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Amplitude Quantization of Event Related Potentials for Brain-Computer Interfaces

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***Abstract*—As neural interfaces continue to progress toward practical applications, there is increased demand for smaller, more efficient and cost effective devices. Event related potentials (ERPs) have recently been demonstrated to be reliable for practical communication in disabled individuals using the P300 Speller paradigm. With the objective of simplifying the processing of ERPs in order to minimize the hardware/computational requirements, and therefore the power consumption (for increased battery life for wireless, etc.), this study examines the effects of the analog-to-digital converter amplitude quantization on the ERP classification accuracy for the P300 Speller.**

Keywords-Stimulus Evoked Potentials; P300 Speller; Analog-to-Digital Conversion

I. Introduction

Recent studies have validated the P300 Speller as a viable communication paradigm for disabled individuals [7][11]. Additionally, several other brain-computer interface (BCI) communication paradigms based on event related potentials (ERPs) have been developed [12]. As these technologies move out of the laboratory and into disabled individuals' homes, several practical hardware considerations must be addressed. Firstly, the size and cost of most EEG recording systems used for research are not feasible for home use. Secondly, the vision for practical BCI systems is to use wireless communication of EEG to the controlling computer to avoid tethering the user with device cables. Therefore, some components will be powered using batteries and power consumption becomes an issue.

The first step toward addressing these issues is to minimize the signal processing requirements without sacrificing performance. This, in turn, will define the minimum necessary hardware requirements, potentially reducing cost and power consumption of the system. This study investigates the number of amplitude quantization levels required for the analog-to-digital conversion of ERPs elicited by the P300 Speller. By determination the minimum number of quantization levels without adversely affecting performance, more efficient and cost effective analog-to-digital converters (ADCs), microprocessors, and other hardware may be utilized. Additionally, the results provide new insight about the nature of nature ERPs elicited by the P300 Speller.

II. Data Collection

The data were collected by the Wadsworth Center BCI Laboratory in accordance with New York State Department of Health Institutional Review Board.

A. Participants

Eight able-bodied people (six men and two women ages 24-50) were the participants in this study. The participants varied in their previous BCI experience, but all participants had either no or minimal experience using a P300-based BCI system.

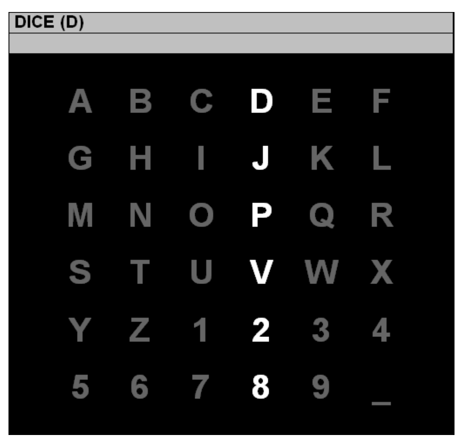

Figure 1. The 6x6 matrix used in the current study. A row or column intensifies for 100 ms every 175 ms. The letter in parentheses at the top of the window is the current target letter "D." A P300 should be elicited when the fourth column or first row is intensified. After the intensification sequence for a character epoch, the result is classified and online feedback is provided directly below the character to be copied.

B. Task, Procedure, & Design

The P300 Speller described by Farwell and Donchin [4] presents a 6 x 6 matrix of characters as shown in Figure 1. Each row and each column are intensified; the intensifications are presented in a random sequence. The user focuses attention on one of the 36 cells of the matrix. The sequence of 12 flashes, 6 rows and 6 columns, constitutes an Oddball Paradigm [3] with the row and the column containing the character to be communicated constituting the rare set, and the other 10 intensifications constituting the frequent set. Items that are presented infrequently (the rare set) in a sequential series of randomly presented stimuli will elicit an ERP if the observer is attending to the stimulus series. Thus, the row and the column containing the target character will elicit an ERP when intensified, because this constitutes a rare event in the context of all other character flashes. With proper ERP feature selection and classification, the attended character of the matrix can be identified and communicated.

