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Functional Near Infrared Spectroscope for Cognition Brain Tasks by Wavelets Analysis and Neural Networks

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***Abstract*—**Brain Computer Interface (BCI) has been recently increased in research. Functional Near Infrared Spectroscope (fNIRs) is one the latest technologies which utilize light in the near-infrared range to determine brain activities. Because near infrared technology allows design of safe, portable, wearable, non-invasive and wireless qualities monitoring systems, fNIRs monitoring of brain hemodynamics can be value in helping to understand brain tasks. In this paper, we present results of fNIRs signal analysis indicating that there exist distinct patterns of hemodynamic responses which recognize brain tasks toward developing a BCI. We applied two different mathematics tools separately, Wavelets analysis for preprocessing as signal filters and feature extractions and Neural networks for cognition brain tasks as a classification module. We also discuss and compare with other methods while our proposals perform better with an average accuracy of 99.9% for classification.

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

I. INTRODUCTION

NEUROPHYSIOLOGICAL and neuroimaging technologies have contributed much to our understanding of normative brain function. Commonly employed techniques such as electroencephalography (EEG), event-related brain potentials (ERPs), magnetoencephalography (MEG), positron emission tomography (PET), singlepositron emission computed tomography (SPECT), and functional magnetic resonance imaging (fMRI) have dramatically increased our understanding of a broad range of brain activities. EEG and ERP paradigms have contributed important data for developing models of cognitive and emotional processing. However, EEG measures are limited in their ability to provide the precise location of an electrical source. EEG does yield spatial information, but this spatial information must be reconstructed by probabilistic models. fMRI is currently considered the "gold standard" for measuring functional brain activation. The limitations of fMRI relative to fNIRs include the fact that participants must lie within the confines of the magnet bore, which limits its use for many applications. The refrigerant systems used to supercool the magnets also produce loud noises, which can interfere with certain protocols. fMRI is also highly sensitive to movement artifact; subject movements on the order of a few millimeters can invalidate the data. Finally, fMRI systems are quite expensive. [1,2]

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. [1,10]

The qualities of fNIRs make it an ideal candidate for monitoring cortical function in the brain while subjects are engaged in various real life or experimental tasks. However, the noise including in fNIRs is an important limitation on the use of optical data in these applications. Motion artifact caused by moving of the head. Head movement 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. These effects cause sudden increases in the NIR data. 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 an important and necessary task in order to deploy fNIRs as a brain monitoring technology in its full potential to many real life application areas.

Adaptive filtering is one approach to dealing with noise signals. Adaptive filtering has been widely used for noise reduction in other biomedical applications involving electrocardiogram (ECG), EEG [7,8], and fNIRs. In [3] the

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Wiener filtering approach was proposed to eliminate the need to use additional sensors and extra wiring required for adaptive filtering. Like adaptive filtering, Wiener filtering is an optimal filtering technique in that minimization of the mean-square error serves as the basis of its function. In [4] authors investigated statistical analysis of fNIRs for purpose of cognitive state assessment while user performs a complex task.

In this work, we proposed wavelets analysis to cancel noise of fNIRs signals. The wavelets transform bases became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications. Illustrations in this paper using wavelets analysis are compared to adaptive filter and Wiener filter. In addition, wavelets processing play a role of extraction algorithm to draw features of fNIRs signals. Extracted features is inputs of final cognition to classify brain tasks by Neural networks.

In [5] authors presented results of signal analysis indicating that there exist distinct patterns of hemodynamic responses which could be utilized in a pattern classifier towards developing a BCI. They applied two different pattern recognition algorithms separately, Support Vector Machines (SVM) and Hidden Markov Model (HMM), to classify the data offline. SVM classified with an average accuracy of 73%, while HMM performed better with an average accuracy of 89%.

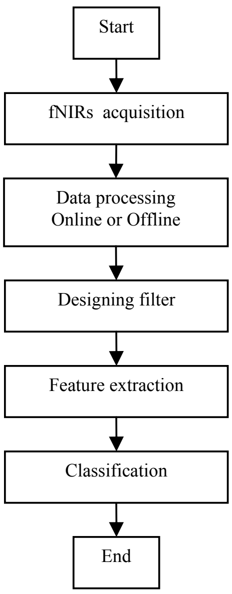


Fig. 1. Structure of fNIRs signals classification.

Neural networks are very powerful tools for pattern recognition [10]. The most well-known advantage is that after training them, neural networks can be readily used for process parameter (or state) assessment without requiring any knowledge of the underlying system. In general, it is necessary to preprocess their input information to eliminate irrelevant information from the inputs and extract features of signals. Results of neural networks model in this paper classified with an average accuracy of 99%, better than SVM and HMM in [5].

