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An Evaluation of Autoregressive Spectral Estimation Model Order for Brain-Computer Interface Applications

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Abstract—**Autoregressive (AR) spectral estimation is a popular method for modeling the electroencephalogram (EEG), and therefore the frequency domain EEG phenomena that are used for control of a brain-computer interface (BCI). Several studies have been conducted to evaluate the optimal AR model order for EEG, but the criteria used in these studies does not necessarily equate to the optimal AR model order for sensorimotor rhythm (SMR)-based BCI control applications. The present study confirms this by evaluating the EEG spectra of data obtained during control of SMR-BCI using different AR model orders and model evaluation criteria. The results indicate that the AR model order that optimizes SMR-BCI control performance is generally higher than the model orders that are frequently used in SMR-BCI studies.**

I. Introduction

A brain-computer interface (BCI) is a device that provides individuals with severe neuromuscular disorders with a non-muscular channel for communication and control [14]. The scalp recorded electroencephalogram (EEG) has proven to produce reliable signals for continuous control of a non-invasive BCI. Specifically, individuals can be trained to voluntarily modulate hemispherical rhythms (SMR) recorded over the sensorimotor cortex [9] that can be translated into device control. Because the information content of coordinated SMRs lies primarily in the amplitude modulations of particular EEG frequency components, it is essential to accurately track these amplitudes. For most modern BCI applications, this is generally accomplished using either a band-pass filtering approach or autoregressive (AR) spectral estimation. The disadvantages of band-pass filtering are that multiple filters must be designed for nonadjacent frequency bands and that phase-delays can become an issue due to the causality restriction of real-time applications. Alternatively, AR spectral estimation does not impose such impediments. AR modeling is also preferred to other spectral estimation techniques such as the FFT because of its superior resolution for short time segments, as typically used for continuous BCI applications. Additionally, it has been posited that filtering a white-noise processed using an AR filter is a suitable model for the generation of EEG [17].

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The main issue with AR modeling of the EEG is selection of the proper model order to accurately model and track the changing spectrum. One approach is to view the EEG as being comprised of 3-6 spectral peaks representing some combination of delta, theta, alpha, beta, and gamma waves [5]. In this case, each peak can be represented as a pole of an AR model, thus only requiring a low model order. This reasoning fails to account for other narrowband and/or wideband activity that contaminate the signal (such as electroculogram (EOG) and electromyogram (EMG)), or distinct spectrally adjacent or overlapping signals (such as alpha and mu band activity). This complex nature of the EEG must be taken into account for accurate spectral estimation and this cannot be accomplished with such small model orders.

One objective measurement of the adequacy of a parametric model is to evaluate the residual modeling error. The Akaike Information Criterion (AIC) is a common metric for assessing the AR model order [1]. It has been shown that, for typical EEG, the optimal AR model order estimates using AIC are variable across EEG frequency bands [12], with the optimum orders being approximately 12 and 11 for the alpha and beta bands, respectively. However, for SMR-BCI applications, the EEG is actively modulated and the dynamics are likely atypical of the EEG examined in the previous studies. Additionally, the AIC does not account for user performance, which is the main objective in BCI applications. The present study evaluates the effect of AR model order on a one-dimensional continuous control SMR-BCI using the AIC and performance (r^2 correlation) as separate model evaluation criteria.

II. Autoregressive Spectral Estimation

Autoregressive spectral estimation is a parametric approach by which the input process is used to estimate the coefficients of an all-pole model [6]. The resulting model can be used to estimate the power spectrum as follows:

$$\hat{P}(e^{j\omega}) = \frac{1}{\left|1 - \sum_{k=1}^{p} a_p(k) e^{-jk\omega}\right|^2} \tag{1}$$

where $a_p(k)$ are the estimated filter coefficients and p is the AR model order. An overly smoothed spectrum results when the model order is too low to model the input process. Conversely, the spectrum may exhibit spurious peaks when the model order is too high for the input process. Therefore it is imperative to determine an appropriate model order for a given input process.

