Frequency Peak Features for Low-Channel Classification in Motor Imagery Paradigms

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***Abstract*—The expansion of brain-computer interfaces (BCIs) to outside the research laboratory has historically been hampered by their difficulty of use. Well-functioning BCIs often require many channels, which can be difficult to properly prepare and require expert support. Low-channel setups, however, can lead to poor or unreliable classification of intent. Here we introduce a novel method for extracting more information from a single EEG channel and test it on a ten subject motor imagery dataset. Instead of looking at bandpower or phase synchrony, we test the average frequency within each trial to see if there are task-dependent changes in the spectral locations of neural frequency peaks. We show that using this feature in combination with standard bandpower features is significantly better than bandpower features alone across subjects, both for standard electrodes and electrodes that include a Laplacian filter.**

I. Introduction

Brain-computer interfaces (BCIs) are moving closer and closer to stable use, as evidenced by their inclusion in events like the Cybathlon BCI race [1]. Across the world, BCIs are getting more and more effective and precise [2]–[4]. However, their use is still mostly confined to the laboratory setting, where technicians can ensure that hardware is properly put on; the entire process of setting up can take a half hour or more. More easy-to-use setups exist, but are hampered by signal quality issues. Part of the problem comes from the fact that most current techniques are not very robust with just a few channels, taking advantage of only a small part of the signal. Neuroscience tells us that neural circuits tend to oscillate [5], and these oscillations project to the EEG signal where they can be isolated by bandpassing or other methods. Further, these oscillations can have different spectral locations depending on the makeup of the underlying circuits. The neural frequency bands used by the brain are well known, and so by taking advantage of the properties of these neural oscillations, modern stimulus-independent BCIs have achieved their current performance [6]–[9]. However, we show in this paper that previously unconsidered properties of the EEG can easily and reliably be used to improve decoding performance.

The two major properties of an oscillation are amplitude and phase, both of which have long histories in the realm of BCIs. The easiest and most-used property of neural oscillations in the context of BCIs is the signal power within a given frequency range [10]. To borrow a term from signal processing, we designate this Amplitude Modulation (AM), as the time-domain amplitude is closely related to the power. After being computed, these powers can be used as features for standard machine learning algorithms, and many fundamental methods in BCIs have also been developed using task-induced differences in spectral power such as CSP [11] and the more recent Riemannian approaches [12], both of which have led to substantial gains in performance.

Phase-related features, though more recently exploited, have also enjoyed great success. Mostly, this has happened through measures of phase synchrony, in which two channels are compared to see how often the phases are identical in both [13]. This value for a given time period is used as a feature for a classifier, and has been shown to be useful for BCIs both offline [14]–[16] and online [17]. Outside of identical phases, consistent phase differences [18] and the average instantaneous phase difference [19] have also been used and shown to add new information, allowing for more accurate classification of intentions. These features, however, rely on pairs of channels to be computed and as such increase exponentially with the number of channels.

However, all the oscillation-based measures previously mentioned are restricted by one thing: the frequency. For all the methods above, a frequency range needs to be assumed to compute the AM or phase features. There is, unfortunately, no good range that works for all people. Differences in the spectral location of neural frequency bands have been attributed to many factors. In the particular case of the μ-band, i.e., oscillations in sensorimotor areas that range from 8 to 13 Hz, it has been show to vary with age [20], genetics [21], [22], and psychological factors [23]. Historically, these sorts of changes in the location of the μ peak have only ever been dealt with as reasons to shift the spectral window for further processing–indeed, the general recommendation for motor imagery is to always use a subject-specific μ frequency window [24], [25]. Other sorts of α rhythms, however, have shown themselves to be related to far more transient features. For the parietal α, Haegens et al. 2014 determined that even within an individual and a single recording session the peak frequency of the α band can vary by up to one Hertz [26], and is related to such factors as cognitive load [26], [27].

Given the findings in other neural α frequencies, we hypothesize that the spectral location of the μ peak in a signal may be a good feature for classification. Outside the field of BCI, this average frequency feature has already been attempted in LFP recordings [28], [29] as well as with EEG for non-BCI usage [30], [31]. However, to our knowledge nobody has ever attempted to use this as a feature in standard BCI paradigms. As we believe that the location of the neural oscillations in the frequency domain may be a feature for classification, we designate this approach Frequency Modulation (FM), as it measures the change in location of a spectral peak.

