayer neural network is built with 3 layers. Input layer consists of 7 neurons corresponding to 7 fNIRs channels. 7 neurons are set for hidden layer and 1 neuron for output layer. The transfer functions of the hidden layer are chosen tagsig-function while the transfer functions of output neurons are purelin-function, a linear function, for representation of many different classes, output equals to +1, 0, -1 corresponding to task 1, 2, 3. The error of Neural training processing shows in Fig. 2, with mean square error of classification is 9.82e-05 in 200 epochs. The output of neural model indicates separately 3 distinguished tasks in Fig. 3.

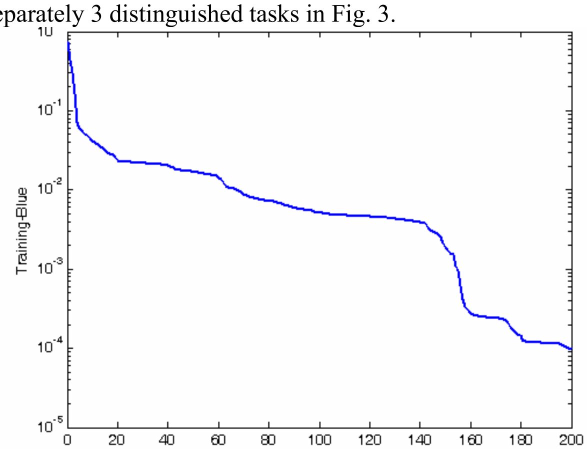

Fig. 2. The error of neural network training processing corresponding to 200 epochs of the first experiment.

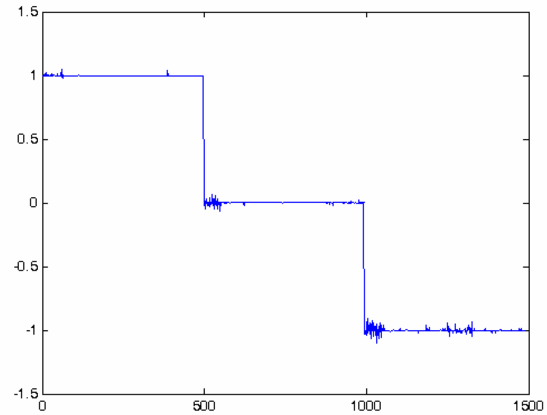

Fig. 3. Output of neural network recognizing 3 distinguished tasks of brain activities

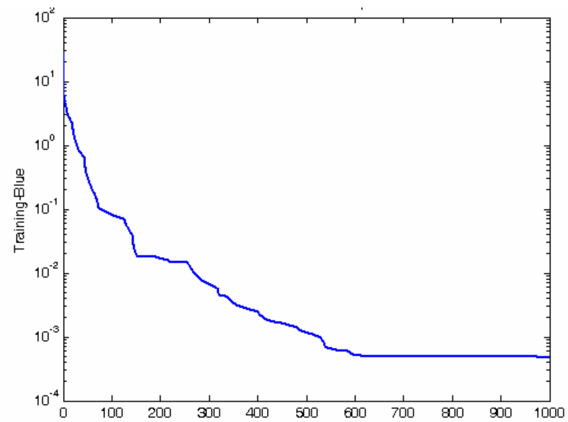

Fig. 4. The error of neural network training processing corresponding to 1000 epochs of the second experiment

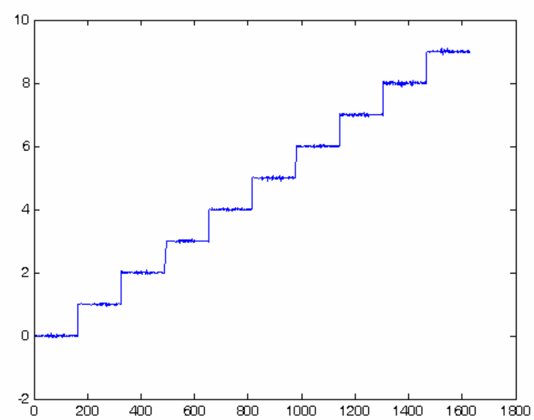

Fig. 5. Output of neural network recognizing 10 distinguished tasks of brain activities.

In the second test, *SNG-gain* average is calcutated as SNR_{gain}-average = 2.97.

Multilayer neural network is built with 3 layers. Input layer consists of 17 neurons corresponding to 17 channels of fNIRs signals. 17 neurons are set for hidden layer and 1 neuron for output layer. The transfer functions of the hidden layer are chosen tagsig-function while the transfer functions of output neurons are purelin-function, a linear function, for representation of many different classes, output values from 0 to 9 correspondind to numerical imaging from 0 to 9. The error of Neural training processing shows in Fig. 4, with mean square error of classification is 4.79e-04 in 1000 epochs. The output of neural model indicates separately 10 distinguished tasks in Fig. 5.

All two experiments show that classified wavelet-neuron models obtain the high accuracy. The results determine advantages of wavelets analysis as preprocessing and neural networks as classified models.

With many advantages of fNIRs, safe, portable, affordable and high accuracy of computing pattern recognition. A Brain-computer interface (BCI) using fNIRs signals will be developed as an alternate mode of communication and environmental control. Especially disable patients with cognitive ability to communicate with their social environment can live with a reasonable quality of life over extended period time.

5 Conclusion

In this study, we have demonstrated the feasibility of fNIRs analysis to recognize human brain activities. fNIRs opens many excellent opportunities to cognition brain activities and interface to computer as future BCIs. The limited paper contributes analyzing nonlinear characteristics of fNIRs by Higuchi's fractal dimension, extracting signal features by wavelet transforms, and recognizing brain activities by neural network. In future, we will indicate the potential use of such techniques to online fNIRs-BCI systems.

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