The participants sat upright in front of a video monitor and viewed the matrix display. The task was to focus attention on a specified letter of the matrix and silently count the number of times the target character intensified, until a new character was specified for selection. All data were collected in the copy speller mode: words were presented on the top left of the video monitor and the character currently specified for selection was listed in parentheses at the end of the letter string (see Figure 1). Each session consisted of 8-12 experimental runs; each run was composed of a word or series of characters chosen by the investigator. The rows and columns were intensified for 100 ms with 75 ms between intensifications. One character epoch (i.e., one trial) consisted of 15 intensifications of each row and column. Specifically, the classification was performed after every row and column has been intensified 15 times. Each session consisted of 36 character epochs, equivalent to 6480 stimuli (row/column intensifications). Each participant completed five sessions (one per day) over the course of several weeks. Each session lasted approximately one hour.

C. Data Acquisition & Processing

The EEG was recorded using a cap (Electro-Cap International, Inc.) embedded with 64 electrodes distributed over the scalp, based on the International 10 – 20 system [10]. All channels were referenced to the right earlobe, and grounded to the right mastoid. The EEG was bandpass filtered 0.1 – 60 Hz and amplified with an SA Electronics amplifier, digitized at a rate of 240 Hz using a 12-bit ADC. All aspects of data collection and experimental procedure were controlled by the BCI2000 system [8].

Responses were collected from the 8 ear-referenced channels shown in Figure 2. The channel selection and data preprocessing are based on results found in [5]. For each of the 8 channels, 800-ms segments of data following each intensification were extracted. The segments were then moving average filtered and decimated to 20Hz. The resulting data segments were concatenated by channel for each intensification, creating a single feature vector for training the classifiers.

The linear classifiers were trained using Stepwise Linear Discriminant Analysis (SWLDA) [2]. SWLDA is a technique for selecting suitable predictor variables to be included in a multiple regression model that has proven successful for discriminating P300 Speller responses. A combination of forward and backward stepwise regression was implemented as detailed in [5].

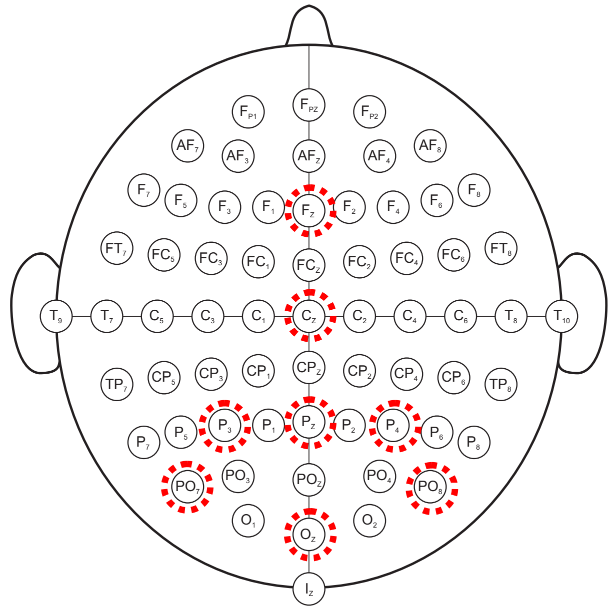

Figure 2. The electrode montage used in the current study [5]. The 8 electrodes selected for analysis are indicated by the dotted circles.

Amplitude quantization values of 1, 2, 4, 8, and 12 (native resolution) bits were evaluated offline. The number of bits relates to the number of discrete amplitude quantization levels as follows:

$$\#\ quantization\ levels = 2^{bits}$$

A larger number of bits used to encode a signal results in a higher amplitude resolution. Essentially, the dynamic amplitude range of the signal is divided into uniformly spaced quantization levels and the signal amplitude is rounded to the nearest quantization level.

