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Efficient Mental Arithmetic Task Classification using Wavelet Domain Statistical Features and SVM Classifier

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***Abstract*—Functional Near Infrared Spectroscopy (fNIRS) has been emerged as a potential technique in the research of BCI. In this paper, we proposed a discrete wavelet transform based feature extraction technique to classify mental arithmetic tasks from fNIRS data. In order to investigate the change in brain activities during mental arithmetic task, recorded data are windowed in several frames. DWT has been employed on different channels of each frame and then a number of statistical features are extracted from both the approximate and the detail coefficients of data in order to distinguish the mental arithmetic task and the rest condition. Six-fold cross validation is performed using SVM classifier to examine the effectiveness of DWT based features. Efficacy of oxyhemoglobin, deoxyhemoglobin, and total hemoglobin data from different selected channel combinations are also examined. It is observed that proposed algorithm provides a satisfactory accuracy of 93.26% using DWT based features extracted from 104 channels.**

***Index Terms*—fNIRS, BCI, Mental Arithmetic(MA), DWT, Support Vector Machine (SVM)**

I. Introduction

Now-a-days fNIRs is a great approach in Brain Computer Interfacing (BCI). Nowadays, it has become an alternative to EEG in order to investigate functional activity of medial area of human brain. In this process no conductive gel is required and there is also no strong impact of electrooculographic artifacts. Moreover, the sensor can be employed in more convenient and practical EEG [1]. Efficient and robust classification of tasks is the most challenging issue for all types of BCI. Selection of effective features along with appropriate classifier is a matter of prime concern in this field. A number of different features, methods and classifiers are used in the classification of various mental or motor imagery task. Autoregressive reflection coefficients based feature extraction along with KNN classifier is used in [5] in order to classify motor imagery tasks. On the other hand, DWT coefficient based features and KNN classifier is employed in [6]. Fluctuation of oxyhemoglobin and deoxyhemoglobin level at the time of mental arithmetic (MA) task is analyzed in [2]–[4]. Difference of mean concentration changes during MA and rest condition to a baseline prior to the task are used as features. Effect of different classifiers (LDA, QDA, sLDA, sQDA, and SVM) are also examined previously [2]–[4].

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In this paper, we examine the effects of some other features used in previous work to distinguish brain activity during mental arithmetic and rest condition. Features are extracted from approximate and detail coefficients of DWT of oxyhemoglobin and deoxyhemoglobin data and SVM is used in classification. Compare to previous MA classification schemes [2]–[4] no prior task information is used here. A 6-six-fold cross validation is employed to examine the performance of our method. This algorithm provides a satisfactory accuracy of 93.26%.

Proposed method is described as follows. In section II, we discuss about data acquisition process. Preprocessing, feature selection, discrete wavelet transform(DWT) and SVM classifier are explained in section III. Observed results of the proposed technique is presented in section IV.

II. Data Acquisition

Dataset described in [2] is used where antagonistic hemodynamic response patterns of eight subjects were recorded. Cue guided mental calculations were performed by the participants. They were instructed to subtract a one-digit number from a two-digit number sequentially. The initial subtraction was presented visually on a monitor and participants run calculation for 12s followed by a 28s of rest. Following figure shows the data acquisition procedure for a single trail.

Participants performed 3 or 4 runs with 12 trials for each class and which resulted in 18 or 24 trials per class respectively. Data were recorded using a continuous-wave fNIRS system (ETG-4000, Hitachi Medical Co., Japan) with a sampling rate of 10 Hz. It was a multi-channel system which consisted of 17 light emitters and 16 photo detectors in a 3 11 grid.The change of oxyhemoglobin, deoxyhemoglobin and total hemoglobin concentration in mile-molar times millimeter (mM.mm) was measured. Each concentration was measured using 52 channels. So total number of channels used in data

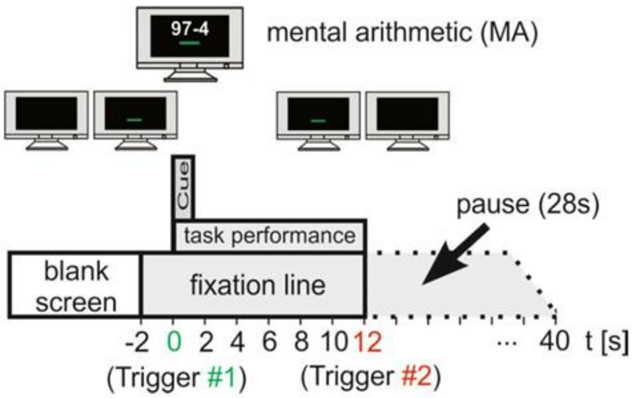


Fig. 1: Time of one trial. Green bar have been appeared before starting of the task. After that subjects would have to perform the MA for 12s ,then take rest for 28s.

recording was 156. Source and detector were kept 3 cm apart. Details of data recordings were discussed in [2]–[4].

