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A Self-Paced BCI Using Stationary Wavelet Packets

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Abstract—**The stationary wavelet packet analysis is exploited for the first time in the design of a self-paced BCI based on mental tasks. The BCI system is custom designed to achieve a zero false positive rate, as false activations highly restricts the applications of BCIs in real life. The EEG signals of four subjects performing five different mental tasks are used as the dataset. The stationary wavelet packets decompose the signal into eight components. The features used are the autoregressive coefficients obtained by applying autoregressive modeling on the resultant wavelet components. Classification is a two-stage process. The first stage is based on quadratic discriminant analysis which is extremely fast. The second stage is a simple majority voting classifier. During model selection, which is performed via 5-folded cross-validation, the combination of decomposed components and the autoregressive model order that yield the best performance are selected. Results show enhancements in the overall performance for three subjects comparing to our previously designed BCI.**

I. Introduction

BRAIN–computer interfaces (BCIs) provide an alternative means of communication and are thus expected to improve the life quality of motor disabled individuals. A self-paced BCI can be used in real-life applications. Unlike synchronized BCIs, a self-paced BCI is controllable at all time instants. The state in which the BCI is activated is called the intentional-control (IC) state. The no-control (NC) state is the BCI inactive state. Classifying the IC and NC states correctly is the ultimate goal in developing BCI systems. The rate of correctly classifying the IC states is referred to as the true positive rate (TPR). Misclassifying the NC states is measured by the false positive rate (FPR). The ideal values for TPR and FPR are 100% and zero, respectively [1], [2].

To operate a BCI, specific features in the brain signals related to neurological phenomena should be recognized. The phenomena related to various brain activities differ in terms of time and frequency specifications. In this paper, the BCI rely on mental tasks as the neurological phenomena, i.e., the user controls the proposed BCI by performing different mental tasks.

In this study, the EEG signals of 4 subjects each performing 5 mental tasks are used. This dataset has been collected by Keirn and Aunon [3] and has been used in many other studies such as [5]-[12]. We design five self-paced BCIs for each subject; each is based on one of the five mental tasks. In each BCI, one mental task is treated as the IC task and the other four mental tasks are considered as NC tasks. Unlike other studies based on this dataset, we pay special attention to FPR values since they are of great importance in real-life BCI applications. We aim at obtaining a zero FPR by custom designing our BCI system for every mental task of each subject.

The design of the proposed self-paced mental-task based BCI is described in section II. Section III presents the results and discussion. The conclusions are in section IV.

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II. Methods

A. Data

The EEG signals used in this paper were recorded from six mono-polar electrodes placed at C3, C4, P3, P4, O1, and O2 based on the International 10-20 System. Electrically linked mastoids, A1 and A2 were the references. Two electrodes were also placed below and at the corner of the left eye for ocular artifact detection. However, we here do not remove any part of the signals due to artifacts.

The sampling frequency was set at 250 Hz. The electrode impedance was kept below 5 kΩ. The EEG signals were recorded using a bank of amplifiers (Grass 7P511) with the band-pass filters (set at 0.1-100 Hz) and a Lab Master 12-bit A/D converter.

Seven subjects seated in a sound-controlled dim-lighted recording room performed the following five mental tasks: the baseline (thinking of nothing); the multiplication task (mentally solving a nontrivial multiplication such as 14×63); the letter composing task (mentally composing a letter to a friend); the rotation task (mentally rotating a given 3D object); and the counting task (visualizing writing a sequence of numbers on a blackboard).

In each recording session, five 10-second trials for each of the five mental tasks (a total of 25 trials) were collected. Different subjects completed different numbers of trials as shown in Table I. The EEG signals of Subject 4 contain some missing data and were not used in this study. The first 10 trials (out of 15 trials) of Subject 5 and the 10 trials of Subjects 1, 3, and 6 were used. Please refer to Table I to see the numbers we newly assigned to the subjects.