For each subject and quantization value, the EEG was bandpass filtered from 0.5 - 30 Hz using a 3rd order Butterworth filter and quantized. An SWLDA classifier was then trained using the first session. The classifiers were tested on four subsequent sessions for each subject. The classification accuracies of the individual ERPs and the predicted target symbols (after averaging the ERPs by respective row and column stimulus as detailed in [5]) are examined.

III. Results

Figure 3 shows, for each number of bits, the single trial classification accuracy averaged across the 8 subjects. This represents the average classification accuracy of the ERPs elicited by each intensification of the matrix using the SWLDA classifier. That is, whether the response is correctly classified to represent a target or non-target symbol. For the actual symbol prediction, the ERPs are weighted using the SWLDA coefficients and averaged for each row and column for every character epoch. The intersection of the row and column having the largest resulting value was selected as the predicted symbol. The symbol prediction accuracies averaged across the 8 subjects as a function of the cumulative intensifications are shown in Figure 4. The symbol prediction accuracies after 15 intensifications for each subject are listed in Table I.

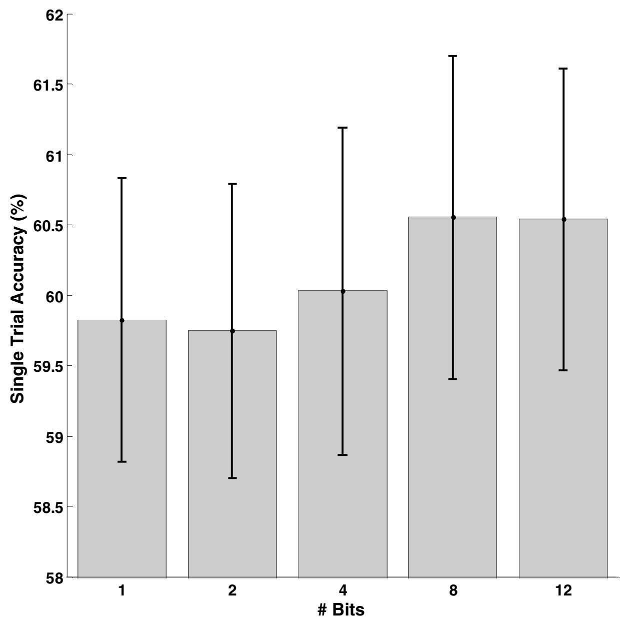

Figure 3. The single trial classification accuracy averaged across the 8 subjects. The error bars indicate the standard error.

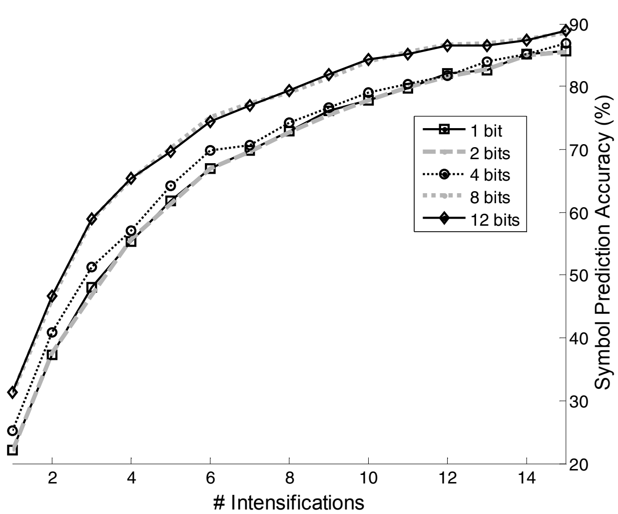

Figure 4. The symbol prediction accuracy averaged across the 8 subjects.

