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Locating Spatial Patterns of Waveforms during Sensory Perception in Scalp EEG

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***Abstract*— The spatio-temporal oscillations in EEG waves are indicative of sensory and cognitive processing. We propose a method to find the spatial amplitude patterns of a time-limited waveform across multiple EEG channels. It consists of a single iteration of multichannel matching pursuit where the base waveform is obtained via the Hilbert transform of a time-limited tone. The vector of extracted amplitudes across channels is used for classification, and we analyze the effect of deviation in temporal alignment of the waveform on classification performance. Results for a previously published dataset of 6 subjects show comparable results versus a more complicated criteria-based method.**

I. INTRODUCTION

The hypothesis is that brief bursts of oscillatory activity in the brain's electric fields, which are phase synchronized across space, carry information by their spatial amplitude patterns—that is, there is a specific spatial amplitude modulation pattern of some waveforms in EEGs that are indicative of the underlying sensory processing. These spatio-temporal patterns in the EEG are referred to as 'frames' [1]. In [2], the authors characterized frames at specific frequency bands and proposed criteria for identifying them. The authors studied the 'frames' as global spatial patterns related to sensory perception and showed these patterns can be used to discriminate simultaneous visual-auditory stimuli [2].

The procedure in [2] for identifying frames consists of linear filtering followed by a series of acceptance criteria. After narrowband filtering the EEG at predefined frequencies, the Hilbert transform is used to estimate the analytic phase and amplitude of the filtered signal. First, sets of contiguous time samples were identified where the instantaneous frequency was within the passband and consecutive samples had the same channels at the minimum and maximum phase. Sets of more than 3 contiguous samples are then considered candidate frames. Candidate frames were discarded if the average instantaneous frequency or the spatial phase gradient were not within specified ranges. Finally, frames were kept if every sample was within thresholds for minimum instantaneous spatial variance and maximum instantaneous phase variance. These thresholds were determined to maximize classification rate. The feature vector consisted of the analytic power across channels at the time point within the frame when the total analytic power was maximal. Due to the numerous criteria, some of which require the electrode spacing, care must be taken when applying this method.

In this paper, we propose a simplified approach to identify spatial amplitude patterns associated with brief bursts of oscillatory activity or frames. The simplification is motivated by the fact that we are searching for frames that are temporally localized, but whose exact temporal location may shift between trials. Thus, we search over time lags to find the largest multichannel response to a predefined waveform. The predefined waveform constrains the temporal and frequency aspects of the frame. In essence, it is a single iteration of multichannel matching pursuit performed on each waveform and trial separately. Matching pursuit [3] has been used to find multichannel (space-time-frequency) atomic decompositions of EEG [4]. Here we use only the first atom for classification. We use a set of gamma-envelope modulated tones as the waveform dictionary and search for the best temporal alignment of the waveform per trial and per waveform. Classification is based on projections of the channel-wise amplitudes and is performed for each waveform separately.

We highlight a key improvement over the original application of multi-channel matching pursuit [4]. To avoid phase changes across channels we use the analytic amplitude estimated via the Hilbert transform instead of the inner product. This allows smooth amplitude changes across different channels that are marginally out of phase with each other. This approach identifies the temporal location and spatial amplitude modulation of a waveform.

We test the method's ability to discriminate different visual-auditory conditioning stimuli using only the spatial pattern of amplitude of the most prominent waveform expressed as a feature vector. We evaluate our method on a 64-channel EEG dataset with 6 subjects [5]. For 5 out of 6 subjects the approximation shows statistically significant classification at rates comparable to the previous algorithm [2].

II. METHOD

The overall method incorporates frame identification and binary classification of EEG trials and is covered in three

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steps:

- *A. Waveform Dictionary*: Define a dictionary of complex valued waveforms localized in frequency and time. Each waveform is the sum of a real-valued waveform and its Hilbert transform. Here we use Gamma-modulated tones as the base waveforms, but Morlet/Gabor wavelets or others may be used.
- *B. Frame Identification*: For each waveform, find its temporal alignment that maximizes the sum of the absolute value of the inner-products, and record the vector of absolute values from the channels, the spatial amplitude vector. Frame identification is performed independently on each trial without knowledge of the class label.
- *C: Classification*: Use the spatial amplitude vector for classification. In this work, we use the first two principal components before using nearest–centroid classification. The class means are estimated from examples in the training set. The remaining trials are assigned to the nearest class mean, and classification performance is evaluated.

