Customized Linear Discriminant Analysis for Brain-Computer Interfaces

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Abstract— **This study presents a procedure to customize mental task discrimination for a specific human subject. Three male subjects, between 20 and 30 years old, were submitted to 4-5 sessions. Each session was composed of 4 blocks of 20 trials. Two block types were implemented. One required that the subject perform feet and tongue movements. The other block required the subject to perform left and right arm movements. Subjects were instructed to perform motor imagery as well as actual movements. In order to avoid previous assumptions on preferable channel locations and frequency ranges, 105 (21 electrodes×5 frequency ranges) electroencephalogram (EEG) features were extracted from the sessions' data. A linear discriminant analysis (LDA) approach was applied to the feature set. The dimensionality of the multivariate data set was reduced through a discriminant stepwise procedure. Only the variables which best discriminated between groups, for a specific subject, were used. Those features predicted group membership during online feedback sessions with error lower than 12%, in each subject best performance. Classification errors for training data were very low and were neglected.**

I. Introduction

Brain-Computer Interface (BCI) enables people to control a device with their brain signals [1]. BCI is expected to be a very useful tool for impaired people both in invasive and non-invasive way. Although subjects using invasive approaches usually show evidence of better device control than non-invasive users, it is less preferred due to the higher risk involved in its research and practical implementation. Because the electroencephalogram (EEG) does not have enough accuracy to detect user movement intention from primary motor cortex, recent studies have tried to use 2 distinct approaches. In the *operant conditioning* approach, the training load is on the subject [1]. The subject must learn to control a specific rhythm in order to produce the desired result on the device that he is controlling. The *pattern recognition* approach is suitable for less trained subjects. The user is instructed to perform distinct mental tasks that should be identified by the BCI system [2]. The features selected to discriminate the mental tasks are usually based on previous assumptions about frequency ranges and electrode placements commonly used to distinguish such mental tasks.

A novel approach of multivariate canonical discrimination is used in this study to discriminate EEG spatiotemporal patterns in response to mental tasks. The aim of this study is to test an approach that enables subjects to control a device with a minor training load. The subjects that participated in this study had no previous BCI experience. This discrimination project is intended to be independent, as much as possible, of previous assumptions with respect to frequency ranges and electrode locations frequently used in motor imagery tasks. Because the available variables are likely to be much more than it is necessary to obtain a satisfactory discrimination, a stepwise method is used to reduce data dimensionality. It first selects the variables with the highest contribution to group discrimination and then it keeps adding or removing other variables to the canonical discriminators according to a discrimination criterion.

Subjects went through sessions conducting mental tasks in each session on movement imagery. Other sessions were completed with executed movements. Sessions with movement execution enable us to determine possible features in common with the motor imagery sessions. The discrimination quality and group prediction were evaluated for all sessions in training data and in feedback sessions.

II. Procedures

A. Experimental Design

Three subjects, 20 to 30 years old, were submitted to 4-5 sessions of motor imagery tasks and 3 sessions of executed movement tasks. Each session had between 3 and 4 blocks of 20 trials. The subject was instructed to perform one of 4 tasks in each trial. Two block types were implemented. One required that the subject perform feet and tongue movements, which we suppose to be 2 easily differentiable groups. The other block type required the subject to perform left arm and right arm movements, which we believe to be 2 similar groups. The same number of blocks per session were recorded during motor imagery and actual movements. Each trial length was 8 s. After the first 2 s a cue warned the subject to be prepared and 1 s later, a cue about the required mental task was presented to the subject. The subject should perform the task during the last 4 s. During sessions with feedback, the subject would see a green light on (reward) if

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its task performance was successful. The feet, tongue, left arm and right arm movement tasks were identified as groups 1, 2, 3 and 4 respectively. The linear discriminant functions and their features used to provide feedback to subject, in a specific session, were determined from previous session data. There was no feedback in session 1.

Data were recorded using a *Labview* platform that receives data from a *BrainProducts® Quickamp* through a socket connection. This platform extracts the subject specific features, provides feedback and graphical interface to the subject. Ag/AgCl sintered electrodes were used (Fig. 1).