TABLE I. INDIVIDUAL SYMBOL PREDICTION ACCURACY

	1 Bit	*2 Bits*	*4 Bits*	*8 Bits*	*12 Bits*
Subject A	84.03	84.72	86.81	93.06	93.75
Subject B	70.50	68.51	73.15	71.84	74.48
Subject C	94.44	93.75	93.06	95.14	93.06
Subject D	89.58	89.58	94.44	97.22	97.22
Subject E	97.92	97.92	97.92	97.92	97.92
Subject F	85.12	85.77	87.92	90.49	90.49
Subject G	63.89	63.89	62.50	65.28	63.89
Subject H	99.31	99.31	99.31	97.92	97.92
AVERAGE	**85.60**	**85.43**	**86.89**	**88.61**	**88.59**

The table lists the symbol prediction accuracy after 15 row/column intensificactions for each subject.

IV. DISCUSSION

As might be predicted, Figure 3 shows a general trend that a lower resolution yields lower accuracy, however what is surprising is that the difference in accuracy is not as high as one would expect. The reduction from 12 bits to only a single bit of resolution results in a loss in accuracy of less than 1% in single trial classification.

The average symbol prediction accuracy over all subjects for the different bit resolutions considered also shows only a small penalty of 3% accuracy incurred when dropping from 12 down to a single bit of resolution. Again, this is an interesting and surprising result.

One bit of resolution may be achieved by the use of a simple comparator which represents a dramatic reduction of hardware over a twelve bit analog to digital converter. This provides a great deal of motivation to consider how the hardware to acquire and process brain signals for P300 interfaces may be simplified, reducing complexity, size, and power requirements.

Given that the P300 response is only one type of ERP that may be used in a BCI, it is possible that these results could be extended to other types of BCIs based on other ERPs. Intuitively, one might expect that dropping to a single bit of resolution may yield useable results when modeling ERPs but this is unlikely to be suitable for phenomenon like ERD/ERS where the amplitude changes in a particular portion of the signal spectrum are of interest. Further investigation is necessary to determine the effect of reducing the quantization resolution in the context of other such types of targeted brain signal features.

One possible explanation for the results may lie in the way that the signal of interest is modeled compared with the noise. Clearly increased resolution will model the ERP of interest better, but perhaps it also models more of the noise. It may be easier to understand this point by considering the opposite situation, specifically the situation where decreased resolution augments the noise and diminishes the signal of interest. Consider, for example, what would happen if the 60 Hz line noise on the analog side is not filtered out as was done in this study and rather it was attempted to be filtered out digitally after using one bit resolution to acquire the signal. In this case the noise predominates the signal and there will clearly be an issue since the line noise cannot be modeled appropriately to allow its removal at that resolution. In fact, there will primarily be a 60 Hz square wave to contend with if this is attempted.

Along these lines, one might consider the expected results if this study were to be applied to data from an SSVEP (Steady State Visual Evoked Potential) experiment. On the one hand, if only the SSVEP signal were present with no noise content, clearly one bit resolution would suffice since we only need to know when the signal is above or below a particular threshold to determine its frequency. However the noise that predominates brain signals in an SSVEP experiment will not be so accommodating. Again, the question that remains is not whether this can work at one bit of resolution, but rather how much resolution is required to achieve reasonable results.

Appropriate filtering of the signal is required prior to digitization primarily to eliminate aliasing and powerline noise, as well as restricting the frequency band. The results are based on EEG that has been conditioned appropriately. Such filtering would require substantially more resolution than the results would indicate if the filtering was implemented by digital filters. The results indicate that such resolutions are not necessary provided appropriate analog filters are employed. The requirement for these filters does add some complexity to the overall circuit; however simple passive filters with minimal circuitry are sufficient to handle the required bandpass filtering. Given the SNR between the powerline line noise and the raw EEG, a basic second-order active notch filter would be sufficient. The relatively limited complexity of these analog solutions is small compared to the complexity of an ADC with sufficient resolution to handle these tasks digitally.

In the case of the P300 speller, the current study shows that a 3% decrement in performance occurs when signal resolution is reduced from 12 to a single bit. With a better understanding of the nature of these ERPs, additional signal processing may compensate for the small performance difference. In any case, the current findings suggest that using simpler, more power efficient and cost effective hardware may not compromise P300-based BCI performance.

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