P300 Latency Estimation Using Least Mean Squares Filter

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***Abstract*— Event-related potentials (ERPs) are the brain response directly related to specific events or stimuli. The P300 ERP is a positive deflection nominally 300ms post-stimulus that is related to mental decision making processes and also used in P300-based speller systems. Single-trial estimation of P300 responses will help to understand the underlying cognitive process more precisely and also to improve the speed of speller brain-computer interfaces (BCIs). This paper aims to develop a single-trial estimation of the P300 amplitudes and latencies by using the least mean squares (LMS) adaptive filtering method. Results for real data from people with amyotrophic lateral sclerosis (ALS) have shown that the LMS filter can be effectively used to estimate P300 latencies.**

I. Introduction

Various assistive technologies are available for people with communication disorders. While these technologies are very effective for moderate to severe movement impairments, certain progressive diseases can cause a total locked-in state. These conditions include amyotrophic lateral sclerosis (ALS), neuromuscular disease (NMD), and several other diseases those can cause impairment between the neural pathways and the muscles. For people in a locked-in state, brain-computer interfaces (BCIs) may be the only possible solution. BCIs could help to restore communication to these people with the help of external devices and neural recordings [1].

The P300 Speller [2] is one of the common application of BCIs which provides a non-invasive form of communication for patients with the above-mentioned diseases [3]. The P300 Speller uses event-related potentials (ERPs) embedded in electroencephalography (EEG) signals to determine the character (target character) users intend to spell. P300 ERPs are brain responses elicited by rare stimuli, with a characteristic positive polarity approximately 300ms post-stimulus. A standard P300 Speller is implemented using a grid matrix of 6×6 or more characters and commands, which are presented to the user. Typically, rows and columns are flashed in a random order. The probability of the flashed row/column containing the target character is $1/6$, which creates a rare event that will elicit a P300 response. But the measured ERPs are mixed with unrelated brain activity, as well as interference from non-neuronal sources (eye-blinks, eye-movements, muscle movements) and instrumental noise. These factors lead to the well-known difficulty in recovering ERPs from single trials. The ERPs are buried under the background EEG signals [4] and that background EEG has much larger amplitude than ERPs. Therefore, ERPs have very low signal-to-noise ratio and, additionally, may contain stimulus artifacts caused by the repetitive presentation of visual stimuli [5].

Hence, most commonly used methods to detect and estimate the P300 ERP rely on signal averaging. Averaging helps to obtain the P300 by suppressing the background EEG signals as the P300 is time-locked according to the stimulus onset [6], [7]. But the averaging does not allow us to do single-trial analysis. In some cases averaging may be useful, but the ERPs can vary in terms of latency and amplitude due to mental fatigue, stress, attention and several other medical conditions. Research has shown that P300 latency variability is strongly related with the cognitive function and provides a measure of cognitive heath [8]. Hence, averaging causes the loss of important information related to the P300 variability.

Single-trial estimation of P300 will help to understand the underlying cognitive process of ERPs and also to improve the speed of BCI systems. It is important to develop a robust single-trial estimation of P300. Single-trial estimation of P300 remains a challenge, despite some recent studies [4], [9], [10]. Two major parameters of the P300 ERP are amplitude and latency. Single-trial P300 latencies have special significance in ERP research for several reasons. For example, single-trial latencies are related to information processing [11] and memory span development in children [12], and are also significantly correlated with cognitive impairment [13]. The variability of latency is commonly referred to as latency jitter.

In this work we present a method based on Least Mean Squares (LMS) adaptive filtering to estimate P300 ERP latencies and amplitudes from single trials. Here in this work, results are based on real rather than simulated data.

II. Data Description

The data used in this work have been previously reported in [14]–[16], and all data were recorded under the same protocol. Each participant visited on three separate days (sessions) and each session has three data files, except the first session which had an additional training file. Here in this work, a subsection of those files have been used. We have used only data of the first session from eleven participants, ten with ALS and one control. The control participant was a 45-year-old male. The ALS participants

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had ages ranging from 45 to 78, with mean 61.7, and included six men and four women. A 16-electrode cap from ElectroCap International with mastoid reference and ground was used for EEG recordings. Electrodes locations were F3, Fz, F4, T7, T8, C3, Cz, C4, Cp3, Cp4, P3, Pz, P4, PO7, PO8, and Oz according to the international 10-20 system. Stimulus presentation and recording was controlled through the BCI2000 software platform. A sample screen capture during stimulus presentation has been shown in figure 1. Each data file contains at least 23 characters from a copy-spelling with correction task. The number of characters may be larger since users corrected mistakes using a backspace selection within the BCI. For further details, see [14]. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board.

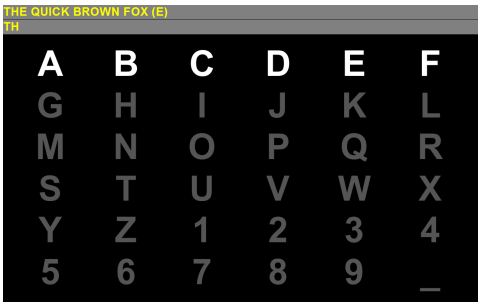


Fig. 1. Screen capture of P300 speller display in BCI2000 environment [17].

III. Methods

A. Linear observation model

Georgiadis et. al., proposed a Kalman filter filter-based approach for estimating ERPs [10]. But the model they used did not consider visual evoked potentials due to the stimulus presentations, which are overlapped with ERPs. Here we will use the widely-accepted linear additive noise model considering the stimulus effects.

$$x(n) = p(n) + e(n) \tag{1}$$

Here, $p(n)$ represents the P300 response and $e(n)$ is the background EEG plus stimulus effect and other non-neuronal activity.

