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Classification of Mental Tasks Using Fixed and Adaptive Autoregressive Models of EEG Signals

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***Abstract*-Classification of EEG signals extracted during mental tasks is a technique for designing Brain Computer Interfaces (BCI). In this paper, we classify EEG signals that were extracted during mental tasks using fixed autoregressive (FAR) and adaptive AR (AAR) models. Five different mental tasks from 4 subjects were used in the experimental study and combinations of 2 different mental tasks are studied for each subject. Four different feature extraction methods were used to extract features from these EEG signals: FAR coefficients computed with Burg's algorithm using 125 data points, without segmentation and with segmentation of 25 data points, AAR coefficients computed with Least-Mean-Square (LMS) algorithm using 125 data points, without segmentation and with segmentation of 25 data points. Multilayer Perceptron (MLP) neural network (NN) trained by the backpropagation (BP) algorithm is used to classify these features into the different categories representing the mental tasks. The best results for FAR was 92.70% while for AAR was only 81.80%. The results obtained here indicated that FAR using 125 data points without segmentation gave better classification performance as compared to AAR, with all other parameters constant.**

I. INTRODUCTION

BCI designs are used to translate brain signals into some actions. In recent years, BCI research has seen tremendous growth due to its numerous useful applications. BCI designs could provide an alternative form of communication for paralysed individuals [1,3,6,8,9,11,13,14]. They are also useful for designing hands off actions like virtual keyboard, on screen menu selection, etc.

There are a few non-invasive methods for obtaining these brain signals to be utilised in a BCI design. The common methods could be grouped into 3 types. The first type uses EEG signals recorded at the scalp during some mental tasks [1,6,8]. The second uses single-trial visual evoked potential (VEP) signals where the subjects gaze at a screen of alphabets or menus [3]. The third uses syncronisation and desynchronisation of µ-rhythm extracted during sensory motor tasks [9]. Reviews of some of these technologies and developments in this area are given by Vaughan *et al* [13] and Wolpaw *et al* [14].

In this paper, we propose a BCI using fixed and adaptive AR models to extract features from EEG signals that are recorded during five different mental tasks from four different healthy subjects. These mental tasks are: geometrical figure rotation, mathematical multiplication, mental letter composing, visual counting and a baseline-resting task. The BCI designs are individual BCIs, that is those that are suitable for use by a particular individual. We show through simulation results that we cannot expect to build universal BCIs because the thought patterns from different individuals are not the same. Four different feature extraction methods are used here:

- FAR coefficients computed with Burg's algorithm using 125 data points, without segmentation
- FAR coefficient computed with Burg's algorithm using 125 data points, with segmentation for every 25 data points
- AAR coefficient computed with LMS algorithm using 125 data points, without segmentation
- AAR coefficient computed with LMS algorithm using 125 data points, with segmentation for every 25 data points

These features are then used by a MLP-BP NN to classify different combinations of two mental tasks. Two mental tasks are chosen because the required output of the BCI design here is bi-state. The output of this BCI design could be used with some translation schemes like Morse Code or to control the movement of a cursor to select a target on a computer screen. This would provide a communication channel for paralysed individuals to communicate with others or for use in virtual keyboards, hands off menu selection, etc.

II. METHODOLOGY

The EEG data used in this study were collected by Keirn and Aunon [6]. The subjects are seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noise-less fan (for ventilation). An Electro-Cap elastic electrode cap is used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 (shown in Figure 1), defined by the 10-20 system [5] of electrode placement. The impedance of all electrode is kept below 5 KΩ. Measurements are made with reference to electrically linked mastoids, A1 and A2. The electrodes are connected through a bank of amplifiers (Grass7P511), whose band-pass analog filters are set at 0.1 to 100 Hz. The data are sampled at 250 Hz with a Lab Master

12-bit A/D converter mounted on a computer. Before each recording session, the system is calibrated with a known voltage. Signals are recorded for 10s during each task and each task is repeated for 10 sessions where the sessions are held on different weeks. The EEG signal for each mental task is segmented into 20 segments with length 0.5 s. The sampling rate is 250 Hz, so each EEG segment is 125 samples in length.