Throughout this paper, we describe signal analysis to filter noises, feature extrations by wavelets techniques and offline classification of the NIRS signal using Neural Networks. The structure of entire signals processing is shown in Fig. 1. The remaining of paper are fNIRs data acquisition in section 2, feature extraction with wavelets analysis in section 3, brain task cognition with neural networks in section 4, illustration and discussion in section 5, and conclusion section.

II. FNIRS DATA ACQUISITION

We used a multichannel fNIRs instrument, OMM-3000 from Shimadzu Corporation, Japan, shown in Fig. 2. 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 acquired at a sampling rate of 18 Hz and digitized by the 16-bit analog to digital converter.

The fNIRs instrument was capable of storing the raw signal intensity values for each of the 3 wavelengths, as well as the derived values of oxygenated and deoxygenated hemoglobin concentration changes for all time points in an output file in a pre-specified format. Fig.3. shows 7 channels of a task as an illustration. The signal preprocessing, analysis and classification programs were implemented to read the data from the file either in an offline mode or in an online mode.

Fig. 2. Shimadzu fNIR-station OMM-3000.

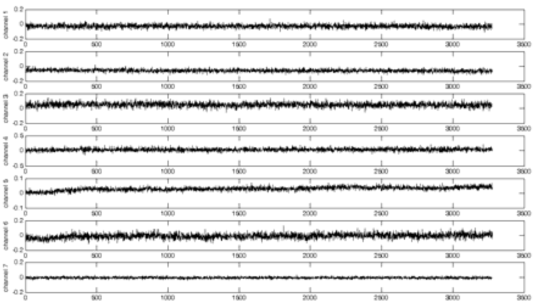


Fig. 3. fNIRs signals of 7 channels.

III. Feature Extraction with Wavelets analysis

Due to desirable properties concerning approximation quality, redundancy, numerical stability, etc., the wavelets bases became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications.

From [5] the wavelets transform of a signal s is the family C(a,b), which depends on two indices a and b. The set to which a and b belong

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

Where:

a=2j , b=k2j , (j,k) $\in$ Z2

ψ is wavelet functions

a is scale of wavelets functions

b is position of wavelets functions on the signal s.

From an intuitive point of view, the wavelets decomposition consists of calculating a "resemblance index" between the signal and the wavelets located at position b and of scale a. If the index is large, the resemblance is strong, otherwise it is slight. The indexes C(a,b) are called coefficients.

Let us fix j and sum on k. A detail Dj(t) is nothing more than the function

$$D_j(t) = \sum_{k\in Z} C(j,k)\psi_{j,k}(t) \quad (2)$$

Now, let us sum on j. The signal is the sum of all the details:

$$s = \sum_{j\in z} D_j \quad (3)$$

The details have just been defined. Take a reference level called J. There are two sorts of details. Those associated with indices j<J correspond to the scales a=2j ≤ 2J which are the fine details. The others, which correspond to j > J, are the coarser details.

We group these latter details into:

$$A_J = \sum_{j>J} D_j \quad (4)$$

which defines what is called an approximation of the signal s. We have just created the details and an approximation.

$$s = A_J + \sum_{j\leq J} D_j \quad (5)$$

The equality signifies that s is the sum of its approximation AJ and of its fine details. From the previous formula, it is obvious that the approximations are related to one another by

$$A_{J-1} = A_J + D_J \quad (6)$$

The total number of computed coefficients in the matrix shown in Fig. 4 is roughly equal to the length of the original sequence s. AJ depicts as feature vectors that server as an input patterns of next processing in section 4.

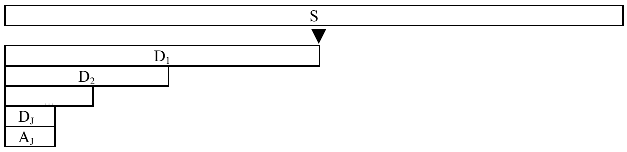


Fig. 4. Wavelets transform of a sequence s.

IV. Brain task cognition with Neural Networks

From [6], neural networks are very powerful tools for classification or pattern recognition. Informative features are extracted from the coefficients computed with the wavelets transform of the process signals and used for classification.

The multi-layer fully connected feed-forward neural network depicted in Fig. 5 is used here; it includes an input layer, one hidden layer and an output layer. Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. Input variables come from AJ, wavelets coefficients, mentioned above section. The outputs are the desired classes. The number of inputs is the number of channels, and the number of hidden nodes, transfer functions affect the training performance hence need to be chosen carefully.

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

$$E = \frac{1}{2}\sum_{n=1}^{N}(y_n - d_n)^2 \quad (7)$$

Where:

N is number of patterns.

yn is output of network

dn is desired output.