As referred above, no electrode locations or frequency ranges were pre-selected. The presence of significant artifact was the only criterion used to exclude electrodes and frequency ranges. In this way, 21 electrodes (F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P7, P3, Pz, P4 and P8) according to the standard 10-20 system were used for feature extraction. All electrodes were referenced to linked earlobes. Data was digitized at 250 Hz and passed through a 6^{th} order (48 dB per octave) band-pass Butterworth filter of 1-50Hz. Data were visually inspected for artifacts after amplitude threshold artifact detection was applied. The trials that contained artifacts in the 3 to 8 s interval were marked and were excluded from the discriminant function analysis. Five frequency bins (10 Hz, 14 Hz, 18 Hz, 22 Hz and 26 Hz bin central frequencies, 4 Hz width bins) were considered for each channel. Each feature is the ratio of the pre-filtered EEG signal power in one of these frequency ranges to its power in the broadband frequency range 1-30 Hz, for the 3-8 s interval. Since 21 channels and 5 frequency bins were selected, 105 variables (features) were available for discrimination.

Fig. 1. Subject EM and the recording set-up.

B. *Canonical Discriminators*

Multivariate canonical discrimination was developed by Fisher [3] in order to quantify the static taxonomic classification of plant species. A more stable approach to this computation was recently implemented for spatiotemporal EEG pattern discrimination [4].

In our study, discrimination was performed on a sequence of measurements, assembled into a matrix Y where the rows are in units of time (4 s intervals) and the columns are the multivariate power ratio calculated from the measurements. The Y columns, the variables selected for discrimination, were determined in the procedure detailed in subsection C.

Y_1, Y_2, Y_3 and Y_4 were generated from matrix Y, and canonical discriminators generated to distinguish Y_1 from Y_2, and Y_3 from Y_4 were determined. Covariance matrices were calculated for the whole dataset Ψ_{total} and within each group Ψ_{within}. The covariance between group means is defined as (1).

$$\Psi_{between} = \Psi_{total} - \Psi_{within} \qquad (1)$$

For any linear combination

$$Z_i(\gamma) = Yb_i^T \qquad (2)$$

the separation of groups implies that the $\Psi_{between}$ should be emphasized with respect to Ψ_{within} .

A modern and stable approach to implement this optimal separation of groups is based on a coordinate system change [4]. The singular value decomposition (SVD) $\Psi_{within} = USU^T$ enables us to define a new variable $v = US^{1/2}U^T b$. Converting back to b-coordinates, the optimal b, called the *first canonical variate,* is defined as

$$b_1 = US^{-\frac{1}{2}}U^T v_1 \qquad (3)$$

The m canonical variates $b_i,\ldots,b_m$ are the m columns of $US^{-1/2}U^T V$ and they provide the coefficients of *m canonical discrimination functions* in (2). V and Λ (diagonal matrix with the eigenvalues of the transformation) are obtained using the following equation

$$V\Lambda V^T = SVD(US^{-1/2}U^T \Psi_{between} US^{-1/2}U^T) \qquad (4)$$

After finding the discrimination functions, 3 tests were done to check discrimination quality. Each multivariate observation vector Y has a transformed vector z with mean u and normal p-variate distribution $f(z)$. Prior probabilities π_j were determined by the ratio of observations in group j to the total observations (N), i.e. $\pi_j = N_j / N$. The posterior probability π_{jz} in (5) is the probability that the data of a given value z came from group j of n groups.

$$\pi_{jz} = \frac{\pi_j f(z)}{\sum_{k=1}^{n} \pi_k f_k(z)}, k = 1,\ldots,n \qquad (5)$$

The *exp[q(z)]* , for $q(z) = u_j^T z - 1/2 u_j^T u_j + \ln \pi_j$, was used as a good approximation of $\pi_j f(z)$ [5]. The highest π_{jz} value for $j=1,\ldots,4$ was the predicted group membership for posterior calculations.

A robust method for quality testing is to leave one multivariate data point out of the discriminant function classification and then test it for predicted group classification given its posterior probability. In order to test the significance of discrimination, we used a normal theory method that analyses the eigenvalues of Λ above. After calculating the log likelihood ratio as $LLRS = N\sum_{i=1}^{m}\ln(1+\lambda_i)$, where λ_i are the diagonal values of Λ, the Wilks' statistic was used as $W = \exp[-LLRS/N]$. A good discrimination yields large eigenvalues and W becomes small. Small eigenvalues and W values close to 1 are typical for poor discriminations. W is chi-square distributed and confidence limits were calculated for discrimination significance [5]. On the other hand, the W statistic is based on the assumption of normal distribution of data variables, which may not be the case. A bootstrap method was therefore used as an alternative method of testing discrimination quality. It randomly permutes the labeling of each multivariate data point (to 1, 2, 3 or 4 groups) and re-tests the goodness of fit [4]. The permutation number was limited to 1000.