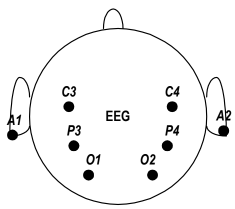

Fig.1. Electrode placement.

In this paper, EEG signals from four subjects performing five different mental tasks are used. The data is available online at http://www.cs.colostate.edu/~anderson. These mental tasks are:

- Baseline task. The subjects are asked to relax and think of nothing in particular. This task is used as a control and as a baseline measure of the EEG signals.
- Math task. The subjects are given nontrivial multiplication problems, such as 22 times 16 and are asked to solve them without vocalising or making any other physical movements. The tasks are non-repeating and designed so that an immediate answer is not apparent. The subjects verified at the end of the task whether or not he/she arrived at the solution and no subject completed the task before the end of the 10 s recording session.
- Geometric figure rotation task. The subjects are given 30 s to study a particular three-dimensional block object, after which the drawing is removed and the subjects are asked to visualise the object being rotated about an axis. The EEG signals are recorded during the mental rotation period.
- Mental letter composing task. The subjects are asked to mentally compose a letter to a friend or a relative without vocalising. Since the task is repeated several times the subjects are told to continue with the letter from where they left off.
- Visual counting task. The subjects are asked to imagine a blackboard and to visualise numbers being written on the board sequentially, with the previous number being erased before the next number is written. The subjects are instructed not to verbalise the numbers but to visualise them. They are also told to resume counting from the previous task rather than starting over each time.

Keirn and Aunon [6] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). For example, it was shown by Osaka [7] that arithmetic tasks exhibit a higher power spectrum in the right hemisphere whereas visual tasks do so in the left hemisphere. As such, Keirn and Aunon [6] and later Anderson *et al* [1] proposed that these tasks are suitable for brain-computer interfacing.

In this paper, we have used 4 different feature extraction methods to extract the feature from the EEG signals. In the first method, FAR coefficients are computed using Burg's method [2, 4, 12] using 125 data points of the original EEG signals. Model order 6 is used for this FAR process based on the suggestions in [1, 6]. The second method is the same as the first method except segmentation is done for every 25 data points, i.e. the FAR coefficients are computed for 1-25, 1-50, 1-75, 1-100, 1-125 data points. In the third method, AAR coefficients are computed using LMS algorithm for 125 data points. The last method is the same as the third, but instead segmentation is done for every 25 data points, i.e. the AAR coefficients are computed for 25th, 50th, 75th, 100th, 125th data points.

The following discussion details of the four different feature extraction process.

Sixth order FAR coefficients

A real valued, zero mean, stationary, nondeterministic, autoregressive process of order p is given by

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

where p is the model order, x(n) is the signal at the 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 noise with finite variance. In applications, the values of a_k have to be estimated from finite samples of data x(1), x(2), x(3), … ,x(N).

In this paper, we use Burg's method [2, 4, 12] to estimate the AR coefficients. The method is more accurate as compared to other methods like Levinson-Durbin as it uses the data point directly. Furthermore, Burg algorithm uses more data points by minimising both forward error and backward error. Order 6 is used for the AR process because other researchers [1, 6] have suggested the use of order 6 for AR process for mental task classification. Therefore, we have 6 FAR coefficients for each channel, giving a total of 36 features for each EEG segment from 6 channels. For the first method, FAR coefficients are calculated upon every 125 data points and a total of 36 features are obtained for each EEG segment from 6 channels. For the second method, AR coefficients are computed upon every 25 data points in the 125 EEG data segment. As a result, a total of 180 features are obtained for each EEG segment from 6 channels.

Sixth order AAR coefficients

An autoregressive model with time-varying coefficients of order *p* is defined by

$$Y_t = a_{1,t}Y_{t-1} + a_{2,t}Y_{t-2} + \ldots + a_{p,t}Y_{t-p} + Z_t, \qquad (2)$$

where Z_t is a white noise process with variance σ_t^2. In this paper, we use LMS algorithm to estimate the time-varying AR coefficients [11]. The difference to FAR model is that the parameters $a_{1,t}$, $a_{2,t}$, ..., $a_{p,t}$ can vary with time, however it is assumed that the parameters change only “slowly”. Since there are 6 AAR coefficients estimated at any time point t, for the third method, we choose the 6 coefficients from the 125^{th} data point as the feature to represent the EEG and overall, we have 36 features for each EEG segment from 6 channels. The number of features is the same as the first method, which is to ensure a fair comparison could be conducted later. For last method, we extract 6 AAR coefficients from the 25^{th}, 50^{th}, 75^{th}, 100^{th} and 125^{th} data points to give 30 features and overall, we have 180 features from 6 channels. Again, this ensures same number of features for fair comparison with method 2.