B. Stationary Wavelet Packet Analysis

To simultaneously analyze the signal specifications in the time and frequency domains, wavelet analysis is considered as a powerful tool. The shift-invariency of the stationary wavelet transform (SWT) makes this analysis more applicable [4].

In our previous study [5], we decomposed the EEG signals into 5 levels using SWT. Then the autoregressive models of the decomposed signals were used as the features. Different wavelet families that were used include: Haar wavelet (‘*db1*’), Daubechies (‘*db2*’, ‘*db3*’, ‘*db4*’, ‘*db5*’, ‘*db6*’, ‘*db7*’, ‘*db8*’, ‘*db9*’, ‘*db10*’), Biorthogonal (‘*bior1.3*’, ‘*bior1.5*’, ‘*bior2.2*’, ‘*bior2.4*’, ‘*bior2.6*’, ‘*bior2.8*’, ‘*bior3.1*’, ‘*bior3.3*’, ‘*bior3.5*’, ‘*bior3.7*’, ‘*bior3.9*’, ‘*bior4.4*’, ‘*bior5.5*’, ‘*bior6.8*’), Coiflets (‘*coif1*’, ‘*coif2*’, ‘*coif3*’, ‘*coif4*’, ‘*coif5*’), Symlets (‘*sym2*’, ‘*sym3*’, ‘*sym4*’, ‘*sym5*’, ‘*sym6*’, ‘*sym7*’, ‘*sym8*’).

Decomposition at each level yields two types of components: the approximations component (the low-frequency high-scale component of the signal) and the details component (the high-frequency low-scale component). The resultant approximations component at each level is decomposed iteratively. Please see Fig. 1.a.

Since the sampling frequency is 250 Hz, the maximum frequency of the EEG signal is assumed to be 125 Hz. The frequency ranges pertaining to each level in the wavelet decomposition is shown in Table II. In study [5], we worked with the frequency ranges 0-3.91, 3.91-7.81, 7.81-15.63, 15.63-31.25, and 31.25-62.5 Hz.

Signal decomposition with the wavelet packet analysis is different from the ordinary wavelet decomposition in the sense that at each level, the details component and not only the approximations component is decomposed iteratively. Therefore, the wavelet packet decomposition offers a more flexible (but at the same time, more complicated) decomposition. In the present work, we decompose the EEG signals using wavelet packet analysis. Fig. 1.b illustrates the scheme of the wavelet packet decomposition. Table III presents the frequency range of each component of the first 3 levels.

It is noteworthy that ordinary wavelet transforms are usually exploited in the wavelet packet decomposition; however, having seen the good performance of the stationary wavelet transform in our previous study [5], we propose to use it in the wavelet packet analysis in this study. Thus we call the whole process *the stationary wavelet packet analysis* (SWPA).

C. Autoregressive Modeling

The autoregressive (AR) model of order R for the one-dimensional signal $z[t]$ is defined as:

$$z[t] = \sum_{r=1}^{R} a_r z[t-r] + u[t] \quad (1)$$

where a_r are the AR coefficients, and the error $u[t]$ is a zero mean, finite variance stochastic process that is independent of the previous values of z. The a_r coefficients are estimated from the finite samples of z.

TABLE I
THE NUMBER OF COMPLETED TRIALS FOR EACH SUBJECT

Subject number	original study	1	2	3	4	5	6	7
	this study	1	---	2	---	3	4	---
Number of completed trials		10	5	10	10	15	10	5

