Neural Network Classification of Brain Waves Using Asymmetry Ratio

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Abstract: In this paper, the asymmetry ratios of spectral bands are combined with spectral band power values to classify brain waves during mental tasks. A multiplayer perceptron neural network (NN) is trained with the backpropagation algorithm to classify these brain waves, which are also known as Electroencephalogram (EEG) signals. We show that this technique performs better and that the NN training converges much faster than using spectral band power values only.

Keywords: Asymmetry ratio, Spectral band power, EEG, Mental tasks, Neural network.

I. INTRODUCTION

Power spectral density (PSD) values extracted using the classical Fourier methods and the modern parametric methods like autoregressive (AR) modelling have been proposed as pattern features to represent Electroencephalogram (EEG) signals. These EEG signals are electrical waves generated by the brain and extracted from the scalp through the use of electrodes. Although raw PSD values can be used in classification experiments with EEG signals, it is seldom the case since raw PSD consists of too much data and neural network (NN) training with these data take significantly large amounts of time to converge. Therefore, other methods like using spectral band power values have been proposed. In general, most mental tasks fall below the frequency of 30 Hz; therefore the spectral bands of delta (0-3 Hz), theta (4-7 Hz), alpha (8-13 Hz) and beta (above 13 Hz) are sufficient to represent EEG signals. PSD values in these spectral bands are summed up and used as representative features to train and test NN for mental task classification purposes.

In this paper, we improve this method by including asymmetry ratios of spectral bands in addition to the individual spectral band power values to represent the mental tasks. Our results show that this proposed method not only improves the classification results but also improves the speed of NN convergence, which is also an important plus point to be considered.

II. METHOD

The spectrum of EEG signals is acquired using autoregressive (AR) method where Burg's algorithm is applied to obtain the AR coefficients. An autoregressive process of order *p* is given by

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n), \tag{1}$$

where p is the model order, $x(n)$ is the data of the signal at sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the error term independent of past samples.

The term autoregressive implies that the process $x(n)$ is seen to be regressed upon previous samples of itself. The error term is assumed to be a zero mean white noise with finite variance, σ_e^2. In applications, the values of a_k and σ_e^2 have to be estimated from finite samples of data $x(1), x(2), x(3), \ldots\ldots\ldots, x(N)$. In this paper, we use Burg's algorithm to derive the AR coefficients. It is as follows:

1. Calculate initial values

Error variance, $\sigma_e^2(0) = \frac{1}{N}\sum_{0}^{N-1}[x(n)]^2$ where $x(n)$ is the n^{th} sampled data with mean value subtracted

Forward error, $e_n(0) = x(n)$

Backward error, $b_{n-1}(0) = x(n-1)$

2. Calculate reflection coefficient and error variance

Reflection coefficient,

$$\pi_m = -2\frac{\sum_{n=m}^{N-1} b_{n-1}(m-1)e_n(m-1)}{\sum_{n=m}^{N-1}[e_n^2(m-1)+b_{n-1}^2(m-1)]}$$

Error variance, $\sigma_e^2(m) = [1-|\pi_m|^2]\sigma_e^2(m-1)$

3. Update Error and AR coefficients

AR coefficients,

$$\left.\begin{aligned} a_k(m) &= a_k(m-1)+\pi_m a_{m-k}(m-1) \\ a_m(m) &= \pi_1 \end{aligned}\right\} \begin{aligned} m &> 1 \\ m &= 1 \end{aligned}$$

Forward Error Update,

$$e_n(m) = e_n(m-1)+\pi_m b_{n-1}(m-1)$$

Backward Error Update,

$$b_n(m) = b_{n-1}(m-1)+\pi_m e_n(m-1)$$

4.Repeat steps 2 and 3 (with m incremented by one) until the selected model order p is reached.

Proofs and details of this algorithm can be found in [2].

After estimating the AR coefficients using Burg's algorithm, we can obtain the power spectral density (PSD) values by using the equation

$$S(f) = \frac{\hat{\hat{\sigma}}_p^2 T}{\left|\sum_{k=0}^{p} a_k e^{-i2\pi fkT}\right|^2}, \qquad (2)$$

where *S(f)* represents the power spectral density function, T is the sampling period, $\hat{\hat{\sigma}}_e^2(p)$ is the unbiased estimated variance of the residuals. The term T is included so that the true power of the corresponding analog signal will be represented digitally.

