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Common Spatio-Temporal Patterns for the P300 Speller

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Abstract— **A brain-computer interface (BCI) is a device that provides an alternate non-muscular communication/control channel for individuals with severe neuromuscular disabilities. The P300 event-related potential has been demonstrated to be a reliable signal for controlling a BCI. The ultimate goal is to continue to improve the classification speed and accuracy of a P300-based BCI. The method of common spatial patterns (CSP) has proven success with sensorimotor rhythm-based BCIs and, with some modifications, can also be used to accurately classify the P300. The present method, Common Spatio-Temporal Patterns (CSTP), extends CSP by incorporating time-delay embedding to extract the prominent spatio-temporal patterns corresponding to each class. The results indicate that CSTP is capable of identifying a decomposition subspace that accurately classifies the P300. In addition, this subspace can be visualized to provide useful insight regarding the discriminable spatio-temporal characteristics of the P300.**

I. Introduction

A brain-computer interface (BCI) is a device that uses brain signals to provide a non-muscular communication channel [20], particularly for individuals with severe neuromuscular disabilities. The P300 event-related potential, evoked in scalp-recorded electroencephalography (EEG) by external stimuli, has proven to be a reliable response for controlling a BCI [7]. Recent studies have demonstrated that a P300-based BCI trained on a limited amount of data can serve as an effective communication device [2][15][16]. In addition, more advanced feature extraction and classification procedures have been implemented, greatly improving the classification performance beyond those reported by Farwell and Donchin [7]. Several classification techniques have demonstrated notable performance for the P300 Speller, including stepwise linear discriminant analysis [2][11][15], support vector machines [9], wavelets [1] and matched filtering [16]. This recent progress has verified the capabilities of P300-based BCI systems and provided the impetus for efforts to improve the speed and accuracy performance of the paradigm.

This study extends the method of common spatial patterns (CSP) for application to P300 classification. By incorporating time-delay embedding and non-centered covariance matrices into CSP, the prominent spatio-temporal components can be identified and visualized from the resulting decomposition. These components differ from simple ensemble averaged waveforms in that they represent the spatio-temporal features that provide the best separation between the two classes in terms of variance. Therefore, CSTP can be used to provide a full spatio-temporal visualization of the prominent patterns attributed to each class, as well as a subspace decomposition to aid classification.

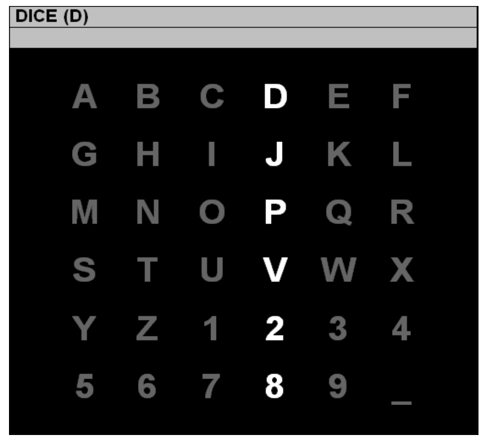

Fig. 1. The 6x6 matrix used in the current study. A row or column flashes for 100 ms every 175 ms. The letter in parentheses at the top of the window is the current target letter 'D'. A P300 should be elicited when the fourth column or first row is flashed. After the flash sequence for a character epoch, the result is classified and online feedback is provided directly below the character to be copied.

The P300 Speller

The P300 Speller described by Farwell and Donchin [7] presents a 6 X 6 matrix of characters as shown in Figure 1. Each row and each column are flashed in a random sequence. The user focuses attention on one of the 36 cells of the matrix. The sequence of 12 flashes, 6 rows and 6 columns, constitutes an Oddball Paradigm [6] with the row and the column containing the character to be communicated constituting the rare set (targets), and the other ten flashes constituting the frequent set (standards). Items that are presented infrequently (the rare set) in a sequential series of randomly presented stimuli will elicit a P300 response if the observer is attending to the stimulus series. Thus, the row and the column containing the target character will elicit a P300 when flashed, because this constitutes a rare event in the context of all other character flashes.