A. Waveform Dictionary

Let $\mathbf{x} \in \mathbb{C}^N$ be a frame waveform, which corresponds to the temporal aspect of the spatio-temporal frame. The frame waveform we use is the "analytic" signal version of a real discrete-time waveform. The discrete-time Hilbert transform estimate of the "analytic" signal [6] of a candidate waveform $\mathbf{m}$ is $\mathbf{x} = \sqrt{-1}h(\mathbf{m}) + \mathbf{m}$ where $h(\cdot)$ denotes Hilbert transform. The Hilbert transform is realized by filtering; for discrete time signals $h(\mathbf{m})$ can be efficiently computed as multiplication in the frequency domain using the FFT and is implemented in the MATLAB function `hilbert`. Frame identification involves taking the inner-product of the waveform with the signal at different lags (convolution); thus, the waveform can be thought of as a time-reversed filter. Since filtering commutes, performing the Hilbert transform on the waveform before convolving with the signal of interest is equivalent and much faster than taking the Hilbert transform of the convolved signal. The Hilbert transform provides a very smooth estimate of the signal peak (as seen in Fig. 1), which will be essential to find the peak across multiple channels that have different phases.

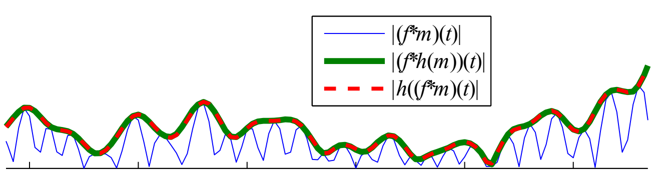

Fig. 1. Comparison of the amplitude of a filtered signal $|(f * m)(t)|$, the "analytic" amplitude (using the Hilbert transform) of a filtered signal $|h((f * m)(t))|$, with the amplitude of a signal filtered with a "analytic" filter $|(f * h(m))(t)|$. There is no noticeable difference in the latter two.

For candidate waveforms, we chose second-order gamma enveloped sinusoids because of the differential rise and fall time often seen in neural oscillations [7]. The base waveform for center frequency f_c is $m(n) = g(n)\sin(2\pi f_c n)$ where the envelope $g(n) = n^2 e^{-2\pi b n}$ has bandwidth b. In particular, we chose 15 center frequencies evenly spaced from 15Hz to 64Hz and a bandwidth of $7.7Hz$ for analysis—a similar choice and more discussion of the effect of bandwidth on the distribution of intervals between minima in the analytic amplitude of filtered EEG signals can be found in [2]. See Fig. 2 for resulting waveforms. The choice in waveforms can vary; we found that using Gamma envelopes performed better than Gaussian envelopes (Gabor wavelets).

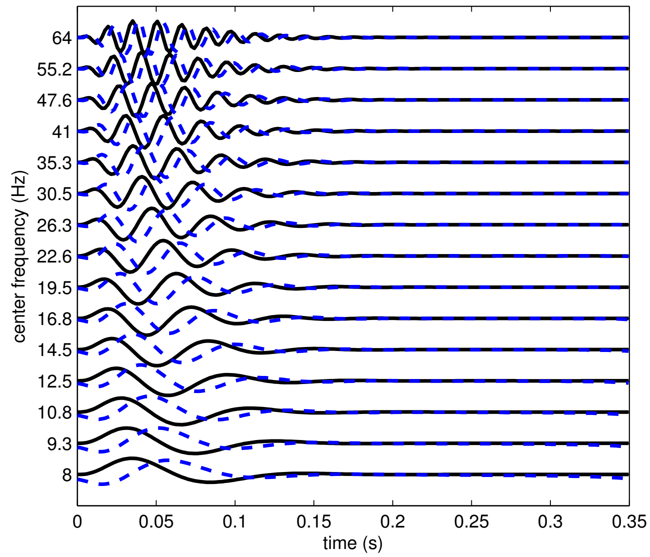

Fig. 2. Frame waveforms $\mathbf{x}$, black solid lines are real components $\mathbf{m}$ and dashed blue lines are imaginary components derived from the Hilbert transform $h(\mathbf{m})$. The length of the waveforms is 180.