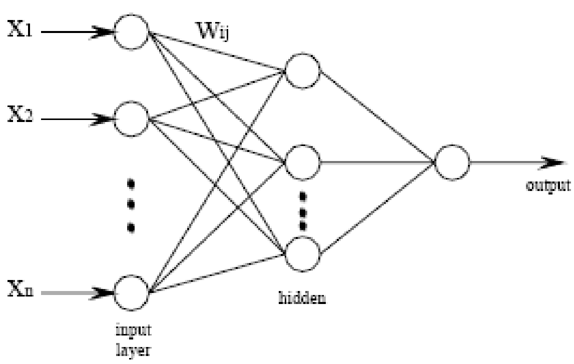


Fig. 5. Neural Network for classification.

V. ILLUSTRATION AND DISCUSSION

fNIRs data acquisition consists of 3 tasks correspondent to controlling physical motion of right arm, imaging the motion of right arm, and relaxing.

5.1 Designing filter

Wavelets mother is chosen discrete approximation of Meyer wavelet.

Level of decomposition is 3.

Results of wavelets analysis show in Fig. 6.

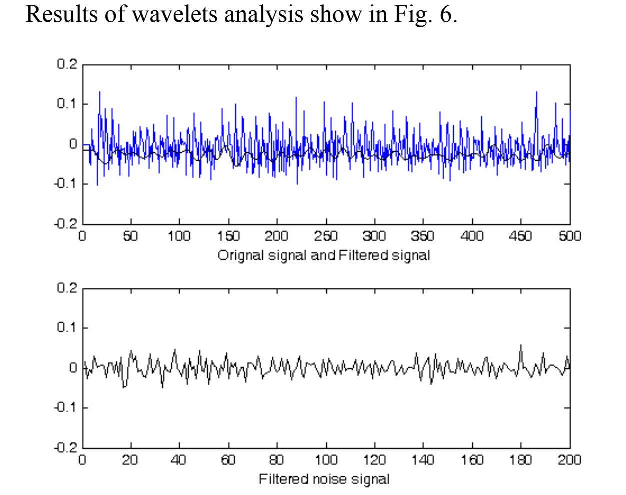


Fig. 6. Wavelets Analysis.

To quantify the improvement, the change in signal to noise ratio (SNR) was used as a measurement of performance. The SNR-gain is computed as

$$SNR_{gain} = 10\log_{10}\frac{AvgPower_{rawSignal}}{AvgPower_{filteredSignal}} \quad (8)$$

The average power for the raw and filtered signals, by Parseval's theorem, is computed by Power Spectral Density (PSD) as

$$AvgPower = \frac{1}{2\pi}\sum_{-\pi}^{\pi} PSD(\omega) \quad (9)$$

Results SNRgain shows in table I. and table II corresponding to oxygenated hemoglobin (Ox-Hb) and deoxygenated hemoglobin (DeOx-Hb).

TABLE I SIGNAL TO NOISE RATIO *(SNR)* GAIN OF 7 CHANNELS AND 3 TASKS OF OXYGENATED HEMOGLOBIN (OX-HB)

Ox-Hb	Ch-1	Ch-2	Ch-3	Ch-4	Ch-5	Ch-6	Ch-7
Task 1	6.3203	6.1218	6.5213	7.7351	2.0037	6.723	3.7922
Task 2	7.364	3.8139	7.8768	7.1166	3.4918	6.7698	3.3553
Task 3	6.3562	5.476	7.2603	7.9489	3.1459	7.2193	4.2159

From table I. and table II. SNG-gain average is calcutated such as

SNRgain-average of Ox-Hb = 5.744

SNRgain-average of DeOx-Hb = 7.746

Table III shows the comparison SNG-gain average of wavelets filter with Adaptive Filter and Wiener Filter in 2).

TABLE II SIGNAL TO NOISE RATIO (SNR) GAIN OF 7 CHANNELS AND 3 TASKS OF DEOXYGENATED HEMOGLOBIN (DEOX-HB)

DeOx-Hb	Ch-1	Ch-2	Ch-3	Ch-4	Ch-5	Ch-6	Ch-7
Task 1	8.8699	8.1896	8.083	9.0927	4.2943	7.3835	8.979
Task 2	8.4423	9.2044	8.5573	8.8604	6.9695	5.8064	7.9978
Task 3	8.0968	9.4663	8.6613	7.8358	3.5975	6.3274	7.9426

Results from table III show the accuracy of wavelets filter a little bit higher than Wiener filter and definitely higher than adaptive filter.

TABLE III COMPARISON SIGNAL TO NOISE RATIO (SNR) GAIN AVERAGE

	Adaptive Filter	Wiener Filter	Wavelets Filter
SNR_{gain}-average	3.4396	6.6879	6.7448

5.2. Cognition Brain Tasks

Multilayer neural network is built with 3 layers. Input layer consists of 7 neurons correspondent to 7 channels of fNIRs signals. 7 neurons are set for hidden layer and 1 output. 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. As an example, output equals to +1, 0, -1 correspondence to task 1, 2, 3.

