

Spatio-temporal Linear Discrimination for Inferring Task Difficulty from EEG

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Abstract- We present a spatio-temporal linear discrimination method for single-trial classification of multi-channel electroencephalography (EEG). No prior information about the characteristics of the neural activity is required—i.e. the algorithm requires no knowledge about the timing and/or spatial distribution of the evoked responses. The algorithm finds a temporal delay/window onset time for each EEG channel and then spatially integrates the channels for each channel-specific onset time. The algorithm can be seen as learning discrimination trajectories defined within the space of EEG channels. We demonstrate the method for detecting auditory evoked neural activity and discrimination of task difficulty in a complex visual-auditory environment.

I. INTRODUCTION

Non-invasive monitoring of neural activity during performance of a complex task offers the potential for new classes of human computer interfaces that adapt to a user's cognitive state. Such neural based cognitive interfaces could be employed to modulate and/or direct information delivery via detection of neural signals that provide information difficult to access through behavioral measures. The cognitive user interface is thus one class of a brain-computer interface (BCI) [1], with the goal being to augment performance of healthy subjects through exploitation of neural signals correlated with task workload, perceived error rate, perceived novelty, etc.

Our previous work has demonstrated that linear spatial integration of high-spatial density EEG can be used to detect single-trial signatures of error-related negative (ERN), and that these signatures can be used to improve the combined human-machine performance during a high-throughput visual discrimination task [2]. The methodology uses spatial integration of the EEG sensors to identify components that maximally discriminated between correct and incorrect trials [3]. These components were identified by training a linear discriminator at predefined (fixed) temporal windows, the timing of which was determined via knowledge of the trial-averaged event related potential (ERP). For example, to detect a single-trial signature of the ERN, a window between 100-150ms post-stimulus was used. The linear discriminator constructs a hyperplane in the space of the sensors to separate trials based on a pre-labeled set of training data—for example in the case of ERN EEG, labels for error vs. non-error trials. However, this method does not explicitly consider temporal variations between electrodes that might be useful for differentiating between task conditions. This is particularly

important in cases when the task is complex and there is no clear event timing relative to which one can train a classifier.

In this paper we describe a spatio-temporal linear discriminator for automatically learning “discrimination trajectories” between two conditions. We apply the discriminator for differentiating (single-trial) task difficulty in a complex visual-auditory environment. This environment and the experimental paradigm are based on previous EEG-based workload studies showing modulation of auditory evoked responses as a function of task difficulty [4], though these previous studies considered trial-averaged responses. We compare results to our previous single-trial methods and show statistically significant discrimination of task difficulty assessed via receiver operating characteristic (ROC) analysis.

II. METHODS

A. Spatio-temporal linear discrimination

In our previous work (e.g. [2][3]) we used a spatial linear discriminator (LD) to discriminate between two conditions, i.e.

$$y = \sum_i v_i x_i(t), \quad (1)$$

where logistic regression (LR) is used at fixed temporal windows to compute an optimal set of spatial weights, v , for the channel array. i indexes the channels (sensors) and $x_i(t)$ is the data recorded from channel i . The v_i 's are optimized to maximally discriminate between two labeled classes of EEG activity. The window onset time can be chosen given prior knowledge of the task/stimulus—e.g. P300 component in oddball tasks [5], N170 in face detection [6], etc.

An assumption of this method is that the discriminating activity occurs within a fixed window of time (e.g. relative to a stimulus or response) and therefore the spatial weights are applied at a fixed time. However, the temporal dynamics of spatially distributed brain activity may in some cases make it difficult to find a single “optimal” time window that is most discriminating. One solution is to search across all possible time windows. However such a procedure is computationally intensive and does not consider the issue of the time dependent activity of individual sensor. For example, activity optimal for discriminating between two conditions may in fact be a trajectory in sensor space—i.e. discriminating hyperplanes in which the optimal subspace for discrimination is a function of time. In addition, when considering a complex task, where minimal prior information may be available for defining the temporal windows or subjects may use different

strategies and which the underlying neural activity between subjects may be highly variable, a more flexible procedure is required to identify the spatio-temporal patterns in the sensor array that are optimal for discriminating task conditions.

To address this problem, we develop a spatio-temporal LD method where optimal temporal windows are automatically identified for each channel. These windows are then used to train the spatial weights of a linear discriminator.