II. Common Spatio-Temporal Patterns

The method of common spatial patterns (CSP) [8][10] determines an optimal set of spatial filters for discriminating between two classes. It has proven successful for sensorimotor BCI applications [4][13][18][19], but can also be modified to handle non-oscillatory signals such as slow cortical potentials [3]. However, standard CSP does not consider the short-time temporal characteristics of the data, such as the phase relationships between channels and frequency bands. The methods of common spatio-spectral patterns (CSSP) [12] and common sparse spectral spatial patterns (CSSSP)[5] extend the spatial filtering approach to include time delay embedding in order to create a more flexible spatial-spectral filter. Because the filtering matrices produced by these methods are temporally sparse, it is not as straightforward to extract the representative spatio-temporal patterns for visualization purposes.

The method of Common Spatio-Temporal Patterns (CSTP) presented here also utilizes time delay embedding. In this case, uniform temporal sampling is used to construct the filtering matrix, enabling a more complete visualization of the discriminable spatio-temporal patterns for the two classes.

The CSP decomposition of a feature matrix is given as:

$$Y = WX \tag{1}$$

where X is an N feature $\times$ T observance matrix, W is an L $\times$ N matrix (L$\leq$N) whose L rows represent the individual components of the decomposition, and Y is an L $\times$ T matrix subspace of X. For a two-class problem, W can be determined such that the resulting projections corresponding to the extreme eigenvalues of the transformed covariance matrices have maximal variance for one class and minimal variance for the other class. First, for the two classes (1 and 2), the class-labeled observations are sorted by the respective class and the class-specific covariance matrices are determined:

$$\Sigma_1 = X_{(1)}X_{(1)}^T \;\; and \;\; \Sigma_2 = X_{(2)}X_{(2)}^T \tag{2}$$

Since the P300 is characterized by amplitude deflections relative to the baseline EEG, the non-centered covariance matrices [3] should be computed in this case. The object of CSP is to determine the transformation W which creates projections that simultaneously maximize the variance for one class and minimize the variance for the other:

$$W\Sigma_1 W^T = D \;\; and \;\; W\Sigma_2 W^T = I - D \tag{3}$$

where D is a diagonal matrix with elements in [0,1]. This can be accomplished through simultaneous diagonalization of the two covariance matrices. First, a whitening transformation is performed:

$$P(\Sigma_1 + \Sigma_2)P^T = I \tag{4}$$

Using spectral theory, the eigenvalue decomposition is then performed for the transformed classes:

$$P\Sigma_1 P^T = RDR^T \;\; and \;\; P\Sigma_2 P^T = R(I - D)R^T \tag{5}$$

where the columns of R are the eigenvectors and the diagonal elements of D and $(D - I)$ are the eigenvalues of classes 1 and 2, respectively. Note that the maximum eigenvalues for one class correspond to the minimum eigenvalues for the other class. By selecting only the eigenvectors corresponding to the largest and smallest eigenvalues that provide the best discrimination between classes, the subspace projection matrix is defined as:

$$\tilde{W} = \tilde{R}^T P \tag{6}$$

For standard CSP analysis of EEG, the features of X are simply the instantaneous bandpass filtered voltages at each electrode. For CSTP, the features are the concatenation of time-windowed voltages for each electrode. The actual EEG patterns corresponding to the two mental states can be visualized by inverting the filtering matrix W.

III. Data Collection and Processing

A. Participants

Seven able-bodied people (six men and one woman ages 24-50) participated in this study. The participants varied in their previous BCI experience, but all participants had either no experience or less than 10 sessions with a P300-based BCI system. The study was approved by the New York State Department of Health Institutional Review Board, and each participant gave informed consent.

B. Task, Procedure, and Design

The participant sat upright in front of a video monitor and viewed the matrix display. The task was to focus attention on a specified letter of the matrix and silently count the number of times the target character flashed, until a new character was specified for selection. All data was collected in the copy speller mode: words were presented on the top left of the video monitor and the character currently specified for selection was listed in parentheses at the end of the letter string (see Figure 1). Each session consisted of nine experimental runs; each run was composed of a word or series of characters chosen by the investigator. This set of characters spanned the set of characters contained in the matrix and was consistent for each participant and session. The rows and columns were flashed for 100 ms with 75 ms between flashes. One character epoch (i.e., one trial) consisted of 15 flashes of each row and column. Each session consisted of 36 character epochs, equivalent to 6480 stimuli (row/column flashes).