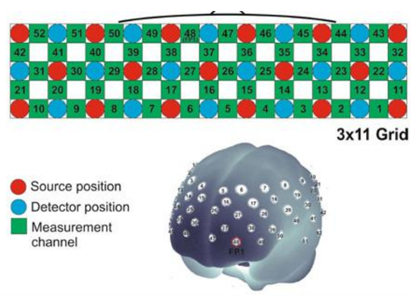


Fig. 2: Illustrated schematic of multichannel positional arrangement for 52 channels(311grid) [2].

III. Methodology

A. Preprocessing and Feature Selection

During a trial, first 12s hemodynamic response data of a participant are labeled as class 'MA'. On the other hand , response data from 13^{th} to 25^{th}s are labeled as class 'REST'. The DWT coefficient values of all channels are calculated at the described fixed times. Features consists of the mean, max, min and energy of approximate and detailed coefficients. So total number of features calculated per channel is eight. Oxy-hemoglobin, deoxyhemoglobin and total hemoglobin features are used in different combination to analyze the effects. For each participant, a six-fold cross validation is done to train and test the classifier and hence the performance of classification scheme is evaluated. Calculation of DWT coefficients and SVM based classification scheme are discussed in the upcoming sections. Majors steps involved in the proposed method is presented in figure 3.

B. Discrete Wavelet Transform Coefficients

Forier transform provides only the localization of frequency. On the other hand, wavelet transform effectively localize both

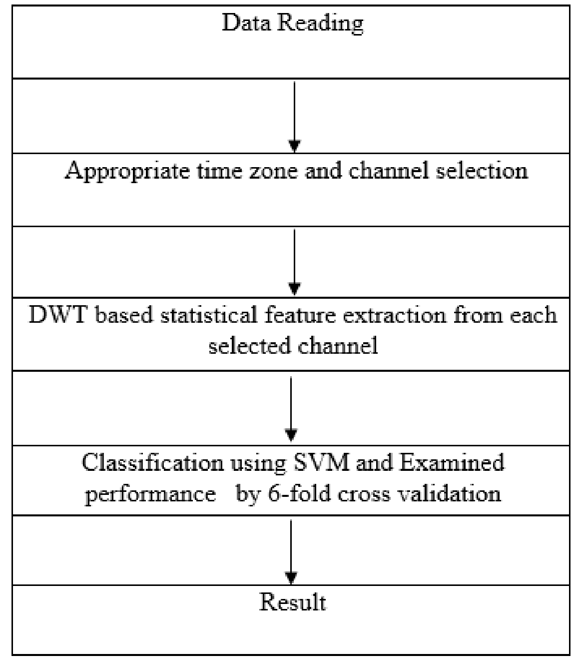


Fig. 3: The major steps involved in the proposed method

in time and frequency which [7]. It provides better time resolution at high frequencies along with good frequency resolution at low frequencies. Computation cost of DWT is low and hence implementation is easy. The DWT coefficients of a signal x (n) can be obtained as

$$W(c,d) = \sum_{ninZ} (x[n]\psi_{c,d}[n]) \tag{1}$$

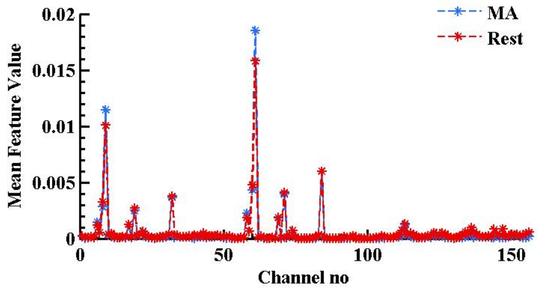
where c and c are the dilation or scale and the translation respectively. $\psi_{c,c}[n]$ represents the discrete wavelet which can be described as

$$\psi_{c,d}[n] = \frac{1}{\sqrt{c}}\psi\left(\frac{n-d}{c}\right) \tag{2}$$

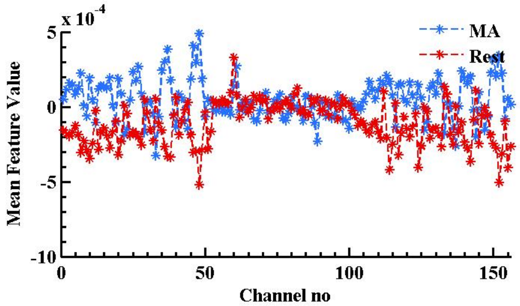
For dyadic wavelet transform, $c = 2^{-j}$, $d = k2^{-j}$, $\psi_{c,d}[n] = 2^{j/2}\psi[2^j n - k)]$, with $k \in Z$, $j \in N$. Approximate and detail coefficients of DWT can be obtain using two complementary filters simultaneously. A low-pass filter with impulse response g[n] followed by down sampling gives approximate coefficients whereas detail coefficients can be obtained using a high-pass filter with impulse response h[n] followed by down sampling. The following two equations correspond to the calculation of these coefficients.