In this paper we present a basic method for extracting the average peak frequency for a given BCI trial and compare FM features versus AM features as well as a joint feature space. We demonstrate that the inclusion of this feature increases average classification in motor imagery paradigms and low-channel setups relative to only AM features.

II. Methods

A. Datasets

Subjects were placed in front of a screen with a centrally displayed fixation cross. Each trial started with a pause of three seconds. A centrally displayed arrow then instructed subjects to initiate haptic motor imagery of either the left or right hand, as indicated by the arrow's direction. After a further seven seconds the arrow was removed from the screen, marking the end of the trial and informing subjects to cease motor imagery. Ten healthy subjects participated in the study (eight males, two females, 25.6 ± 2.5 years old). One subject had already participated twice in other motor imagery experiments while all others were naïve to motor imagery and BCIs. EEG data was recorded from 128 channels, placed according to the extended 10-20 system with electrode Cz as reference, and sampled at 500Hz. BrainAmp amplifiers (BrainProducts, Gilching, Germany) with a temporal analog high-pass filter with a time constant of 10s were used for this purpose. A total of 150 trials per class (left/right hand motor imagery) per subject were recorded in pseudorandomized order, with no feedback provided to the subjects during the experiment.

B. Pre-processing

In order to simulate a reasonable two-channel setup we chose the channels above the left and right motor cortices, respectively C3 and C4. There is also work showing the Laplacian filter to be beneficial in motor imagery imagery paradigms [32]–while a standard discrete Laplacian requires many more channels, there is also work on bipolar and even tripolar [33] designs that can incorporate this sort of filtering into a single electrode. Therefore, we decided to simulate the effect of such filtering on our feature by computing a discrete Laplacian filter and testing our feature again with two simulated Laplacian-filtered electrodes over C3 and C4.

C. Feature Extraction

The neural frequency band used in this analysis, μ, was assumed to be the standard $8 - 13$ Hz for all subjects, in order to limit the possibility of overfitting. In order to ensure the features were compared as fairly as possible, we employed identical preprocessing to generate both AM and FM features. In all cases the signal was initially bandpassed offline with a 3rd order Butterworth filter in the band of interest. To preserve phase, this was done once forwards and once backwards on the full data from each continuous recording.

1) Amplitude Modulation: As the variance of a signal is equal to the sum of the powers in the spectral domain, we use the log variance of the bandpassed signal for a given trial as our amplitude modulation feature. The variance in each channel was computed per trial and the logarithm of the resulting values were used for classification.

2) Frequency Modulation: To calculate the average frequency location for each trial, we employed the Hilbert transform. While the Hilbert transform has been used in BCI before [19], [34], [35] it has exclusively been used to calculate the envelope or phase of a signal–we are the first to look at the instantaneous frequency in the context of BCIs. For each channel and trial, we first used the Hilbert transform to compute the analytic signal of the bandpassed time-series, and then computed the angle of the analytic signal to obtain the instantaneous phase. The instantaneous phase was then differentiated to get the instantaneous frequency. For each trial, the median frequency was chosen from all data points within the trial.

3) Joint feature space: For both paradigms we wanted to compare purely AM and FM features as well as the combination of them. To do this we simply concatenated the two-dimensional feature spaces of each feature type to create an joint four-dimensional feature space. One could also think of this as simply computing two features per channel per trial. As the number of trials is so much higher than the dimensionality of this joint feature space it is very unlikely that the concatenation described here affected results negatively.

D. Classification

In order to better test the raw separability and usefulness of the FM feature in comparison to the AM feature, we used the simplest binary classification tool employed in BCIs: Linear Discriminant Analysis (LDA). While more complicated methods could possibly get far better performance, LDA allows us to better test how separable the data is in multiple dimensions under the most basic assumptions of homoskedastic Gaussianity. In the single-feature cases each trial was represented by a two-dimensional vector and for the joint feature space each trial was represented by a four-dimensional vector. Accuracies were calculated by 10-fold cross-validation within each subject over paradigms and spatial filtering choices.