C. Data Acquisition

The EEG was recorded using a cap (Electro-Cap International, Inc.) embedded with 64 electrode locations distributed over the entire scalp, based on the International 10 - 20 system [17]. All 64 channels were referenced to the right earlobe, and grounded to the right mastoid. The EEG was bandpass filtered

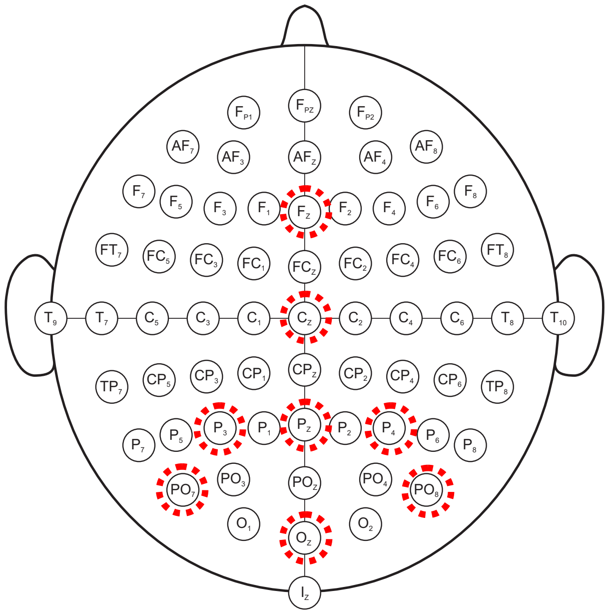

Fig. 2. The electrode montage used in the current study [11]. The eight electrodes selected for analysis are indicated by the dashed circles.

0.1 - 60 Hz and amplified with a SA Electronics amplifier (20,000X), digitized at a rate of 240 Hz, and stored. All aspects of data collection and experimental procedure were controlled by the BCI2000 system [14].

D. Preprocessing and Classification

The channel selection and data preprocessing methods are based on [11]. The eight-channel ear-referenced subset shown in Figure 2 was used. For each channel in the subset, 800 ms segments of data following each flash were extracted. The segments were then moving average filtered and decimated by a factor of 12. The resulting data segments were concatenated by channel for each flash, creating a single feature vector of 128 features (192/12 samples X 8 channels) for construction of the covariance matrices. The CSTP weight matrices were derived using each participant's first session and tested on the four subsequent sessions. Various combinations of the CSTP projections representing the extreme eigenvalues for both the targets and standards were classified using Fisher's Linear Discriminant (also trained on the first session).

IV. Results

The classification results are provided in Table I. The classification results using stepwise linear discriminant analysis (SWLDA) and Fisher's Linear Discriminant (FLD) on the raw feature vectors (without performing CSTP) are also provided for comparison purposes [11]. It should be noted that linear classification using all CSTPs should, theoretically, be equivalent to FLD results since they both equate to a linear transformation of the data in its entirety.

Due to the uniform temporal sampling, the actual spatio-temporal patterns can be visualized by inverting the CSTP filtering matrix W. A sample of the patterns representing the extreme eigenvalues for each class is illustrated in Figure 3.

TABLE I

The average classification accuracy (% correct) for the 4 test sessions using all 15 flash sequences. The leftmost column indicates the prominent CSTPs (ordered by eigenvalue) for each class (standards (S) and targets (T)) used for classification. The CSTP combination(s) that produced the highest accuracy is bolded for each participant. FLD and SWLDA are included for comparison purposes [11].