AR modeling is well suited for EEG for several reasons. First, EEG is highly non-stationary and must be evaluated using short time segments over which the data are presumed to be stationary. The spectral resolution of an AR model is not explicitly limited by the length of the input process and therefore is capable of providing superior resolution for short data segments. This is not the case for other spectrum estimation techniques such as the Fast Fourier Transform (FFT). Second, EEG is essentially comprised of the superposition of mass single unit activity through volume conduction, which can be considered a filtered white noise process. This filtering of a white noise process is the basis for AR modeling and therefore it is a reasonable model for EEG [17].

A. *The Burg Algorithm*

The Burg Algorithm is a popular method for estimating the coefficients of an AR model because, unlike most other methods, it is guaranteed to produce a stable model. The algorithm recursively estimates the reflection coefficients of an AR lattice filter by minimizing the mean of the forward and backward least squares linear prediction errors [6].

B. *The Akaike Information Criterion*

The Akaike Information Criterion (AIC) [1] is a common method for selecting an appropriate AR model order based on the input process. Assuming that the input process has Gaussian statistics, the AIC for an AR process is given as follows:

$$AIC = \ln(\varepsilon) + \frac{2p}{N} \tag{2}$$

where ε is the modeling error, p is the AR model order, and N is the number of data samples. The second term in eq. (2) is the penalty for use of extra AR coefficients that do not result in a substantial reduction in the prediction error variance.

III. Methodology

In one- and two-dimensional cursor control studies [8] [15][16], users are able to effectively modulate 8-12 Hz (μ band) and 13-26 Hz (β band) spectral components over the sensorimotor cortex to move a cursor toward a randomly positioned target on a monitor. Three sessions of data from ten able-bodied users (four males and six females ranging in age from 29-45) who performed a one-dimensional two-target cursor control task were used to evaluate the effects of AR model order offline. All users were successfully trained on the task (consistently > 80% accuracy) and ranged in experience from 1 to 20 sessions on the task prior to this data set. The study was approved by the New York State Department of Health Institutional Review Board, and each user gave informed consent.

A. *One-Dimensional SMR Cursor Control Task*

The one-dimensional SMR cursor control task is detailed in Figure 1. For the task, the users were presented a target randomly positioned at the top or bottom right edge of the monitor as shown in Figure 1. The trial began with the cursor at the left center of the monitor. It moved at a constant rate toward the right, reaching the right side of the monitor after 2 seconds. The users' goal was to move the cursor upward or downward to the height of the target so that it hit the target when it reached the right side of the monitor. The trials continued in 3-minute runs, with a 1-minute break given between runs. Between 18 and 30 trials were completed in a single 3-minute run and 8 runs constitute a single session. Sessions were conducted one per day over a period of several weeks.

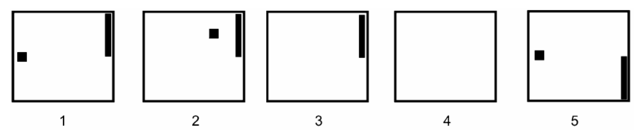

Figure 1: One-dimensional two-target task trial structure. (1) The target and cursor are present on the screen for 1 s. (2) The cursor moves steadily across the screen for 2 s with its vertical movement controlled by the user. (3) The target flashes for 1.5 s when it is hit by the cursor. If the cursor misses the target, the screen is blank for 1.5 s. (4) The screen is blank for a 1-s interval. (5) The next trial begins.

B. *Data Collection*

The details of the data collection and analysis are as follows: Using BCI2000 software [10], the EEG activity was collected using 64 channels at standard locations [11] distributed around the scalp. All 64 channels were referenced to the right ear, bandpass filtered 0.1-60 Hz and digitized at 160 Hz. A large Laplacian spatial filter [7] was applied to the electrode over the right or left hand area of the sensorimotor cortex that was predetermined as optimal for each user based on analysis of prior sessions. For each user, a 3-Hz bin at the predetermined mu-band fundamental frequency from a 16th order AR model (using the Burg Algorithm) was extracted from the spatially filtered signal and used as the online control feature. The AR feature was calculated every 50 ms using 400 ms of data.

C. *Offline Evaluation*

Because the one-dimensional two-target cursor control task requires the user to provide a ballistic binary response in order to hit the target, the effects of feedback can generally be disregarded for offline simulations. For the offline evaluation, the Laplacian control channel and the contralateral, hemispherically symmetric channel were analyzed in order to examine any potential differences between the estimated mu and beta band model orders for the actual control channel and a presumably equivalent channel for which no feedback was given. Depending on the user, this non-control channel may produce features that are correlated with the control channel, or merely uncorrelated background EEG. The two channels were normalized to have zero mean and unit variance in order to provide an unbiased comparison of the AIC residual error.