$$y_g[n] = \sum_{m=-\infty}^{m=\infty} x[m].g[2n-m] \tag{3}$$

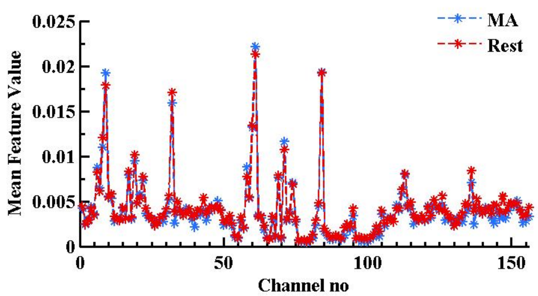
$$y_h[n] = \sum_{m=-\infty}^{m=\infty} x[m].h[2n-m] \tag{4}$$



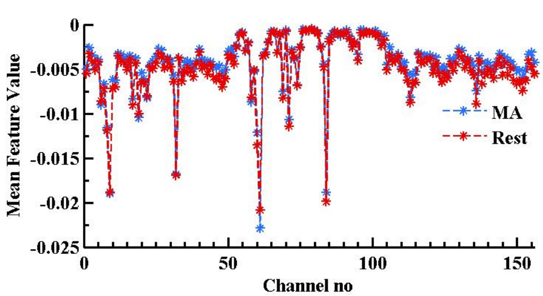
(a) Energy of detail coefficients



(b) Mean value of detail coefficients

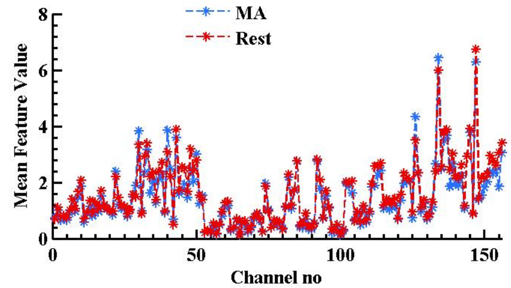


(c) Maximum value of detail coefficients

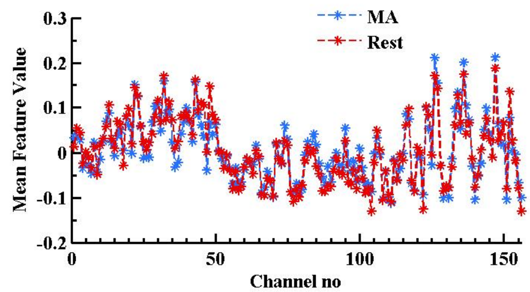


(d) Minimum value of detail coefficients

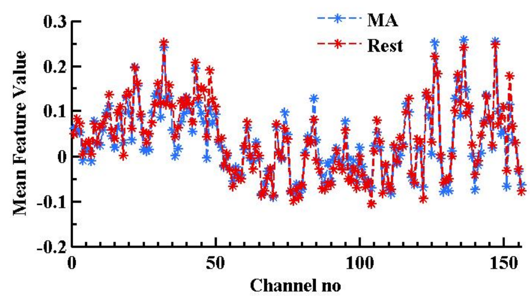
Fig. 4: Mean feature values of all the trails extracted from detail coefficients are shown for all the channels



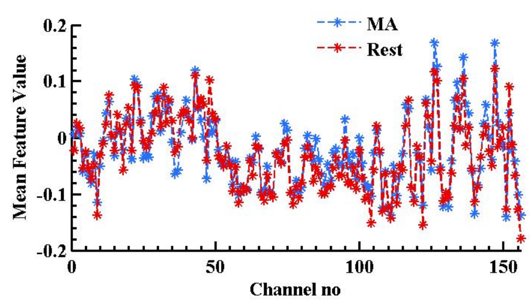
(a) Energy of approximate coefficients



(b) Mean value of approximate coefficients



(c) Maximum value of approximate coefficients



(d) Minimum value of approximate coefficients

Fig. 5: Mean feature values of all the trails extracted from approximate coefficients are shown for all the channels

$y_h[n]$ are termed as detail coefficients and $y_g[n]$ are termed as approximate coefficients, respectively. Thus DWT filtering operation causes change in signal resolution and scale. A large number of wavelet functions are available in the literature to analyze a signal in different resolution in different bands. In this paper, we use the Haar wavelets of the Daubechies family for feature extraction. Mean feature values of all the trails extracted from detail and approximate coefficients of discrete wavelet transform of 156 channel data are presented in fig. 4 and fig. 5 respectively. These plot shows that there exists significant separation between features for mental arithmetic and rest condition which helps in the classification of brain activities in an efficient manner.

