Comparison of Averaging and Regression Techniques for Estimating Event Related Potentials

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Abstract— **The traditional method of estimating an Event Related Potential (ERP) is to take the average of signal epochs time locked to a set of similar experimental events. This averaging method is useful as long as the experimental procedure can sufficiently isolate the brain or non-brain process of interest. However, if responses from multiple cognitive processes, time locked to multiple classes of closely spaced events, overlap in time with varying inter-event intervals, averaging will most likely fail to identify the individual response time courses. For this situation, we study estimation of responses to all recorded events in an experiment by a single model using standard linear regression (the *rERP technique*). Applied to data collected during a Rapid Serial Visual Presentation (RSVP) task, our analysis shows: (1) The rERP technique accounts for more variance in the data than averaging when individual event responses are highly overlapping; (2) the variance accounted for by the estimates is concentrated into a fewer ICA components than raw EEG channel signals.**

I. Introduction

The Event Related Potential (ERP) averaging method for electroencephalographic (EEG) data [1] is one way to gain insight into how specific cognitive processes are related to brain electrical activity. Traditionally, the way of increasing the signal to noise ratio (SNR) of an ERP estimate is to average epochs time-locked to a stimulus class of interest. This technique places severe restrictions on the experimental protocol: only a small number of stimulus categories can be used, stimulus events must be well separated in time and all other cognitive processes must be held constant. Violating the latter conditions will cause the ERP to be estimated sub-optimally. Here we study using multiple regression as a way to overcome this limitation, extending the work of N. J. Smith [2]. In [3], Hinrichs et al. have suggested a highly similar approach for deconvolving fMRI responses. [4-6] have suggested using separate regression models for each individual latency, such as massive univariate general linear analyses. [7, 8] have proposed using Generalized Additive Models (GAMs). In [2], Smith offers a unified conceptual framework for ERP regression and shows how these different techniques relate to averaging for the purposes of ERP estimation.

We continue this discussion by applying linear regression and averaging to a real EEG dataset and exhaustively comparing the results of the two approaches. The goal is to make clear that in practice, regression can offer a significant performance increase compared to averaging. Indeed, as EEG experiments become more sophisticated, with many (intermittent or continuous) processes being monitored simultaneously, averaging ceases to be an effective option. Independent Component Analysis (ICA) [9] has become a popular and often effective method for separating EEG sources [10, 11]. Thus, we also compared how regression and averaging compare with one another in both ICA component activations (ICs) and EEG channels.

II. Background

A. A Problem With Averaging

If events in an experiment occur sufficiently close in time to one another, the EEG brain responses to these events will overlap. Taking an average of these event time-locked epochs will produce a summed and/or blurred ERP estimate.

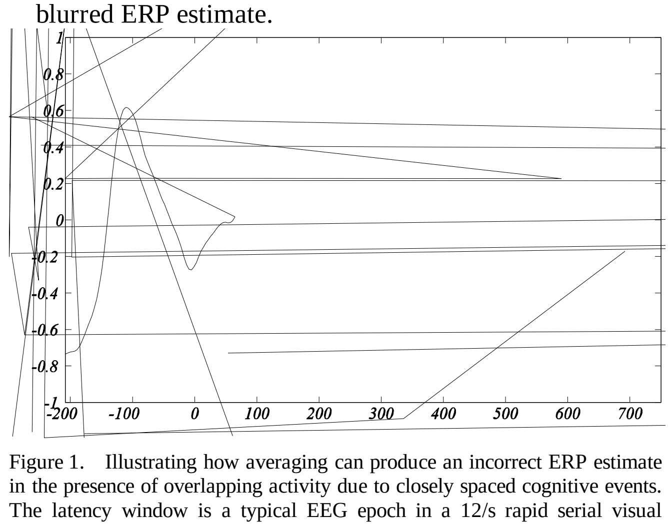

Figure 1. Illustrating how averaging can produce an incorrect ERP estimate in the presence of overlapping activity due to closely spaced cognitive events. The latency window is a typical EEG epoch in a 12/s rapid serial visual presentation (RSVP) experiment. An ERP of interest (*blue*), is produced following each visual stimulus every 83 ms (*black*). These ERPs combine additively, giving a misleading (*red*) averaged Steady State Response (SSR) ERP estimate. Regression considers all the experimental events in a single additive model, taking into account this overlap.

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B. Data

The experiment is fully described in [12]. 127-channel EEG data were collected during a Rapid Serial Visual Presentation (RSVP) task involving satellite picture presentation. The subject was shown bursts of 49 satellite images in 4.1 seconds (12/s.). In 60% of the bursts, a (flying airplane) target feature was randomly added to one image. At each burst end, the participant indicated by button press whether or not that burst contained the target feature. During training, they were told whether they were correct or not.

There were nine recorded event types in the experiment, listed by *(event-code) event-description*: (1) non-target stimulus, (2) target stimulus, (4) "no targets" button press, (5) "one target" button press, (6) trial block start, (16) trial start, (32) "correct" feedback given, (64) "incorrect" feedback shown, and (129) image burst start.

III. Methods

We calculated ERP estimates for a single subject across nine different events using averaging and linear regression. This analysis was repeated for all 127 channels of EEG data and again for all 127 ICs, derived by extended Infomax ICA [13]. We used five-fold cross-validation to obtain our performance figures: the ERPs were calculated with training data and validated on test data [14].