C. Features Selection

A discriminant stepwise method was used to decrease data dimensionality [5]. As mentioned above, there are 105 variables available to apply in the linear discriminator. Although the addition of each new variable improves the discrimination (W value decreases) on the training data set, the preferred criterion for this discriminative stepwise procedure was the leave-one-out error rate, since it is a classification error of data out of the training data set, as well as test data.

The first step of this procedure is to select the first variable to start with. The canonical function that best discriminates the multivariate data observations (for 2 groups) for all 105 variables is determined. The likelihood between the canonical discriminant function and each variable is given by their correlation. From (2), it can be calculated using the correlation between each column of Y and the transformed observations z (Z just has one column since it is a 2 group discrimination). The largest absolute value of the correlation corresponds to the first selected variable. Then canonical functions were determined for the training data set considering only the first selected variable. Afterwards, 3 options are possible. Iteratively, the criterion was compared with canonical functions generated from: 1) adding an extra variable from the remaining variables set; 2) replacing a previously selected variable by one from the remaining variables set, or 3) removing a previous selected variable. The action from these 3 options, which produces the largest decrease in leave-one-out error, was actually performed. This procedure was run iteratively until no additional criterion improvements were possible. Once this procedure was finished, we have an optimized variable set and new canonical discriminant function available to predict group membership on test data (feedback sessions).

III. Results

Table I presents the canonical functions with the best classification errors on training data as well as their discrimination quality evaluation. From Table I, we can highlight the essentially perfect discriminations for training data, for all 3 subjects, in feet vs. tongue movements, since both plug-in and leave-one-out error rates were 0% with W values much lower than the 99% confidence interval limits. Significance of the discrimination is also shown by the bootstrap method. The features extracted from the stepwise method for all subjects are frontally oriented since the variables with the highest coefficients correspond to the channels located in the frontal regions of the skull. The main EEG component selected for FF is in the 12-16Hz range, 20-24Hz for EM, and for JC, it is predominantly in the 16-20Hz frequency range.

The online classification errors in group membership prediction for motor imagery tasks with feedback are presented in Table II and for tasks with actual movements are presented in Table III. Since we are evaluating BCI online classification errors for 2 groups (discrimination between 1 and 2 or between 3 and 4), 50% is the expected value for non-existent control of the subject. In Table II, subjects are ordered from left to right in decreasing order of overall performance. Subject FF reached classification errors lower than 18% for both group pairs, the subject EM had errors around 22% for group pairs 1-2 and barely controlled the BCI for group pair 3-4. Subject JC had almost no control for both group pairs.

The classification errors for tasks with movement, Table III, are slightly lower. The subject FF reached classification errors lower than 10% and 15% for group pairs 1-2 and 3-4 respectively. Subject EM performed perfectly for groups 1-2 (0% error) and significantly worse for groups 3-4. Subject JC had good control for groups 1-2 and did less well for groups 3-4.

TABLE I
OFFLINE PERFORMANCE OF THE CANONICAL FUNCTIONS WITH BEST ONLINE PERFORMANCE

Canonical Functions with best online performance						
Subject(Groups)	Channel(Freq)	Coef	W	PIER (%)	LOOER (%)	Online error (%)
FF (1-2)	C3(8-12)	-10,4305	0,1642	0,00	0,00	10,00
	F8(8-12)	16,3038	0,7359[a]			
	F7(12-16)	39,5900	0,7915[b]			
EM (1-2)	F4(20-24)	-65,6901	0,2825	0,00	0,00	0,00
			0,7627[a]			
	Cz(20-24)	41,0651	0,8259[b]			
JC (1-2)	P4(8-12)	-8,5656	0,1219	0,00	0,00	11,11
	FC5(8-12)	17,2910				
	FC5(16-20)	72,3496	0,6116[a]			
	F7(8-12)	-7,1256	0,6589[b]			

Groups 1-2 means a block of trials for feet vs. tongue movements tasks respectively. Channel(Freq) field refers to the channels and frequency bins delimited from low cut-off to high cut-off frequencies. Coef field stands for the variables coefficients in the canonical function. W is the Wilks' statistic values. [a]Limit value for 99% confidence interval of W significance. [b]Significance level for W from bootstrap test. PIER field means plug-in error rate and LOOER means leave-one-out error rate.