B. Frame Identification

Let $Y = [\mathbf{y}_1 \cdots \mathbf{y}_M] \in \mathbb{R}^{L \times M}$ be a L length window of EEG from M channels and $\mathbf{x} \in \mathbb{C}^{N \times 1}, N \leq L$ be a particular temporal frame waveform. A frame is characterized by the temporal waveform $\mathbf{x}$, its temporal alignment $\tau^\star \in \mathbb{Z}$, and its channel amplitudes $\mathbf{v} = [v_1 \cdots v_M] \in \mathbb{R}^{1 \times M}$. The goal is to align $\mathbf{x}$ to maximize the sum of the inner products with $\mathbf{y}_1, \dots, \mathbf{y}_M$. Define T_τ to be the linear operator $\mathbb{C}^{N \times 1} \mapsto \mathbb{C}^{L \times 1}$ such that $T_\tau \mathbf{x}$ temporally aligns a waveform $\mathbf{x}$ such that it starts at time τ. Then $\tau - 1$ is the number of zeros that need to be pre-padded to $\mathbf{x}$; if $\tau < 1$ the initial $1 - \tau$ elements of $\mathbf{x}$ are truncated, and if $\tau > L - N + 1$ the final $\tau - (L - N + 1)$ elements are truncated. Fig. 3 shows the range of alignments for $\mathbf{x}, \mathbf{y}_m$.

The temporal alignment $\tau^\star$ and channel amplitudes $\mathbf{v}$ are found via (1) and (2).

$$\tau^* = \text{argmax}_\tau \sum_{m=1}^{M} | < \mathbf{y}_m, T_\tau \mathbf{x} > | \quad (1)$$

$$v_m = | < \mathbf{y}_m, T_{\tau^\star} \mathbf{x} > | \quad m = 1, \dots, M \quad (2)$$

For notational compactness, we denote the function $f_\mathbf{x}(.)$ that maps Y, a window of EEG, to the channel amplitudes $\mathbf{v}$ for frame waveform $\mathbf{x}$—that is, $f_\mathbf{x}(Y) = \mathbf{v}, f_\mathbf{x} : \mathbb{R}^{L \times M} \mapsto \mathbb{R}^{1 \times M}$.

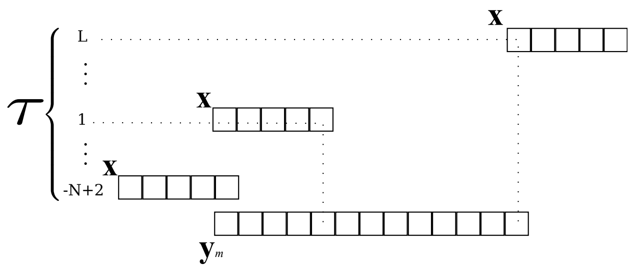

Fig. 3. The possible alignment ranges for $\tau \in \{-N+2, \ldots, 1, \ldots, L\}$ of a frame waveform $\mathbf{x}$ of length N to a single channel of the L-length signal $\mathbf{y}_m$.

C. Classification

We are interested in how well the frame identification can identify common spatial features of sensory perception. We found that using the first two principal components from the matrix of the channel amplitudes across training trials was enough for classification.

Let the set of trials be denoted $\{(Y_i, c_i)\}_{i=1}^{T}$ where $Y_i \in \mathbb{R}^{L\times M}$ are the discrete time sampled EEG traces with L samples and M channels and $c_i \in \{1, 2\}$ is the discrete binary class label.

Let $\mathcal{I}_{\text{train}}, \mathcal{I}_{\text{test}}$ be the indexes of trials for training and testing such that $\mathcal{I}_{\text{train}} \cup \mathcal{I}_{\text{test}} = \{1, \ldots, T\}$ and $\mathcal{I}_{\text{train}} \cap \mathcal{I}_{\text{test}} = \emptyset$. Define a matrix where each column is the channel amplitudes for a trial $V = [f_{\mathbf{x}}(Y_i)^{\mathrm{T}}]_{i\in\mathcal{I}_{\text{train}}}$. Find the singular vector decomposition of $V = USW^{\mathrm{T}}$ such that $U = [\mathbf{u}_1 \cdots \mathbf{u}_{|\mathcal{I}_{\text{test}}|}]$ and W are unitary matrices and S is a diagonal matrix. We project onto the first two eigenvectors denoting the function $g_{\mathbf{x}}(Y) = f_{\mathbf{x}}(Y)[\mathbf{u}_1\mathbf{u}_2]$.

