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POWER AND ASYMMETRY RATIO OF SPECTRAL BANDS FOR MENTAL TASK RECOGNITION

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ABSTRACT

In this paper, we use power and asymmetry ratio of spectral bands to recognise mental tasks from Electroencephalogram signals using a Fuzzy ARTMAP neural network. Classical spectral analysis using Wiener-Khintchine theorem and modern parametric spectral analysis using autoregressive are used to obtain these features. The highest classification results of 90% for a subject recognising two mental tasks validate the method.

1. INTRODUCTION

Power spectral density (PSD) values 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 power of spectral bands 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. The total power in these spectral bands are summed up and used as representative features to train and test NN for mental task classification purposes. This method is improved by including asymmetry ratios of spectral bands in addition to the individual spectral band power values to represent the mental tasks [3], which is especially useful for recognising mental tasks that elicit interhemispheric differences. In this paper, we follow a similar approach and a Fuzzy ARTMAP (FA) neural network [2] is used to recognise 2 different mental tasks from the EEG data for 4 subjects. The FA performance shows that the proposed method can recognise the mental tasks to a high degree of accuracy.

2. METHOD

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. 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 two different mental tasks are analysed. These tasks are

- Math task, for which the subjects were given nontrivial multiplication problems, such as 32 times 13, and were asked to solve them without vocalising 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

Data is 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 with an overlap of quarter second, giving 39 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. Power of spectral bands are 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 [3]. 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 giving a total of 60 features. The spectrum of EEG signals is acquired using autoregressive (AR) model with Burg's algorithm to obtain the AR coefficients and Wiener-Khintchine (WK) method. AR process of order p is given by

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

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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 error term is assumed to be a zero mean white noise with finite variance, σ_e^2. A model order of 6 is used since many authors have used it for EEG mental task recognition [1,3]. Wiener-Khintchine (WK) theorem shows that the spectral content of a wide-sense stationary random signal is obtained by taking the Fourier transform of its autocorrelation function. It is given by

$$S(f) = T \sum_{k=-N}^{N} C(k)^{e-j2\pi kfT}, \qquad (2)$$

where the signal has N number of sampled points and the autocorrelation function is defined as

$$C(k) = \sum_{n=0}^{N-k-1} x(n)x(n+k) \Big/ \sum_{n=0}^{N-k-1} [x(n)]^2, \qquad (3)$$

Modern spectral analysis makes some modifications to (2) and (3) which are designed to improve the estimate of the population function. First, not all N-1 autocorrelation coefficients are used. We use a maximum of $L \le N-1$, where L is the truncation point. This is to compromise insight into details of the spectrum without increasing the variance too much, which might cause peaks where there should be none. Using rule of thumb, the truncation limit, L is chosen to be approximately 25% of the segment length. Second, modern spectral analysis smoothes the spectral estimates by use of a lag window. These lag windows are used to reduce the variance of the sample spectral density function. Tukey lag window is used in this paper.

3. RESULTS

FA is trained with varying vigilance parameter of 0 to 0.9 in steps of 0.1 and with voting strategy run for 20 simulations [2]. The results are shown in Tables 1 and 2 for WK theorem and AR model, respectively.

Table 1: FA classification for WK theorem

	Classification (%)				
Vigilance parameter	**S1**	**S2**	**S3**	**S4**	**Average (across subjects)**
0.0	77.50	72.50	85.00	73.75	77.19
0.1	76.25	72.50	86.25	78.75	78.44
0.2	78.75	75.00	86.25	77.50	79.38
0.3	80.00	76.25	83.75	80.00	80.00
0.4	80.00	71.25	83.75	77.50	78.13
0.5	80.00	72.50	85.00	81.25	79.69
0.6	85.00	78.75	88.75	81.25	83.44
0.7	80.00	80.00	87.50	78.75	81.56
0.8	80.00	83.75	86.25	78.75	82.19
0.9	75.00	68.75	81.25	75.00	75.00
Average (each subject)	79.25	75.13	85.38	78.25	

Table 2: FA classification for AR model

	Classification (%)				
Vigilance parameter	**S1**	**S2**	**S3**	**S4**	**Average (across subjects)**
0.0	82.50	77.50	86.25	80.00	81.56
0.1	82.50	78.75	87.50	78.75	81.88
0.2	82.50	80.00	87.50	80.00	82.50
0.3	82.50	78.75	87.50	81.25	82.50
0.4	81.25	77.50	88.75	80.00	81.88
0.5	81.25	87.50	88.75	78.75	84.06
0.6	86.25	82.50	90.00	85.00	85.94
0.7	83.75	86.25	90.00	85.00	86.25
0.8	87.50	83.75	86.25	87.50	86.25
0.9	78.75	80.00	87.50	77.50	80.94
Average (each subject)	82.88	81.25	88.00	81.38	

The results show that the proposed method using AR method performs better than WK for all the cases. The grand FA average classification result of 79.5% for WK and 83.38% for AR show that the proposed method could be used to recognise mental tasks.

4. CONCLUSION

This paper has used spectral asymmetry ratio and band power features for mental task recognition. WK theorem and AR methods have been applied to obtain the power spectrum of EEG signals. FA classification using the proposed technique gives good performance thereby validating the ability to discriminate different mental tasks.

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6. REFERENCES

1. Anderson, C.W., Stolz, E.A., and Shamsunder, S., "Multivariate Autoregressive Models for Classification of Spontaneous Electroencephalogram During Mental Tasks," *IEEE Trans .on Biomedical Engineering*, vol. 45, no. 3, pp. 277-286, 1998.

2. G.A. Carpenter, S. Grossberg and J.H.Reynolds, "A Fuzzy ARTMAP Nonparametric Probability Estimator for Nonstationary Pattern Recognition Problems," *IEEE Trans. on Neural Networks*, vol. 6, no. 6, pp. 330-1336, 1995.

3. Keirn, Z.A., and Aunon, J.I., "A new mode of communication between man and his surroundings," *IEEE Transactions on Biomedical Engineering*, vol. 37, no.12, pp. 1209-1214, December 1990.