CSTP		**Participant**						
S	**T**	**A**	**B**	**C**	**D**	**E**	**F**	**G**
1	X	49.3	4.7	75.7	79.9	63.9	51.0	26.4
2	X	2.1	1.3	2.1	4.2	88.2	6.2	54.9
3	X	2.1	4.0	3.5	3.5	13.9	5.6	17.4
4	X	6.3	4.0	4.9	11.1	9.7	2.7	2.1
5	X	6.9	6.7	2.8	1.4	5.6	11.2	6.9
1:5	X	54.9	6.7	75.0	78.5	88.9	60.6	74.3
1:10	X	55.6	12.0	81.9	78.5	90.3	63.9	76.4
1:20	X	61.8	16.8	79.2	79.9	95.8	59.8	81.3
X	1	**95.1**	6.7	93.8	94.4	96.5	83.0	97.2
X	2	12.5	8.1	32.6	6.3	7.6	1.3	4.2
X	3	4.9	4.7	15.3	18.8	2.8	2.7	22.2
X	4	7.6	5.4	9.7	7.6	0.7	0.7	2.8
X	5	16.0	4.0	2.1	0.0	2.8	7.4	6.3
X	1:5	93.8	14.8	95.1	94.4	96.5	83.7	97.2
X	1:10	93.1	12.8	94.4	93.8	96.5	87.8	97.2
X	1:20	94.4	66.4	93.8	95.8	96.5	87.8	96.5
1	1	93.1	6.7	93.8	96.5	96.5	87.1	**97.9**
1:5	1:5	92.4	18.8	95.8	96.5	**97.2**	87.8	97.2
1:10	1:10	92.4	17.5	**97.2**	95.8	**97.2**	**89.9**	97.2
1:20	1:20	93.8	**68.4**	95.1	**97.2**	**97.2**	**89.9**	**97.9**
FLD		94.4	74.5	94.4	95.8	97.2	90.5	97.9
SWLDA		93.8	71.8	93.8	98.6	98.5	90.6	97.9

V. Discussion

The classification results from Table I indicate that CSTP is capable of producing a P300 subspace decomposition that identifies the discriminable information of the responses. The results suggest that this information is often contained in the first few components (extreme eigenvalues) of the subspace for each condition. A lack of obvious eigenvalue extrema is indicative of response variability (as is evident for Participant B). Often, the most prominent component associated with the targets accounted for the majority of discriminable information. However, the most prominent component associated with the standards also contains significant information for discrimination. In general, the other components from the target and standard classes do not provide a significant individual contributions. Nevertheless, when used in combination, these components tend to improve classification slightly with diminishing returns. Depending on the chosen CSTP subspace, the classification results are comparable with results generated by FLD and SWLDA classification on the raw data. However, since more than one prominent CSTP component appears to account for response variability, the CSTP subspace may best be utilized with a more advanced nonlinear or ranking-based classification scheme that accounts for this variability.

The spatio-temporal patterns representing the extreme eigenvalues illustrated in Figure 3 are from a participant

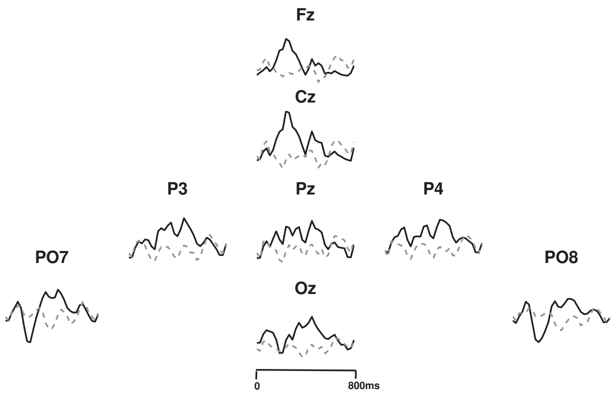

Fig. 3. Sample CSTP patterns from Participant G representing the most extreme eigenvalue for the targets (solid) and standards (dashed).

exhibiting very stable P300 responses, having little variability. Therefore, the patterns closely resemble the ensemble averages of the responses as evidenced by the classical P300 waveforms at Fz and Cz for the targets and the oscillatory waveforms at the occipital locations for the standards (a result of the unattended periodic flashing). However, this is not necessarily always the case since the patterns account for information from both conditions. The true utility of this visualization is to identify and characterize additional patterns, other than those represented by the single eigenvalue extreme for each condition, that contribute favorably to classification.

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