Let τ represent the temporal shift (or window onset time) of each channel. The LD equation can be rewritten as,

$$y = \sum_i v_i x_i(\hat{\tau}_i), \quad (2)$$

where for each channel i , $\hat{\tau}_i$ is the window onset time that results in the largest area under the ROC curve (A_z),

$$\hat{\tau}_i = \underset{\tau}{\operatorname{argmax}} A_z(b_i(\tau)), \quad (3)$$

where $b_i(\tau)$ will be defined below.

To find the optimal window onset times, we compute the separability of the two labeled classes of brain activity, individually for each channel, by evaluating each sensor's A_z value as a sliding window is moved across a predefined time period. The window onset time with the highest A_z value, for each channel, is then used as the window onset time for spatial integration. Moreover, since the data is noisy and nearby sensors are highly correlated, we model the spatial correlation before computing the individual A_z values,

$$b_i(\tau) = \sum_j A_{ij} x_j(\tau), \quad (4)$$

where x and i are the same as in (1), and A_{ij} represents spatial correlations between neighboring sensors and is given by,

$$A_{ij} = \alpha^{d(i,j)}. \quad (5)$$

Here $d(i, j)$ is the Euclidian distance between sensors i and j as computed from the lattice shown in Fig. 1, where each unit of the lattice has a length of one. α is a constant: $0 \leq \alpha < 1$. In our analysis, we set α to be 0.2.

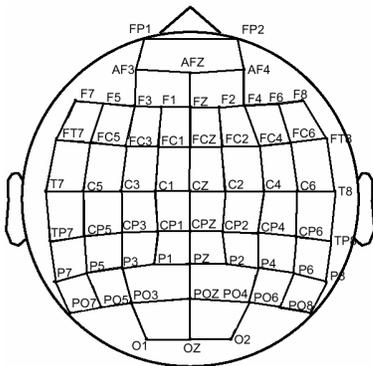


Fig. 1. Lattice across the sensor array defining the spatial correlations. The distance of each unit is one.

In our experiments, we compute A_z using a leave-one-out (LOO) procedure, and this is used as the measure of the

algorithm's performance. A significance level for A_z is determined via a bootstrapping procedure whereby the LOO procedure is repeated given a randomization of the truth labels for each trial. This procedure is repeated 30 times to construct a distribution of A_z for the randomly labeled trials and we use this distribution to estimate the significance level $p < 0.05$.

B. Experimental paradigm

During the experiment, subjects play a video game for approximately an hour in which the difficulty alternates between two possible states: hard or easy. In the game, the subject controls a ship (using left/right arrow keys) and attempts to avoid oncoming torpedoes fired by a fleet of submarines. Submarines are colored yellow or green and move across the screen, left or right, underwater. A submarine shoots a torpedo at the ship with a certain probability of releasing a torpedo if the ship is directly above it. The workload (task difficulty) is controlled by varying the probabilities with which torpedoes are emitted, and by toggling whether the subject should perform a secondary task. The secondary task requires the subject to detect changes in submarine color and/or direction by pressing the "up arrow" key as soon as they detect a change. A "hard" block is defined as one in which torpedo probability is high ($p \approx 1.0$) and the subject is required to perform the secondary task. An "easy" block is one in which the torpedo probability is low ($p \approx 0.2$) and no secondary task is performed. Blocks randomly alternate between hard and easy.

During the play of the video game 1300Hz auditory tones having 20ms duration are played, randomly distributed in each 5-minute block. Within each block the number of auditory tones ranges from 20-30. During play of the game, the subjects may be asked, for some of the blocks, to silently count the number of tones within the block. Thus, the experiment can be divided into four conditions: Easy game with counting (EC), easy game without counting (ENC), hard game with counting (HC), and hard game without counting (HNC). Our goal is to discriminate between these four conditions by analyzing the neural activity evoked by the auditory tone. Specifically, we wish to infer task difficulty (hard vs. easy) through analysis of the auditory evoked response.

The experiment is challenging in terms of analysis of the EEG both because of the complex visual-auditory stimuli as well as the free-viewing and response conditions that make it a "real-world" task. For example, broad and frequent eye movement artifacts are generated by the subjects as they search for torpedoes and/or submarine changes. Motor activity also potentially generates artifacts and confounds. Previous work on inferring task difficulty and workload has focused on more controlled experimental paradigms [4]. Our goal is to demonstrate that our single-trial linear methods can be used to infer task difficulty even during realistic real-world tasks.

D. Subjects

Five young subjects (3 females and 2 males, mean age 28 years, right-handed) volunteered for the experiment. All

subjects had normal or corrected to normal vision and reported no history of neurological problems. Informed consent was obtained from all participants in accordance with the guidelines and approval of the Columbia University Institutional Review Board.