TABLE II

ONLINE ERROR CLASSIFICATION FOR MOTOR IMAGERY TASKS

day#	session#	Error classification for motor imagery tasks (%)					
		FF		EM		JC	
		Groups 1-2	Groups 3-4	Groups 1-2	Groups 3-4	Groups 1-2	Groups 3-4
1	1	no feedback					
2	2	45,00	46,67	47,56	40,32	36,51	42,86
2	3	a	a	23,68	31,25	a	a
3	4	20,00	53,75	28,75	42,00	30,00	35,90
3	5	15,00	17,50	21,88	37,78	35,00	50,00

Groups 1-2 means a block of trials for feet vs. tongue movements tasks and 3-4 means left vs. right arms movement tasks respectively. FF, EM and JC are the subject's identification codes.

[a]Values not available because the respective subject was not submitted to that specific session.

TABLE III

ONLINE ERROR CLASSIFICATION FOR TASKS WITH MOVEMENT

day#	session#	Error classification for tasks with movement (%)					
		FF		EM		JC	
		Groups 1-2	Groups 3-4	Groups 1-2	Groups 3-4	Groups 1-2	Groups 3-4
1	1	no feedback					
3	2	53,33	38,33	12,50	52,50	31,67	50,00
3	3	10,00	15,00	0,00	28,21	11,11	30,00

Groups 1-2 means a block of trials for feet vs. tongue movements tasks and 3-4 means left vs. right arms movement tasks respectively. FF, EM and JC identify subjects.

IV. DISCUSSION AND CONCLUSIONS

In offline analysis, the canonical functions in Table I, show that the most discriminative channels, for feet vs. tongue movements, are localized frontally and the frequency ranges deviate from the μ-rhythm 8-12Hz range used for motor imagery experiments [6]. Additionally, the plug-in and leave-one-out classification error rates, in Table I, are low, and each group's transformed data points are tightly clustered about their group mean (Fig. 2). The online classification errors of the canonical discrimination functions, in Table III, are low enough to permit a 2 group BCI implementation.

During sessions with feedback, the online results for motor imagery tasks tend to improve with sessions (Table II), with the exception of subject JC for session 5. This lack of control could be due to inadequate features extracted from the previous session. Subjects FF and EM had reasonable control for both group pairs in session 5, otherwise subject JC achieved rudimentary or non-existent control for any group pair. Since all the three subjects confessed to have some difficulty to concentrate on motor imagery tasks, we believe there exists an optimal subject-dependent interval for this procedure to acquire the feature set that better describes the subject's task performance. Furthermore, the canonical functions with best online performance for each subject, in the last row of Table III, were tested in sessions with movement tasks and for feet vs. tongue movements. This supports the expected best performance on tasks with actual movements when compared to motor imagery tasks. From both Table II and Table III, groups 1-2 were easier to discriminate than groups 3-4.

The results from tasks with online feedback show that error improvements are better between 2 consecutive sessions, on the same day, than for sessions from different days. This suggests 2 sources of variability: that the subject's mental state changed from day to day or that electrode locations varied due to cap application (the cap was applied just once for consecutive sessions on the same day). Further sessions of motor imagery tasks should be performed to check if the classification error reduction is consistent. Since the classification was done once per trial, the output update rate of a BCI system based on this study would be 4s. This time frame is not sufficient for many real-time systems, and we are working to reduce this time lag in future work.

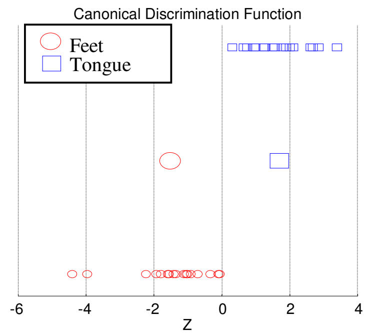

Fig. 2. The graph represents the canonical discriminator function for groups 1 vs. 2 (feet vs. tongue movements) from subject EM, detailed in Table I. The discrimination was performed on horizontal axis (Z). Groups are vertically level shifted for interpretation simplicity. Large symbols represent group means.

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