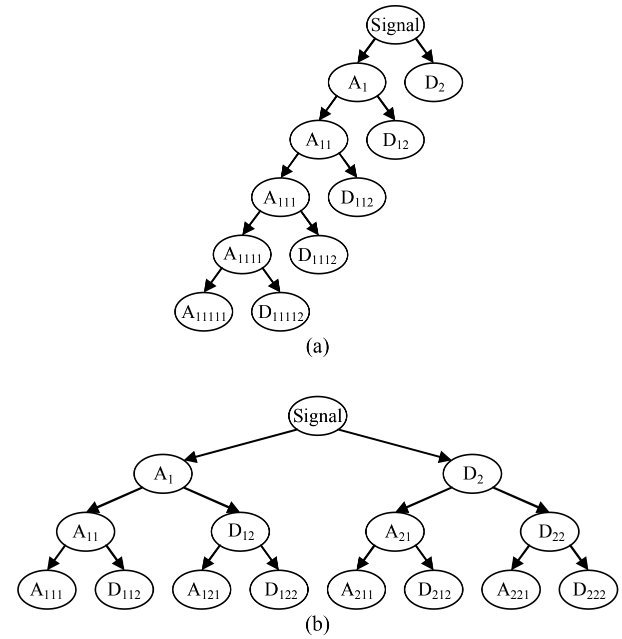

Fig. 1. Decomposition:
(a) wavelet decomposition, (b) wavelet packet decomposition.

TABLE II
FREQUENCY RANGES IN WAVELET DECOMPOSITION (HZ)

Level	Approximations	Details
1	0–62.5	62.5–125
2	0–31.25	31.25–62.5
3	0–15.63	15.63–31.25
4	0–7.81	7.81–15.63
5	0–3.91	3.91–7.81

It is assumed that the original signal has the frequency band 0-125 Hz.

TABLE III
FREQUENCY RANGES IN WAVELET PACKET DECOMPOSITION (HZ)

		Frequency							
		0–125							
Level	1	0–62.5				62.5–125			
	2	0–31.25		31.25–62.5		62.5–93.75		93.75–125	
	3	0 – 15.625	15.625 – 31.25	31.25 – 46.875	46.875 – 62.5	62.5 – 78.125	78.125 – 93.75	93.75 – 109.375	109.375 – 125

It is assumed that the original signal has the frequency band 0-125 Hz.

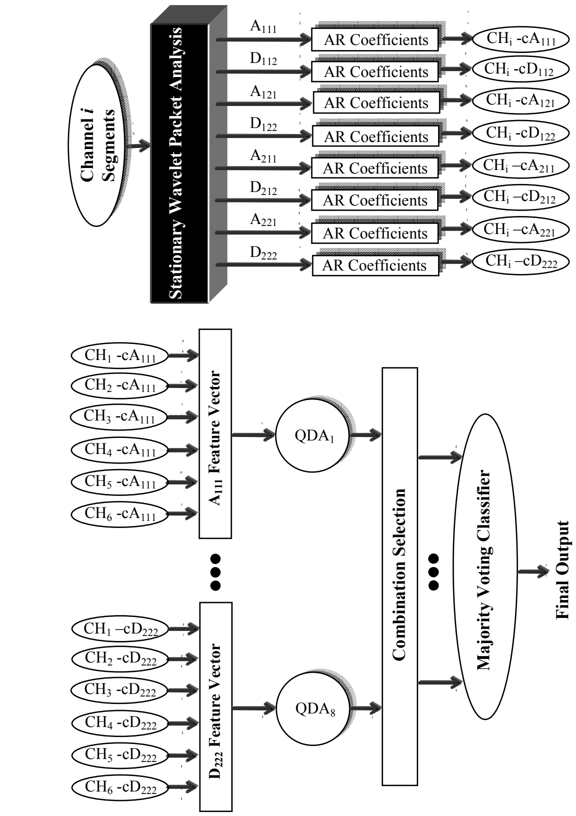

Fig. 2. Overview of the system.

D. Procedure

Since each trial is 10 seconds long and the sampling rate is 250 Hz, each trial has 2500 samples. Trials are broken into 45 segments. Each segment has 256 samples and overlaps by 206 samples with the next segment. There are 10 trials for every mental task of each subject; hence, 450 segments exist for every mental task of each subject.