E. Data acquisition and preprocessing

EEG data are recorded in an electrostatically shielded room (ETS-Lindgren, Glendale Heights, IL) using the Sensorium EPA-6 Electrophysiological Amplifier (Charlotte, VT). The sampling frequency is 1000 Hz. Sixty Ag/AgCl scalp sensors mounted on a standard electrode cap (Electro-Cap, Eaton, OH) are recorded (see Fig. 1). Three periocular electrodes placed below the left eye and at the left and right outer canthi are used to record eye movements. All channels are referenced to the left mastoid and chin ground.

After the data are acquired, a software-based second-order 0.5 Hz Butterworth high pass filter is used to remove DC drifts and a sixth-order Butterworth 40Hz low-pass filter is applied to remove high frequency noise. Stimulus events recorded on separate channels are delayed to match latencies introduced by filtering EEG. Eye-blink and eye-movement activities are recorded prior to the task so that these artifacts can be removed from the EEG recordings [7].

III. RESULTS

A. Auditory-evoked response detection

To test our spatio-temporal LD method, we first evaluate the ability of the algorithm to detect, single-trial, activity evoked by the auditory tone while the subjects play the video game. In particular, we use our spatio-temporal LD algorithm to discriminate between 3 seconds before the auditory tone and the period up to 1 second after the tone. Three subjects participated in this experiment. The length of each time window for classification is set to be 50ms (50 data points). Results are shown in Fig. 2. The top panel shows the temporal shift/window onset (in millisecond) for each channel. The second panel illustrates the spatial weights for the specific onset time for each channel. Trial-averaged ERP studies have identified well-known auditory-evoked responses [8][9]. For the first subject, the optimal time window for centro-frontal and central areas is about 340-390ms, which corresponds to the peak ERP amplitude within this area (see bottom panel in Fig. 2). For subjects 2 and 3, there is a third negative component. We see from Fig. 2 that the best discriminating window onset time for the second subject's fronto-central electrodes is when this late negativity dominates. In this case the sign of spatial weights is reversed relative to subject 1 because of the negativity. For subject 3, the temporal delays and spatial weights are similar to those for subject 1, but as the positive component is much earlier (around 200ms), the optimal window onset times are also earlier (from 190-240ms for the central electrodes).

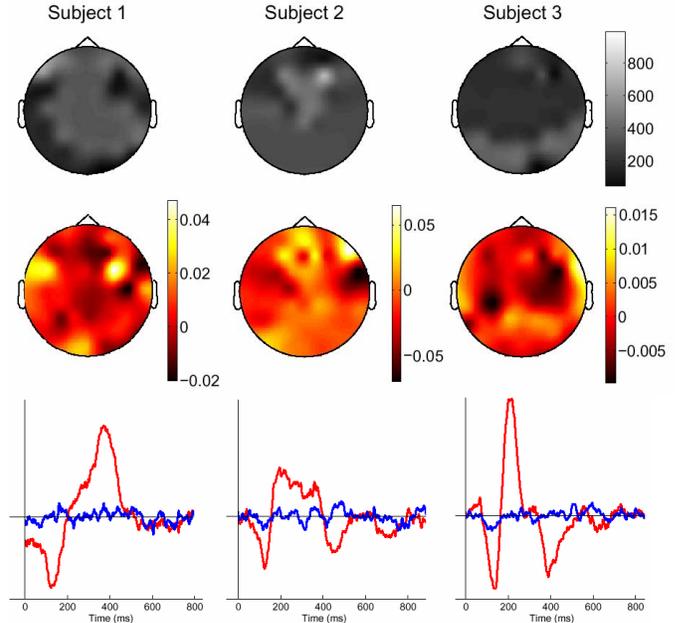


Fig. 2. Single-trial spatio-temporal LD of auditory-evoked responses during video game play. Each column corresponds to a subject. Top row: temporal delay/window onset time for each channel (in milliseconds). Second row: spatial weights for each channel at the window onset time. Third row: subjects' trial averaged ERPs for channel CZ. The red curve shows auditory-evoked response; the blue curve shows mean brain activity 3 seconds before the auditory stimulus. The vertical lines at 0ms mark the onset of auditory stimuli.

In Fig. 3 we compare our spatio-temporal LD and the fixed-time LD. We find all discrimination results are significant and that in most cases the spatio-temporal LD method results in better performance than the fixed window LD method. In addition there is significant variation in the A_z values for the fixed window method indicating sensitivity to the precise window onset time that is chosen.