III. MLP-BP NEURAL NETWORK

A MLP-BP NN with a single hidden layer is trained by the BP algorithm [10] to classify different combinations of two mental tasks represented by the four different EEG features. Figure 2 shows the architecture of the MLP-BP NN used in this study. The output nodes are set at two so that the NN can classify into one of the two categories representing the mental task. The hidden layer nodes are varied from 20 to 100 in steps of 20.

A total of 200 EEG patterns (20 segments for each EEG signal x 10 sessions) are used for each subject for each mental task in this experimental study. Therefore, for each simulation, there is 400 EEG patterns from two mental tasks, where half of the patterns are used in training and the remaining half in testing. The selection of the parts for training and testing are chosen randomly. Training is conducted until the average error falls below 0.01 or reaches a maximum iteration limit of 10000. The average error denotes the error limit to stop NN training. The average error is the average of NN target output subtracted by the desired target output from all the training patterns. The desired target output is set to 1.0 for the particular category representing the mental task of the EEG pattern being trained, while for the other category, it is set to 0.

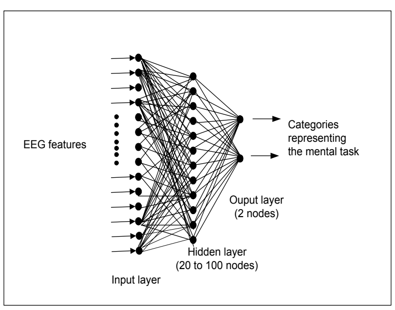

Fig. 2. MLP-BP NN.

IV. RESULTS AND DISCUSSION

Table 1 shows the result of NN classifications for different combinations of two mental tasks using 6^{th} order FAR coefficients computed using Burg’s algorithm and 6^{th} order AAR coefficients computed using LMS. For both methods, coefficients are calculated using 125 data points, without segmentation. The NN classification accuracies are shown in terms of average percentages for the hidden units ranging from 20 to 100 in intervals of 20. The highest classification percentage is different for different subjects and different methods except for subject 2 where the highest classification percentage is letter-composing and counting mental tasks for both FAR and AAR. In terms of average, FAR performs better than AAR for all the subjects where the lowest average for FAR is 67.41%, which is higher than for AAR, which is 54.0%. It can be seen that none of the best mental task combinations involved baseline for FAR method. The best mental task combinations for AAR involved rotation mental task for three subjects (maths-rotation for subject 1, baseline-rotation for subject 3 and baseline-rotation for subject 4)

Table 2 shows the classification results using the two methods as mentioned earlier but with segmentation of 25 data points. So, instead of 36 features per mental task, we have 180 features per mental task. The results still show that FAR performs better than AAR not only in term of highest percentage, but also in every task combination, i.e. none of the task combinations for AAR is better than FAR. In addition, the highest difference in percentage between the two methods is 28.50% for Subject 1 for baseline-count task combination. Again, none of the best combination for FAR involves baseline but best combination for AAR involves all the mental tasks.

From Table 1 and Table 2, it can been seen that FAR with without segmentation (74.09% in average for all the 4 subjects) is the best among the four methods, followed by FAR with segmentation (72.04%), AAR without segmentation (62.30%) and AAR with segmentation (59.53%). Besides, the performance for FAR is more stable than AAR where it can be seen from the best combinations for 3 subjects is the same for both FAR with and without segmentation, which is Letter-Count for Subject 2, Letter- Rotation for Subject 3 and Maths-Count for Subject 4. On the other hand, the best combination for each subject for AAR method varies for different subjects.