In this study, we decompose the segments into 3 levels with the stationary wavelet packet analysis. For each mental task of each subject, we use the wavelet family that had the best performance in [5]. We estimate the autoregressive model of the decomposed wavelet components using the Burg algorithm [13]. The AR coefficients are then exploited as the features.

Since there is no straightforward way to find the optimum AR model order, we varied the AR model order from 2 to 22 for each subject and each mental task. The optimum model order is then selected based on the obtained TPR and FPR values of the BCI. To this end, a 5-folded cross-validation is used.

During the model selection, we also obtain the combination of the decomposed components (at level three) that yields the best performance in terms of TPR and FPR. To do this, for each 8 components of the third decomposition level, a different classifier is trained. For each classifier, the AR coefficients of the corresponding component of the different channels are concatenated into a vector. This vector forms the feature vector.

The final output of the BCI is based on majority voting between the classifiers corresponding to the selected components. See Fig. 2. If the number of classifiers voting for the IC task is equal to the number of classifiers voting for the NC task, the final output of the BCI is considered to be NC, since we want to have FPR as less as possible.

E. Quadratic Discriminant Analysis

Quadratic discriminant analysis (QDA) [14] is used as the classifier, since it is simple, fast, and easy to implement. QDA assumes the classes have normal distributions. For a 2-class problem, the quadratic discriminant function is simplified as:

$$qdf(z) = -\frac{1}{2} z^T (\hat{\Sigma}_1^{-1} - \hat{\Sigma}_2^{-1}) z + (\hat{\mu}_1^T \hat{\Sigma}_1^{-1} - \hat{\mu}_2^T \hat{\Sigma}_2^{-1}) z$$
$$-\frac{1}{2} \ln[\frac{|\hat{\Sigma}_1|}{|\hat{\Sigma}_2|}] - \frac{1}{2}(\hat{\mu}_1^T \hat{\Sigma}_1^{-1} \hat{\mu}_1 - \hat{\mu}_2^T \hat{\Sigma}_2^{-1} \hat{\mu}_2) - \ln[\frac{C_{21}}{C_{12}} \frac{\pi_2}{\pi_1}] \quad (2)$$

where z is the vector to be classified, $\hat{\mu}_1, \hat{\mu}_2$ are the estimated mean vectors of the classes, $\hat{\Sigma}_1, \hat{\Sigma}_2$ are the estimated covariance matrices of the classes, π_1, π_2 are the prior probabilities, C_{12} is the cost of misclassifying a member of class 1 as class 2, and C_{21} is the cost of misclassifying a member of class 2 as class 1. The decision rule is as follow:

$$z_0 \in \omega_1 \quad if\ qdf(z_0) \geq 0$$
$$z_0 \in \omega_2 \quad if\ qdf(z_0) < 0 \quad (3)$$

where ω_1, ω_2 represent classes 1 and 2, respectively.

In this study, the last term in equation (2) is zero since we assume the same value for the two costs, and the same value for a-priori probabilities.

III. Results and Discussion

The performance of the proposed BCI during testing process is given in Table IV. We compare the results of this study with the results of our previous study [5]. For the present study, the FPR value always reaches zero.

According to Table IV, the present method outperforms the method of [5] for Subjects 1, 3, and 4. For Subject 1, the TPR values of all mental tasks (except the baseline) are higher. For Subject 3, the performance of every BCI is enhanced. For Subject 4, the mean TPR of the rotation task is reduced by 2.89%. For the multiplication task, TPR decreases but FPR reaches zero. Hence the performance improves. The TPR values of other tasks increase. For Subject 2, the performance degrades for three mental tasks.