Spectral band power values are then computed for each spectral band i.e. delta, theta, alpha and beta. The asymmetry ratio is computed using *(R-L) / (R+L)* where R is the total spectral power in a specific band in one of the right hemispheric leads and L is the total spectral power in a specific band in one of the left hemispheric leads [5]. Since in our analysis, there are 6 channels (3 on each hemisphere) and 4 spectral bands, we have 24 spectral band power values. The asymmetry ratio calculation results in 36 features.

III. EXPERIMENTAL SETUP

The subjects are seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noiseless fans for ventilation. An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2, defined by the 10-20 system of electrode placement [3]. The electrodes are connected through a bank of amplifiers and bandpass filtered from 0.1--100 Hz. The data was sampled at 250 Hz with a 12-bit A/D converter mounted on a computer. For this paper, the data from four subjects performing five different mental tasks are analysed. These tasks are

- Baseline task, for which the subjects were asked to relax and think of nothing in particular

- Math task, for which the subjects were given nontrivial multiplication problems, such as 72 times 38, and were asked to solve them without vocalizing or making any other physical movements. The tasks were non-repeating and designed so that an immediate answer was not apparent

- Geometric figure rotation, for which the subjects were asked to visualize a particular three-dimensional block figure being rotated about an axis

- Mental letter composing, for which the subjects were asked to mentally compose a letter without vocalising

- Visual counting, for which the subjects were asked to mentally count imaginated numbers being written on the blackboard

Although we have 5 mental tasks, we study only pairs of two tasks at a time. Data was recorded for 10 seconds during each task and each task was repeated for two sessions. With a 250 Hz sampling rate, each 10 second trial produces 2,500 samples per channel. Each EEG signal is segmented with a half-second window, i.e. for a length of 125 points giving 20 patterns for each file. For all the experiments, 50% of available patterns are used for training, while the rest 50% are for testing. The patterns for each data set are chosen randomly at the beginning and are fixed for all the experiments.

The spectral values in the range of 0-30 Hz are extracted and the asymmetry ratios of the left and right hemisphere EEG channel are obtained. The spectral band power values are also computed. Three different sets of experiments are run with a multiplayer perceptron neural network (trained with the backpropagation algorithm [6]) to classify these pairs of EEG signals. The network size is fixed at 100 hidden units and the training is conducted until the error falls below 0.09 or reaches the maximum iteration limit of 1000.

IV. RESULTS

The first experiment is run with the spectral band power values only; the second uses the asymmetry ratio factors where as the final experiment combines both features. The results are shown in Tables 1 and 2. Table 1 shows the classification accuracy while the next table shows the speed of convergence and the number of iterations.

Table 1: NN Classification percentage

Task pair			NN classification %		
			Spectral band power	Asymmetry ratio	Combined
1	math	base	64.38	64.38	66.88
2	letter	base	56.25	55.63	69.38
3	rotate	base	58.13	57.5	62.5
4	count	base	56.88	56.25	61.88
5	math	rotate	58.75	58.13	63.75
6	math	count	61.25	65	66.88
7	math	letter	60.63	55	63.75
8	letter	rotate	66.88	62.5	72.5
9	letter	count	61.88	55.63	63.75
10	rotate	count	51.88	56.25	63.13

Table 2: NN Convergence

Task pair			NN convergence					
			Spectral band power		Asymmetry ratio		Combined	
			I	T	I	T	I	T
1	math	base	474	275	172	154	154	225
2	letter	base	NC	580	192	171	137	198
3	rotate	base	NC	580	171	152	139	200
4	count	base	344	200	208	183	118	184
5	math	rotate	578	335	185	164	117	171
6	math	count	348	209	218	192	124	184
7	math	letter	NC	589	198	170	136	199
8	letter	rotate	NC	581	213	190	141	205
9	letter	count	NC	581	212	196	155	222
10	rotate	count	NC	580	237	212	129	191

**I denotes the number of iterations, T denotes the time taken in seconds, NC denotes no convergence after 1000 iterations*

Asymmetry ratios used alone perform better in certain cases only as compared to using spectral band power values. However, the asymmetry ratios achieve convergence much faster. Combining both the spectral band power values and asymmetry ratios results in much higher classification accuracy and faster NN convergence. As far as the task pairs as concerned, relaxing task vs letter task seems to be the easily distinguishable task pair. Higher classification accuracy can be obtained if the signals are treated for stationary behaviour and if the ocular artefacts like eye movements are removed from the data.

V. CONCLUSION

The proposed method of using asymmetry ratios together the individual spectral band power values give better results than using the delta, theta, alpha and beta band power values used alone. The NN training using the proposed method is also faster to converge. As a conclusion, we show that it is possible to discriminate accurately between different mental tasks using the proposed method.

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