C. Support Vector Machine

Support vector machines (SVMs) have more attention in biomedical application because of their accuracy and ability to manage a bulk number of predictors. SVM utilize the concept of hyperplane separation by mapping the predictors onto a new, higher-dimensional space in which they can be separated linearly. Details are given in [8]. The classification rule for a given sample $y \in R^N$ in case of a binary decision is performed by

$$sign(a^T y + b) \quad (5)$$

where b denotes the bias and a is the projection vector. For calculating a and b ,the margin can be defined as difference between nearest data points of each class perpendicular to that hyperplanes. For maximizing safety distance everyone trying to maximize margin between every classes [10].

IV. Results

A number of feature combination is used to analyze the effect on the performance of classification. As mentioned earlier, 8 features are taken from each channels. A number of feature channel combinations is used to evaluate the performance. Significant response is revealed from three region of interest discovered by Pfurtscheller et el [2]. These regions are named as ROI1, ROI2, and ROI3 respectively. ROI1 consists of three channels (channel no. 46, 47, and 48) from APEC. Whereas ROI2 consists of channels 18, 28 and 29 and ROI3 consists of channels 13,23,24. Corresponding deoxyhemoglobin response can be found from the channels 65,70,76,75,80, 81,98,99,100 and total hemoglobin response can be found from channels 65,70,76,75,80, 81,98,99,100. Different combination of these channels along with other channels are analyzed and mean classification accuracy for each combination are presented in the following table.

TABLE I: Different Channel Combination and Corresponding Mean Accuracy(%) for all Participants

Combination Name	Channel No	Mean Accuracy(%)
C1	{13,18,24,23,28, 29,46,47,48}	86.99
C2	{65,70,76,75,80,81,98,99,100 }	81.63
C3	{117,122,128,127,132, 133,150,151,152}	86.47
C4	{C1,C2}	89.13
C5	{C1,C3}	90.4
C6	{C2,C3}	89.4
C7	{C1,C2,C3}	91.2
C8	{1-52}	92.4
C9	{53-104}	84.24
C10	{105-156}	89.95
C11	{C8,C9}	93.26
C12	{C8,C10}	91.85
C13	{C9,C10}	90.3
C14	{C8,C9,C10}	90.8

Variation of classification accuracy with the increment number of channels used is presented in Fig. 6. This shows that, maximum classification accuracy is obtained using 104 channels. However, using a less number of appropriate channels also provides very close accuracy which offers a trade-off between computational complexity and efficiency.

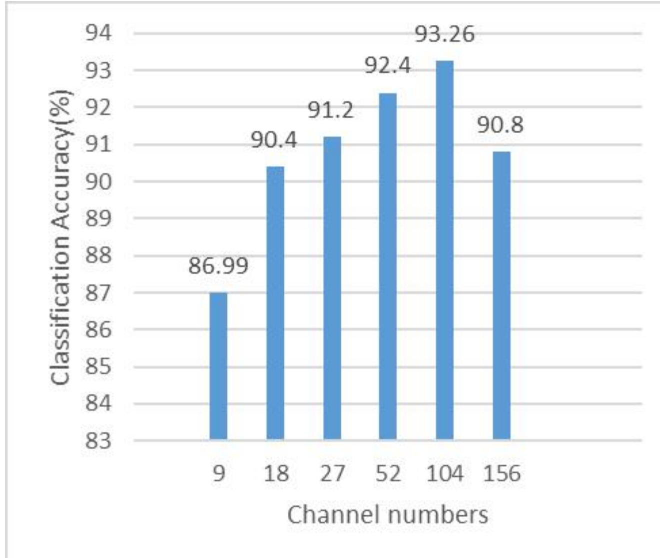


Fig. 6: Change of classification accuracy(%) with number of channels. Here channel combination with maximum accuracy has been showed.

V. Conclusion and discussion

In this paper, a new feature extraction method based on DWT is employed in order to distinguish the brain activity during mental arithmetic tasks and rest condition. Maximum accuracy obtained using this method surpassed other previous methods. Previously, maximum accuracy of 86.6% was obtained in [4] utilizing the change in mean oxyhemoglobin concentration to prior task baseline and SVM classifier. In our algorithm, no prior task information is needed. It is also revealed that, oxyhemoglobin response based features shows batter performance than deoxyhemoglobin or total hemoglobin response based features as also found in [4].
In a nutshell, DWT based statistical features performs better than mean concentration changed based features used previously and using significant channels, high reduction in feature dimension is possible with a very low decease in accuracy.

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