A. Cognition Task 1 vs Task 3

Original signals and Wavelets approximation coefficients of Task 1 vs Task 3 show in Fig. 7.

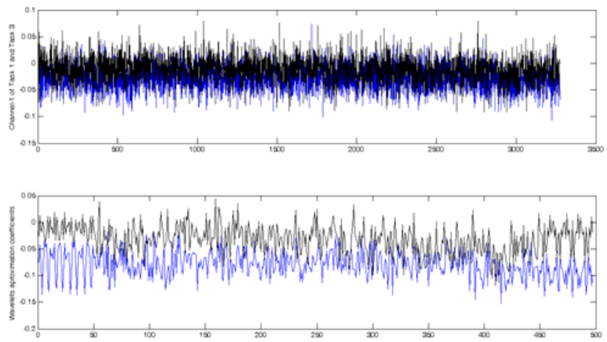
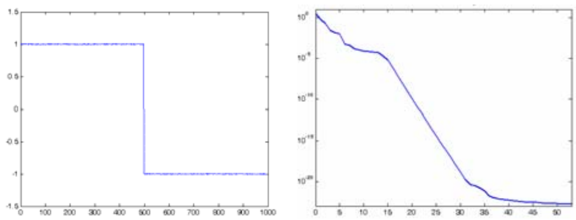


Fig. 7. Original signals and Wavelets approximation coefficients of Task 1 vs Task 3.

Output of Neural Classification with 2 distinguished classes, and the error of Neural training processing shows in Fig. 8.



(a) (b)

Fig. 8. (a). Output of Neural Classification with 2 distinguished classes, (b) the error of Neural training processing

Mean square error of classification is 1.6662e-023.

B. Cognition Task 2 vs Task 3:

Original signals and Wavelets approximation coefficients of Task 2 vs Task 3 show in Fig. 9.

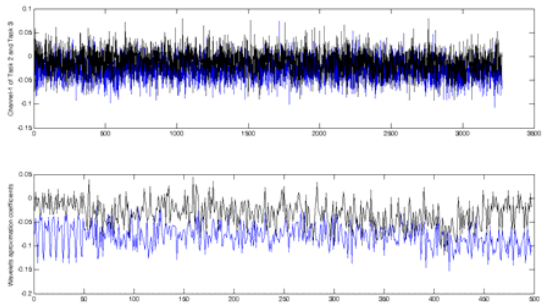
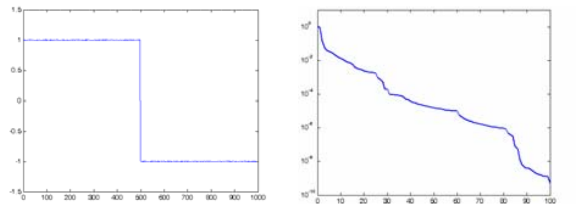


Fig. 9. Original signals and Wavelets approximation coefficients of Task 1 vs Task 3.

Output of Neural Classification with 2 distinguished classes, and the error of Neural training processing shows in Fig. 10.



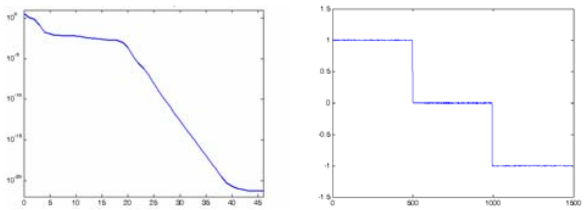
(a) (b)

Fig. 10. (a). Output of Neural Classification with 2 distinguished classes, (b) the error of Neural training processing.

Mean square error of classification is 5.47322e-010.

C. Cognition Task 1, Task 2 and Task 3

Output of Neural Classification with 3 distinguished classes, and the error of Neural training processing shows in Fig. 11.



(a) (b)

Fig. 11. (a). Output of Neural Classification with 3 distinguished classes, (b) the error of Neural training processing

Mean square error of classification is 4.91857e-022.

Comparing to [5] all three experiments show that classified wavelet-neuron models obtain the accuracy much more than 99.9%. The results determine advantages of wavelets analysis as preprocessing and neural networks as classified models.

VI. Conclusion

In this paper we present a novel approach for noise cancellation in fNIRs signals using Wavelets analysis. We show through some preliminary real data that the proposed algorithm works better than the existing algorithm providing better SNR-gain. Features extractions from wavelets analysis are set as inputs of neural networks classification. Our result of high accuracy of offline pattern classification of fNIRs signals is up to 99.9%. One disadvantage of the proposed algorithm is it works offline. In future, we indicate the potential use of such techniques to online fNIRs-BCI systems. fNIRs opens many excellent opportunities to cognition brain activities and interface to computer as future BCIs.

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