We choose a simple nearest centroid method as our classifier. Here we do not use the temporal timing of the frame $\tau^\star$, we will only need the function $g_{\mathbf{x}}$ that gives the projection of the channel amplitudes onto the singular vectors for a particular frame waveform $\mathbf{x}$. The class mean for class k is

$$\bar{\mathbf{v}}_k = \frac{1}{|\mathcal{I}^k_{\text{train}}|} \sum_{i\in\{l\in\mathcal{I}_{\text{train}}:c_l=k\}} g_{\mathbf{x}}(Y_i) \quad (3)$$

where $|A|$ is the cardinality of set A. Each sample in the test set is then classified by the nearest class mean using Euclidean distance.

$$\hat{c}_i = \operatorname{argmin}_k \|\bar{\mathbf{v}}_k - g_{\mathbf{x}}(Y_i)\| \quad i \in \mathcal{I}_{\text{test}} \quad (4)$$

A measure of performance is simply the percent of correct classifications

$$p_{\text{correct}} = \frac{|\{i \in \mathcal{I}_{\text{test}} : \hat{c}_i = c_i\}|}{|\mathcal{I}_{\text{test}}|}. \quad (5)$$

III. Dataset and Results

Data was collected at the Psychology Department of the University of California Berkeley and approved by the UC Berkeley Institutional Review Board. Six male subjects (five right handed) aged 23 to 44 gave informed consent. The original description of the experiment can be found in [5]. Subjects were presented with a combined auditory and visual stimuli: a monitor displayed either a solid red or blue pattern for 125ms and simultaneously either a comfortable loud or much softer 100ms burst of white noise from two speakers on either sides of the monitor. Only three patterns were applied: solid red with a loud tone or a solid blue pattern with a soft tone or a solid blue pattern with a loud tone. The subjects had a keyboard with three keys and were instructed to learn correspondence between the keys and the stimuli by trial and error. The monitor would give text feedback as soon as a key was pressed. There were two blocks: in the first block 180 presentations were given and feedback was also random (no learning was possible), and in the second block 200 presentations were given and correct feedback was given. We are interested in discriminating between the first two classes of sensory cues (red-loud versus blue-soft) from the EEG alone without the key press information.

The EEG was recorded with a 64 electrode cap using the BioSemi™ system. The analog filtering had a pass band of DC to 134 Hz. The sampling rate was 512 Hz. After importing to MATLAB, a digital notch filter was used to remove 60Hz and 180Hz line noise, and a digital high-pass was used with cutoff of 1 Hz. There were at least 50 trials per class per block. Classification performance was tested across 200 Monte Carlo divisions of the trials between 70 trials for testing (35 trials from each class) and the remaining trials for training.

The frame identification and classification was performed for each frame waveform in Fig. 2 in different 0.5s length windows surrounding the sensory cue.

There were 5 subjects $\{S1, S2, S3, S5, S6\}$ with classification performance significantly better than chance $p < 0.01$ (198/200 Monte Carlo runs had better than 50% correct). An example of the classification performance across frequency and different time intervals is shown in Fig. 4. The mean classification rate for the best performing waveform for each subject is shown in Fig. 5.

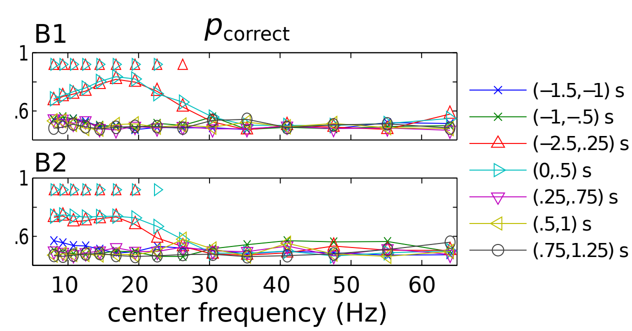

Fig. 4. Example of the classification performance (Subject 1) on both blocks $\{B1, B2\}$, versus the center frequency of the frame waveforms. Each line indicates a different time window relative to the cue from which the frames were extracted. Small markers above traces indicate significantly better than chance classification performance $p < 0.01$ for 200 Monte Carlo runs.

The temporal alignment of the frames for subjects with significant classification in both blocks is shown in Fig. 6.