A. Preprocessing

First, we addressed the issue of outliers and artifacts. We identified outlier data portions by two methods: Low Probability and Mutual Information Reduction (MIR). For the probability method we first whitened the data and performed a rank transform to obtain a two-tailed significance value for each sample. We then found 200 ms windows where the average log significance over all the sphered dimensions and time-frames was higher than 2.1 and marked them as outliers. For the MIR method, we first calculated the mutual information reduction index [15] in 2s windows with 80% overlap using the sphering matrix. Then we found regions with MIR Z score of lower than 1.5 and marked them as outliers. We discarded events occurring during or near outlier periods. Out of 23,477 events, 1,654 were identified as contaminated and discarded. The data were highpass filtered (3 dB at 1 Hz) to reduce DC bias.

All ERPs were estimated using the same maximum length, heuristically set for this analysis at 1 second (256 samples), from -125 ms to 875 ms around each event. This defined 256 variables per event. For nine event types, each regression or averaging model thus contained 2304 ERP parameters for each EEG channel or IC.

B. Regression Framework

First we looked at the case of only one event type, E_1, producing an ERP response . The observed signal (IC or channel) y is then a linear transformation of plus a Gaussian noise term,

$$= [\quad {}_N]^T \tag{1}$$
$$y = \boldsymbol{A_1} \quad + \tag{2}$$

We position y and as a column vectors of length M (the length of the data) and N (= 256) respectively. $\boldsymbol{A_1}$ is the M x N matrix of *predictors*, x_{mn}, constructed from latency recordings. x_{mn} has a value of 1 when the n^{th} sample of ERP is predicted to occur at latency m.

If we want to estimate the response to more than one event type, we stack the ${}_n$ in a column vector, and concatenate their corresponding $\boldsymbol{A_n}$ along the second dimension

$$\boldsymbol{A} = [\ \boldsymbol{A_1}\ \boldsymbol{A_2} \ldots \boldsymbol{A_n}\ ] \tag{3}$$
$$= [\ (\quad (\quad (\ {}_n \quad]^T \tag{4}$$

and subsequently

$$y = \boldsymbol{A} \quad + \tag{5}$$

with least squares solution

$${}_{reg} = (\boldsymbol{A^T A})^{-1}\boldsymbol{A^T} y \tag{6}$$

C. Performance Metrics

We subtract the

$$ {}^{av}{}_{i} = y_{i} \qquad {}_{av} \tag{9}$$

$$ROV_{av} = < var[y_{i}] \qquad var[\ {}^{av}{}_{i}] > \tag{10}$$

where the mean is taken across all the events of that type. For regression, we computed a signal estimate

$$y^{reg} = \boldsymbol{A}\ \ {}_{reg} \tag{11}$$

then, extracted each epoch from the estimated signal significant difference between the two methods for both ICs and channels. For the most frequent event type (1), regression has the advantage for both channel and IC measures. Compare the difference in the regression versus the average ERP (SSR) estimates in *Figure 2* (top panel). The averaging method clearly did not estimate ERP for this event type. For the other event types, which are less affected by overlap, the two methods performed similarly.

2) Comparing IC and channel results, we notice a peak of ROV within the first 2-3 ICs for each stimulus type. Since ICs are thought to typically represent the synchronous field activity across a single cortical patch [16], broadly projected to the scalp electrodes by volume conduction, we may expect the regression result to show higher performance for a smaller number of ICs than scalp channels. The ROV for channels is indeed distributed across a larger number of channels. This is expected, since EEG signals at scalp electrodes that are physically close are highly correlated [10].

3) Normalized ROV is quite low across the board: no more than 12% of the variance in any channel or component signal is accounted for by either method, and usually much less. This is consistent with the frequent observation that most EEG signal variance is not produced by time locked responses to external events.

V. Discussion

As suggested by N. J. Smith in [2], regression can be thought of as a natural extension of averaging that can be applied in a larger range of experimental conditions. For instance, regression yields identical results as averaging when there is no overlap between experimental responses (*Figure 2*, bottom panel). To see this, note that in the regression problem

$$y_m = \quad x_{m1} + \ldots + \quad {}_n\, x_{mn} + \quad {}_m \tag{15}$$

where y_m is the voltage measurement at a scalp electrode channel at latency m. ${}_n$ are the stimulus response weights (perhaps from previous events of different types).

The case of non-overlapping responses is a special case of (15), in which all the x_{mn} are zero except for one variable, say ${}_t$. Then, (15) simplifies to

$$y_m = \quad {}_t + \quad {}_m \tag{16}$$

with least squares solution

$${}_t \quad \langle y_m \rangle \tag{17}$$

the *sample mean* of the observed data points at which the x_{mn} predicted event ${}_t$ occurred.

VI. Conclusion

When overlapping responses are produced by experimental events closely spaced in time, multiple stimulus events may contribute to any given event-related response feature and some additional assumption is necessary to properly attribute this variance. The regression (rERP) technique assumes that ERPs to distinct events sum linearly. In all other ways, the rERP technique is identical to the averaging technique. Yet, as we show here, it is capable of out-performing the averaging technique by explaining more total data variance. This shows that the rERP assumption is a viable one for analyzing data from rich and complex EEG data-sets.

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