This normalization has no effect on the r^2 performance metric.

Using the same data segment length as the online sessions (N=64), the data were detrended to reduce low frequency trends that can impede SMR detection. The data segments were then analyzed using the Burg Algorithm for AR model orders from p = 2 to 32 in increments of 2. For each model order, the AIC was evaluated for the two channels. In order to examine the effects on the key individual SMR frequency bands, the r^2 between the mu and beta bands (3 Hz widths) for each of the two channels and the target position was calculated using the same data segments and AR models. These four spectral features were also used in an ordinary least squares regression with target position. The r^2 between the regression output and the target position was calculated in order to simulate the effects on overall combined performance using a single model order to generate different spectral features.

IV. RESULTS

The results are the averages of three sessions from ten users (approximately ~30,000 400 ms data segment observations per user). For comparison purposes, the five features used to evaluate r^2 performance were categorized into control channel mu band (μ_c), control channel beta (β_c), contralateral channel mu (μ_n), contralateral channel beta (β_n), and the regression output of the four spectral features ($Y_{regress}$).

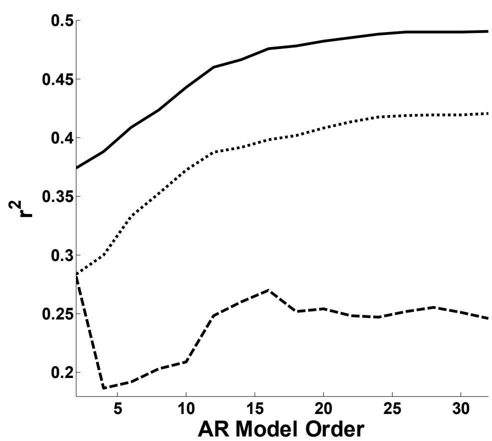

Figure 2: Estimated r^2 performance vs. AR model order averaged across users for the control features: $Y_{regress}$ (solid), μ_c (dotted), β_c (dashed).

The average across users for the control features with respect to AR model order is shown in Figure 2. The non-control features (μ_n and β_n) were not included in the plot because the average r^2 values for all model orders were sufficiently low (~0.1). For each of the five features, a repeated measures ANOVA was conducted on r^2 performance of the users. All five features individually exhibited a statistically significant difference ($p<0.05$) between the model orders. A posthoc Tukey-Kramer was then performed on each of the results to assess the model order significance.

The posthoc analysis of μ_c suggests that the minimum model for which there is no significant improvement for higher model orders is 10. However, the average performance continues to increase and asymptotes at a model order of 26. Similarly, the posthoc analysis of $Y_{regress}$ suggests that the minimum model for which there is no significant improvement for higher model orders is 12 and again the average performance continues to increase and asymptotes at a model order of 26.

The posthoc analysis of β_c interestingly indicates that model orders 4-10 perform significantly worse, with order 2 providing the best average performance of the remaining model orders. Identical model order trends where exhibited between the left and right channels for the mu and beta bands. However, because of the relatively low average r^2 values, it is concluded that μ_n and β_n have little effect on overall performance in general and therefore no conclusions are drawn.

Figure 3 compares the estimated r^2 performance for the optimal $Y_{regress}$ model order as determined by r^2 performance, the optimal $Y_{regress}$ model order determined by the AIC, and two commonly used model orders 6 and 10. AIC curve varied for each user, as noted by maximums. As indicated by Figure 3, the results produced by the AIC were not consistent across users, but the AIC curves and optimal model orders were consistent between the left and right channels for each user.