V. CONCLUSION

In this paper, a BCI design using MLP-BP NN classification of EEG features recorded during mental tasks is proposed. We analyse combination of two mental tasks from four subjects and compare the NN classification performance for each subject using four different methods to extract features from the EEG signals. Our results indicate that the performance using 6th order FAR coefficients with Burg's algorithm without segmentation performs better than the other three methods: 6th order FAR coefficients with Burg's algorithm with segmentation; 6th order AAR coefficients with LMS algorithm without segmentation and 6th order AAR coefficients with LMS algorithm with segmentation. Besides, the training time for 6th order FAR coefficients with Burg's algorithm without segmentation is also the lowest among the four methods. The results show that FAR performs better than AAR for the EEG signals recorded during the five different mental tasks that have been studied here.

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TABLE I
MLP-BP NN CLASSIFICATION RESULTS USING 6TH ORDER FAR AND AAR COEFFICIENTS USING 125 DATA POINTS, WITHOUT SEGMENTATION

	Subject 1		Subject 2		Subject 3		Subject 4	
Task	FAR	AAR	FAR	AAR	FAR	AAR	FAR	AAR
Base, Count	82.20	64.20	71.30	63.60	57.60	51.60	76.40	69.40
Base, Letter	76.80	60.90	80.60	64.20	59.85	51.80	63.30	57.50
Base, Maths	80.20	68.50	74.50	61.60	67.85	50.00	86.10	72.70
Base, Rotate	76.25	65.10	70.90	57.40	74.25	63.40	80.95	81.80
Letter, Count	68.80	59.90	88.80	65.90	61.85	56.50	71.35	64.50
Letter, Rotate	72.30	65.00	73.90	63.10	76.65	60.50	72.55	70.70
Maths, Count	83.10	64.70	72.95	53.90	63.40	49.90	92.70	77.60
Maths, Letter	82.65	68.40	74.30	62.20	71.15	50.00	78.20	74.30
Maths, Rotate	82.55	76.70	68.85	54.30	71.55	50.00	75.20	66.70
Rotate, Count	72.05	53.60	66.00	50.20	69.90	56.30	73.75	73.20
Average	77.69	64.70	74.21	59.64	67.41	54.00	77.05	70.84
Maximum	83.10	76.70	88.80	65.90	76.65	63.40	92.70	81.80
Best Combination	Maths, Count	Maths, Rotate	Letter, Count	Letter, Count	Letter, Rotate	Base, Rotate	Maths, Count	Base, Rotate

TABLE II
MLP-BP NN CLASSIFICATION RESULTS USING 6TH ORDER FAR AND AAR COEFFICIENTS USING 125 DATA POINTS, WITH SEGMENTATION FOR EVERY 25 DATA POINTS

	Subject 1		Subject 2		Subject 3		Subject 4	
Task	FAR	AAR	FAR	AAR	FAR	AAR	FAR	AAR
Base, Count	78.40	49.90	68.10	62.60	54.90	52.50	75.00	63.10
Base, Letter	74.50	53.50	77.60	64.10	61.30	53.10	65.20	51.80
Base, Maths	75.50	64.70	72.60	62.80	63.90	49.90	84.30	69.80
Base, Rotate	76.40	69.10	68.40	52.10	72.70	54.80	80.40	74.40
Letter, Count	64.20	56.80	82.50	63.70	62.80	54.80	69.70	63.20
Letter, Rotate	67.40	58.70	69.30	62.60	77.30	55.80	74.10	71.30
Maths, Count	81.50	60.70	71.60	56.20	63.80	49.90	88.70	78.60
Maths, Letter	79.00	66.70	68.60	51.70	68.00	51.30	75.40	67.90
Maths, Rotate	82.30	68.90	66.80	49.70	67.00	51.30	74.60	66.10
Rotate, Count	71.40	49.40	68.00	50.50	66.60	58.80	71.60	68.30
Average	75.06	59.84	71.35	57.60	65.83	53.22	75.90	67.45
Maximum	82.30	69.10	82.50	64.10	77.30	58.80	88.70	78.60
Best Combination	Maths, Rotate	Base, Rotate	Letter, Count	Base, Letter	Letter, Rotate	Rotate Count	Maths, Count	Maths, Count