E. Statistical analyses

To test statistical significance of differences between conditions (AM, FM, or joint feature spaces) within a paradigm, a permutation test was used. We wanted to test two hypotheses: (1) that subject accuracies using only the FM features are significantly higher on average than AM features, and (2) that the joint feature accuracies are significantly higher, on average, than the AM only accuracies. For both of these we took a pair of values from each subject (AM accuracy/FM accuracy or AM accuracy/joint accuracy) and computed the pairwise t-statistic over the subjects within a paradigm. We then shuffled the pairings 1000 times and computed the t-statistics for these to generate the empirical t-statistic null distribution. The computed p-value is the proportion of t-statistics from the null distribution higher than the t-statistic generated with the true subject-accuracy pairings.

III. Experimental Results

We tested cross-validated classification accuracy with only AM features, only FM features, and the joint feature space for both setups, no spatial filtering and Laplacian spatial filtering, to determine whether FM performs as well as AM and whether adding the new features increases classification accuracy for simulated low-channel setups. The results of this analysis are shown in Figure 1. We find that the joint space significantly increases the cross-validated accuracy when compared to AM alone for both standard (68.7% vs 64%, $p = 0.01$) and Laplacian electrodes (74.1% vs 71.3%, $p = 0.04$).

Despite these significant changes on average, a closer inspection of Figure 1 reveals a great deal of heterogeneity with regards to which set of features is best on its own. It is unclear whether these changes are coincidental to the choice of decoder and channels or whether these reflect biological origins. For the regular electrodes, FM features slightly outperform AM features on average and the joint feature space shows a substantial improvement, validating our initial hypothesis. In comparison with the regular electrode data, however, the Laplacian electrode data is quite intriguing because it shows a reversal of trends. While adding a Laplacian filter often increases the cross-validated accuracy for just the AM features (true in 8 of the 10 subjects) it decreases the FM accuracies (see subjects $2, 5, 6, 8, 9$). However, despite of this, the overall accuracy from the augmented space is still significantly better than the accuracy from the AM space alone, albeit by a smaller amount than in the case of non-filtered channels.

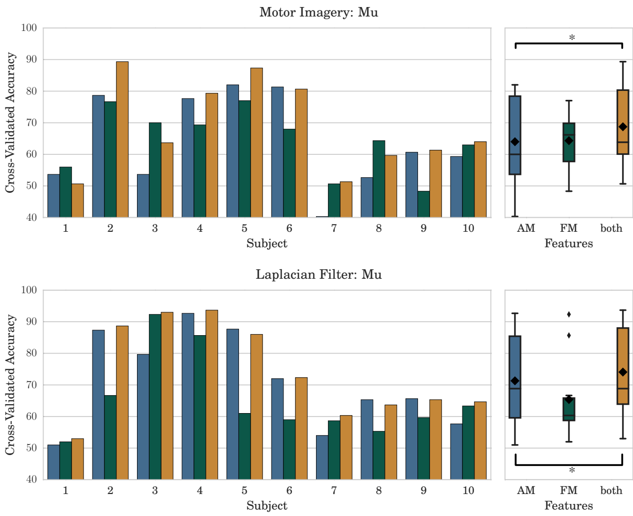

Fig. 1: Comparison of cross-validated accuracies for different feature sets in the motor imagery data. Channels selected were C3 and C4. Blue shows accuracies using only AM features, green shows accuracies using only the FM features, and gold shows accuracies using the combined feature space. The left plot shows the per-subject cross-validated accuracies and the right plot shows a box-and-whiskers plot with the mean (diamond), median (line) and upper and lower quartiles over subjects; outliers are shown as small black diamonds. Symbols indicate significant differences according to a permutation-based pairwise t-test. (top) Accuracies computed using standard wet electrodes. The joint feature space significantly out-performs AM only. (bottom) Accuracies computed on the electrodes after a Laplace filter was applied. The joint feature space significantly out-performs the AM features. *: $p < 0.05$.