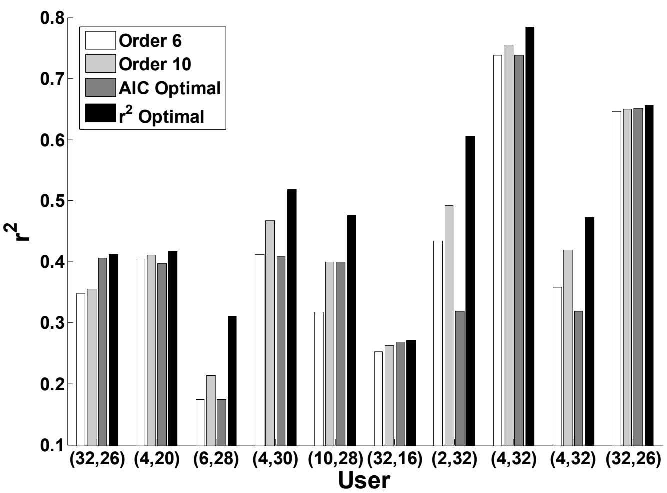

Figure 3: A comparison of the r^2 performance of the $Y_{regress}$ feature for the ten users using four different AR model orders. Commonly used model orders of 6 and 10 are compared to the optimal model orders as determined by the AIC and r^2 criteria. The x-axis label for each user indicates the model order selected for the AIC and r^2 criteria as (AIC,r^2).

V. DISCUSSION

The results indicate that, for the mu control band (μ_c) and combined mu and beta features ($Y_{regress}$), r^2 performance generally exhibits an asymptotical increase with increasing AR model order. This suggests that, for models involving the mu band with or without the beta band, higher model orders tend to provide superior performance with diminishing returns after an order of 26, although it is conceivable that further increasing the model order could eventually abate performance. It is difficult to speculate about the dissimilar model order curves produced for the mu and beta bands. This could be an effect of using 3 Hz bin widths to represent mu and beta bands that may differ in spectral extent, the relative signal to noise ratio of each band, or that online feedback was not given for the beta band. Nevertheless, the results indicate that a model order of 2 could be sufficient for modeling the beta band when not used in conjunction with the mu band. This suggests that unique model orders for each frequency band may improve performance when different frequency bands are combined for control.

For classification applications, the AIC may provide a reasonable metric for evaluating the generalization (robustness) of a classification model. However, for short-time AR spectral estimation, generalization is not the ultimate goal. Instead, the goal is to acquire an appropriate model structure to capture the dynamics of actively modulated EEG. Therefore, the penalty introduced by the AIC for increasing model order is not appropriate for obtaining an optimal structure (model order) for continuous short-time AR spectral estimates, as evidenced by the extremely low estimates produced (see Figure 3). A pre-whitening technique is suggested in [2] that can improve the model order estimates of similar criteria based on residual error.

Despite the apparent evidence, it is common for SMR-BCI studies to employ model orders that are well below the optimum for wideband, actively modulated EEG. Possible rationales for this are that the investigators are using oversimplified assumptions of the dynamics of the EEG or because of the biased results obtained from the AIC or similar criteria. This misconception persists in the BCI community as investigators continue to base AR model order selection on earlier works that used the AIC and/or non-BCI generated EEG signals.

The most commonly cited reference for AR model order in BCI applications is [3], in which the optimal AR model order for EEG was determined to be approximately 10. In [13], the optimal model order to model rhythmic, non-"featureless background" EEG was found to be 5. However, these estimates are based on typical EEG, which may not exhibit the dynamics of the type of actively modulated EEG required to control a BCI. For BCI control, the AR spectral estimation must capture both the rhythmic and "featureless background" components of the EEG, which may reflect the different mental states used for control. Since the dynamics of the various mental states need to be captured using a single AR structure (model order), higher model orders may result in more accurate spectral estimates and therefore better discrimination of mental states.

Several issues complicate the evaluation of AR model order. Firstly, different methods for estimating the AR coefficients (Burg Algorithm, Yule-Walker, etc. [6]) can result in different optimal model orders using the AIC. Additionally, other model error criterion (FPE, RIS [13]) can also produce drastically different model order estimates. Furthermore, bandpass filtering of the signal should tend to produce lower model order estimates when spectral content having considerable variance is removed from the signal (i.e. less signal variance to model). Lastly, the length and sampling rate of the data that the AR model is derived from can have a significant effect on the model order estimates since higher sampling rates and longer data segments may capture increased spectral content, thus requiring a higher model order [13]. All of these issues greatly complicate the determination of the optimal AR model order and must be considered when generating a model. In the end, for BCI applications, the final evaluation criterion must always be user performance.

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