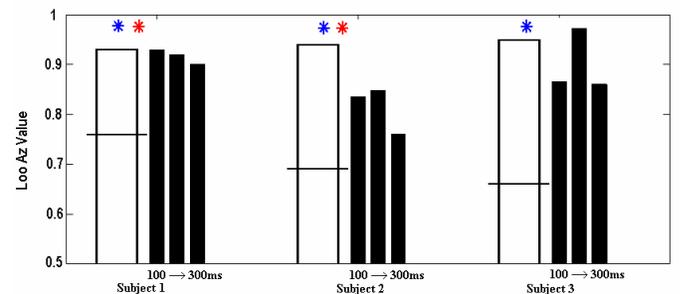


Fig. 3. Comparison of spatio-temporal LD with the fixed window LD method. The white bars show the A_z values using the spatio-temporal LD method. The horizontal lines show the $p=0.05$ significance level for A_z values (see Methods). A_z values greater than this are considered significant and blue stars indicate results that are above this significance level. Black bars indicate A_z values for the fixed window algorithm where window onset times are manually set between 100-300ms (100, 200, 300ms), relative to stimulus (auditory tone) onset. Red stars mark those cases where the spatio-temporal LD method has a higher A_z than the fixed window for all three window onset times.

B. Discriminating task conditions

We next evaluate the utility of using the spatio-temporal LD to infer task difficulty from the auditory evoked response. Three subjects participated in this experiment. As mentioned earlier, task conditions can be divided into four groups: EC, ENC, HC, and HNC. Fig. 4 is a matrix of the A_Z values for the discrimination of each condition. Using the same format as Fig. 3, the A_Z values for the spatio-temporal LD method are presented with white bars and the fixed window method with black bars. We see that in most cases (indicated with blue stars) our discrimination of task conditions with the spatio-temporal LD is significantly better than chance. In addition, in about half of the cases the completely automated spatio-temporal LD method gives results better than any of the fixed window methods. Also important to note is that for the cases where the fixed window method performs better than the spatio-temporal LD, there is no consistency in terms of which fixed window gives the best results. The only case in which the spatio-temporal LD performance is not significant is for the EC vs. HNC case, which is understandable given the workload difference between EC and HNC is the smallest among all the conditions.

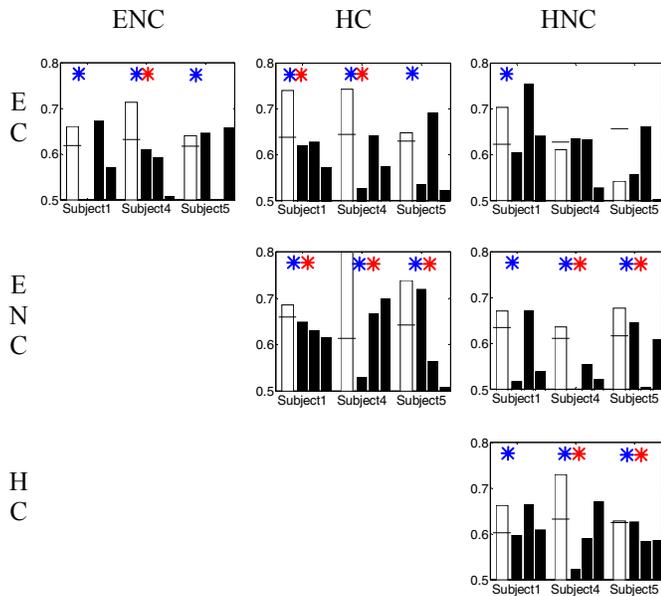


Fig. 4. Comparison between classification results- A_Z values using spatio-temporal LD (white bars) and traditional LD method (black bars) for discriminating different task conditions. Horizontal lines show the $p=0.05$ significance level for A_Z values (see Methods). A_Z values greater than this are considered significant and blue stars indicate results that are above this significance level. Red stars mark those cases where the spatio-temporal LD method has a higher A_Z than the fixed window for all three window onset times.

IV. CONCLUSION

In this paper we describe a spatio-temporal linear discriminator for differentiating between task conditions, learning a low dimensional discrimination trajectory in sensor space. The method exploits high-spatial density arrays that have become increasingly available for EEG recordings. The algorithm is fast and computationally efficient, and thus the algorithm may prove useful for both BCI systems and cognitive user interfaces.

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