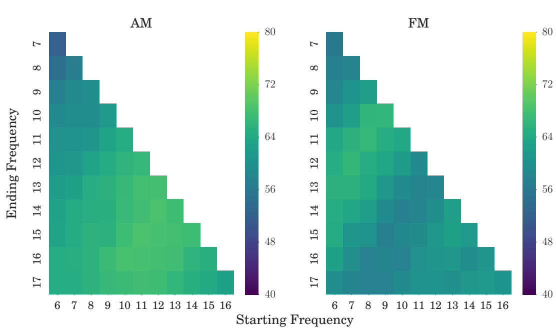

Fig. 2: Cross-validated accuracy using channels C3 and C4 for frequency bands of varying spectral location and size. The horizontal axis shows starting frequency and the vertical axis shows ending frequency for both AM (left) and FM (right) features. The colorbar shows the average cross-validated accuracy over all ten participants. Between bandpower and frequency features, the best band varies in both location and size.

IV. Discussion

We show with these experiments that the location of a neural frequency peak on the frequency axis can be used as a reliable feature for BCI decoding in motor imagery. Especially for studies with few electrodes, this has the potential to markedly improve performance by allowing another useful feature to be extracted without increasing the hardware. For both filtered and unfiltered channels the joint feature space significantly outperforms the AM only feature space, and in the case of the non-filtered electrodes FM is actually more predictive on average than AM.

The frequency range chosen for this analysis is the standard for the field. However, that standard was set using only AM features, which leads to the question of whether it is also optimal for FM features. As a preliminary test, we tested many different bandpasses for both features to determine which range performs best on average. For both AM and FM features, we varied the frequency band between 6 and 17 Hz in 1Hz steps for each subject. We then computed the cross-validated accuracy using the same procedure as explained in Section II and averaged across subjects. The results can be seen in Figure 2. As can be seen, the average best frequency band location is quite different for AM and FM features. AM features tend to prefer high bandpasses, while the FM features have their best average performance closer to the standard α range. This could be due to many factors, but one to consider is that the β range is also predictive in motor imagery and begins, traditionally, at 13 Hz; perhaps, given the imperfections inherent in any discrete time bandpassing procedure, the AM features benefit from this bleeding over of the β range.

In a neuroscientific light, these findings are quite curious. The unique information that the FM feature appears to carry suggests that either it comes from the same anatomical source but has a different noise profile, or that it is generated from a different circuit than the one that generates condition-related bandpower differences. The fact that Laplacian filtering can sometimes change the ratio of the predictiveness of FM versus AM features suggests that the latter is at least partly true. Laplacian filtering is well-known to increase the sensitivity of electrodes to sources directly underneath them–if only AM features are improved by this, and not FM features, that suggests that the underlying signal is not identical. This is not, however, the only possible explanation. Perhaps there are components of the FM modulation generated by the same circuits as AM modulation, but also components from elsewhere that are phase-and-frequency locked.

The method we use to compute the average frequency also leads to many questions. Previous approaches to using instantaneous frequency, or even average frequency, have relied on autoregressive models and computed instantaneous frequency and amplitude from there [28], [29]. These require a separate optimization and must be given model orders in advance; we have shown that using a simple transform like the Hilbert is sufficient to get features for classification. However, that is not to say this is the only simple option. The Hilbert transform on a bandpassed signal–and the median we use beyond it–were chosen for their stability to outliers of the instantaneous frequency within a trial. It is very likely that there are more stable approaches to determining the peak frequency yet to be discovered.

V. Conclusion

Our goal was to test whether these features are usable for classification in a very simple way, and not to over-optimize. Given that we have established our hypothesis, the space for optimization is enormous. Further, the usefulness of this feature lead to many questions of just how this fits into our current body of knowledge about the neural processes that are exploited to create BCIs. While we show results using a Laplacian filter, it is unclear how supervised spatial filtering such as CSP would affect FM features. These results also need to be expanded to include other physiological rhythms and tested to see if they are usable for impaired subjects. Finally, the projection of muscle and eye artifacts into the spectral power of measured signals is well known–but whether they have a similar task-related change in peak location has not yet been studied. Perhaps FM features are more robust to artifacts than AM features, which would be a crucial step forward in the quest for more stable ways of reading the brain.

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