The most discriminatory mental task for each subject is the task with the lowest FPR and the highest TPR. Most discriminatory tasks are shaded in Table IV. The most discriminatory task was changed for Subjects 1, 2, and 4. For subjects 1, 3, and 4, the TPR value of the new most discriminatory task is higher than the TPR value of the previous most discriminatory task. For Subject 1, the most discriminatory task is changed from the letter composing task to the multiplication task with a TPR improvement of

TABLE IV
TESTING RESULTS FOR DIFFERENT SUBJECTS AND MENTAL TASKS
STUDY [5] (AT TOP) AND PRESENT STUDY (AT BOTTOM)
(THE MOST DISCRIMINATORY TASK FOR EACH SUBJECT IS SHADED. THE CASES WITH PERFORMANCE DEGRADATION ARE IN WHITE.)

Subject	Baseline						Multiplication						Letter Composing						Rotation						Counting					
	Wavelet	AR Order	TPR		FPR		Wavelet	AR Order	TPR		FPR		Wavelet	AR Order	TPR		FPR		Wavelet	AR Order	TPR		FPR		Wavelet	AR Order	TPR		FPR	
			Mean	SD	Mean	SD			Mean	SD	Mean	SD			Mean	SD	Mean	SD			Mean	SD	Mean	SD			Mean	SD	Mean	SD
1	bior3.3	3	71.33	3.28	0.00	0.00	bior1.3	4	63.56	6.16	0.00	0.00	db2	3	64.22	5.74	0.00	0.00	db2	4	54.67	4.93	0.00	0.00	bior2.2	4	54.22	3.72	0.00	0.00
		16	66.89	9.24	0.00	0.00		14	77.11	4.20	0.00	0.00		17	64.89	2.30	0.00	0.00		16	64.67	5.79	0.00	0.00		16	65.56	4.51	0.00	0.00
2	db1	6	35.11	7.10	0.00	0.00	bior3.1	4	50.89	2.53	0.00	0.00	bior3.1	4	63.11	4.61	0.00	0.00	bior3.1	4	49.78	5.06	0.00	0.00	bior3.1	4	55.56	4.30	0.00	0.00
		20	61.11	7.29	0.00	0.00		15	48.44	7.01	0.00	0.00		19	53.78	3.82	0.00	0.00		18	55.11	6.69	0.00	0.00		19	48.00	8.07	0.00	0.00
3	db3	4	49.56	6.12	0.06	0.12	bior2.2	4	53.78	6.17	0.00	0.00	bior2.2	4	61.11	3.77	0.00	0.00	coif1	4	63.78	2.68	0.00	0.00	db2	4	54.44	4.91	0.00	0.00
		15	65.33	3.88	0.00	0.00		13	68.22	3.74	0.00	0.00		16	66.22	2.90	0.00	0.00		13	77.78	6.03	0.00	0.00		16	61.33	3.96	0.00	0.00
4	bior3.5	4	55.78	4.80	0.00	0.00	coif1	4	68.00	3.96	0.06	0.12	db1	4	56.22	3.57	0.00	0.00	bior3.1	4	64.89	4.88	0.00	0.00	bior3.1	4	58.22	3.30	0.00	0.00
		14	60.00	6.76	0.00	0.00		13	67.78	4.51	0.00	0.00		15	62.22	4.44	0.00	0.00		17	62.00	7.18	0.00	0.00		13	61.78	3.98	0.00	0.00

12.89%. For Subject 3, the rotation task remains as the most discriminatory task, but TPR increased by 14%. For Subject 4, the most discriminatory task is changed from the rotation task to the multiplication task with 2.89% increase in the TPR value. For Subject 2, the most discriminatory task is changed from the letter composing task to the rotation task with 8% decrease in TPR. The results showing that the new system is not working well for Subject 2, supports the idea of custom designing BCI systems for different subjects [15].

IV. CONCLUSION

In this paper, we presented a new self-paced mental task-based BCI using the stationary wavelet packet decomposition approach. Our work was compared to our previous work that was also carried using the same data, and it showed that the present method has a better performance for three out of four subjects.

For our future work, we plan on considering other feature extraction methods and classifiers (such as support vector machines) to further enhance the performance of our BCI system.

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