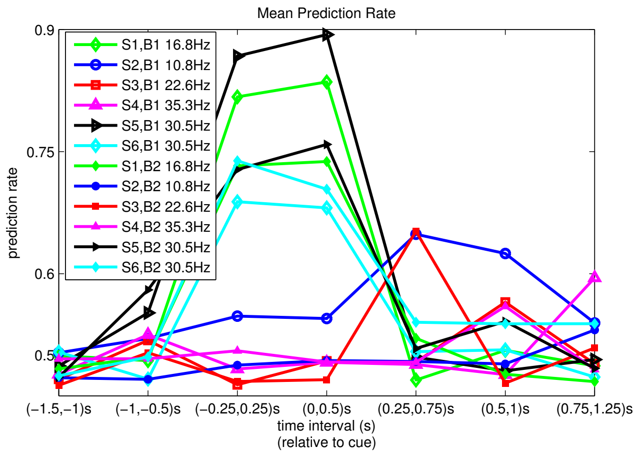

Fig. 5. The mean classification performance, p_{correct} in (5), for the best performing waveform (frequency listed in legend) for each subject. The mean is taken over the 200 Monte Carlo divisions of the trials into test and training sets.

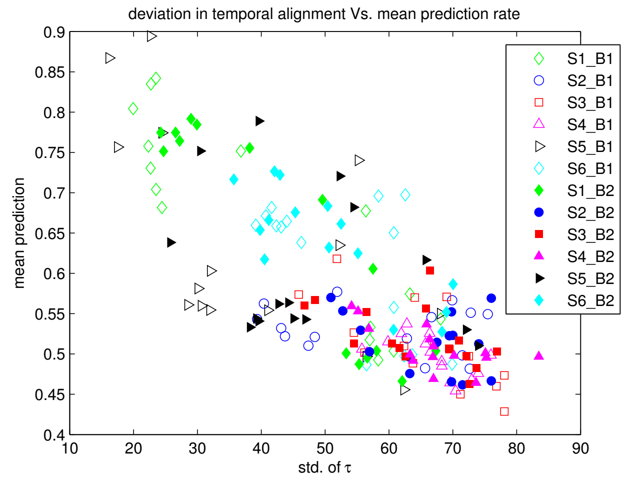

Fig. 7. The standard deviation of frame alignments in class c_1 for all waveforms versus the waveforms prediction performance in the interval(0,0.5)s.

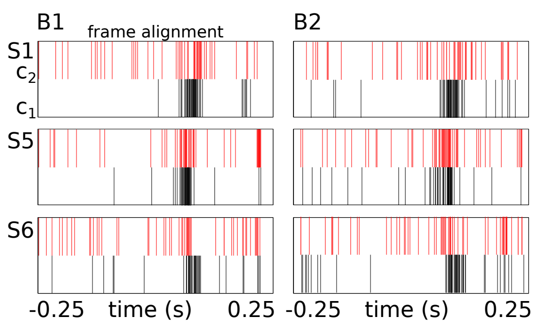

Fig. 6. (Left) The classwise (c_1, c_2) distribution of frame alignments for three subjects, $\{S1, S5, S6\}$, at their best performing frequency $16.8, 30.5, 30.5$Hz respectively. The same waveform is used for both blocks $\{B1, B2\}$ and the time interval (-.25,.25)s is shown.

IV. Discussion

While the method is meant to find global spatial patterns of amplitude modulation irrespective of time lag, we did find a strong inverse correlation between the standard deviation in the timing of the frames and the prediction rate.

A mode in the temporal alignment of the frames for both stimuli is seen in Fig. 6. Whereas, there was no consistent temporal alignment of the frames for the other subjects (data not shown), with almost uniform distribution of frame alignment. Either the subjects do not have consistently timed spatial patterns or the current method is not able to find them.

The relationship between frame timing and prediction is consistent across subjects and within subjects across data blocks as seen in Fig. 7; consequently, the variance of the temporal alignment could be used as pre-classification feature selection criterion. A more comprehensive classifier may choose a set of multiple waveforms that all have low variance in the temporal alignment; however, this approach would need testing on more subjects.

We chose not to make a direct comparison of the proposed method versus the previous work [2] since the previous work uses two classification optimized thresholds. Overall, the results are comparable, but the proposed method is much simpler to implement and requires no knowledge of the electrode location. Thus, it can be readily applied to other datasets such as those used for brain computer interfaces.

V. Conclusion

Brain oscillations are thought to carry prominent signatures of underlaying sensory activity in brain. However, the activity may not be time locked to a trial nor phase locked over the scalp. In this study, we apply a method to find the amplitude modulation of predefined waveforms across multiple EEG channels and utilize the spatio-temporal information to discriminate between two different sensory stimuli. Finding the best alignment of a pre-defined waveform yields significant classification accuracy across five out of six of the subjects.

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