B. Detection of the P300

Least square weights, $\hat{\mathbf{W}}_{LS}$, are calculated using the following equations [18] :

$$\hat{\mathbf{W}}_{LS} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} \text{ where, } \mathbf{X} = \begin{bmatrix}\mathbf{1} & \mathbf{x}\end{bmatrix} \tag{2}$$

$\hat{\mathbf{W}}_{LS}$ is computed from the training session and then used for other sessions to detect the presence of P300 from $\hat{y}(\mathbf{x}) = sign(\mathbf{X}\hat{\mathbf{W}}_{LS})$. Here, $\hat{y}(\mathbf{x})$ is 1 when the P300 is believed to be present and -1 when it is not believed to be present.

C. Least Mean Squares Filter

The least mean squares (LMS) filter is a good candidate to extract $p(n)$ from single trials since LMS has the ability to mimic a desired filter by finding coefficients that produce the least mean square error of the given signal with respect to the target signal. Here, our goal is to estimate $p(n)$ for each channel separately and use that for estimating amplitude and latency of the P300. Let $x^{(c)}(n)$ represent the Nth trial from channel c. Now to estimate the component of $p(n)$ in each channel, we need a reference of $p(n)$. Here, we have used the average of all non-target single-trials subtracted from the average of all target single-trials collected during each participant's training session as the reference for $p(n)$. Let's assume this reference signal is denoted as $r(t)$. We now want to estimate the filter coefficients, $\mathbf{w}$ related to $p(n)$ from each trial $x(n)$ using the reference $r(n)$. Then the least mean square formulation in matrix vector form for an M-point LMS filter is:

$$\begin{bmatrix} r^{(c)}(0) & r^{(c)}(1) & \dots & r^{(c)}(M-1) \\ r^{(c)}(1) & r^{(c)}(2) & \dots & r^{(c)}(M) \\ r^{(c)}(2) & r^{(c)}(3) & \dots & r^{(c)}(M+1) \\ \vdots & \vdots & \ddots & \vdots \\ r^{(c)}(N-M-2) & r^{(c)}(N-M-1) & \dots & r^{(c)}(N-1) \end{bmatrix}_{(N-M\times M)} \begin{bmatrix} w_1^{(c)} \\ \vdots \\ w_M^{(c)} \end{bmatrix} - \begin{bmatrix} x^{(c)}(M) \\ x^{(c)}(M+1) \\ \vdots \\ x^{(c)}(N-1) \end{bmatrix} = \begin{bmatrix} e^{(c)}(1) \\ e^{(c)}(2) \\ \vdots \\ e^{(c)}(N-M) \end{bmatrix}$$

$$\Rightarrow \mathbf{R}^{(c)}\underline{w}^{(c)} - \underline{x}^{(c)} = \underline{e} \tag{3}$$

Our goal is to minimize $\zeta^{(c)} = \underline{e}^T\underline{e} = \sum_{n=1}^{N-M} e_n^2$ with respect to $\underline{w}^{(c)}$.

$$\zeta^{(c)} = (\mathbf{R}^{(c)}\underline{w}^{(c)} - \underline{x}^{(c)})^T(\mathbf{R}^{(c)}\underline{w}^{(c)} - \underline{x}^{(c)})$$

$$\zeta^{(c)} = \underline{w}^{(c)T}\mathbf{R}^{(c)T}\mathbf{R}^{(c)}\underline{w}^{(c)} - 2\underline{w}^{(c)T}\mathbf{R}^{(c)T}\underline{x}^{(c)} + \underline{x}^{(c)T}\underline{x}^{(c)}$$

$$\frac{\partial\zeta^{(c)}}{\partial\underline{w}^{(c)}} = 2\mathbf{R}^{(c)T}\mathbf{R}^{(c)}\underline{w}^{(c)} - 2\mathbf{R}^{(c)T}\underline{x}^{(c)} \tag{4}$$

We set $\frac{\partial\zeta^{(c)}}{\partial\underline{w}^{(c)}} = 0$ to find the $\underline{w}^{(c)}$, which yields $\underline{w}^{(c)} = (\mathbf{R}^{(c)T}\mathbf{R}^{(c)})^{-1}\mathbf{R}^{(c)T}\underline{x}^{(c)}$. The estimated component of $p^{(c)}(n)$ is, $\hat{p}^{(c)}(n) = \mathbf{R}^{(c)}.\underline{w}^{(c)}$ and following same method will give us $\hat{p}(n) = [\hat{p}^{(1)}(n), \hat{p}^{(2)}(n), \cdots, \hat{p}^{(C)}(n)]$.

After estimating $p^{(c)}(t)$, now we will select one channel where P300 is dominant to estimate the latency. We assume the latency for a single trial is the same in all channels. To find the P300-dominant channel we took the Fourier transform of the reference signal $r(t)$ and chose the channel which has maximum SNR around 10Hz. Assume the selected channel is l and for the channel reference signal is $r^{(l)}(t)$ and the estimated P300 component signal is $\hat{p}^{(l)}(t)$. Now we will use cross-correlation-based latency estimation technique between $r^{(l)}(t)$ and $\hat{p}^{(l)}(t)$

$$R_{r^{(l)}\hat{p}^{(l)}} = \mathbf{E}[r^{(l)}(t)\hat{p}^{(l)}(t-\tau)] \tag{5}$$

$$Latency = \arg(\tau)\max R_{r^{(l)}\hat{p}^{(l)}} \tag{6}$$

And the amplitudes are given by

$$\mathbf{A} = \max\hat{p}^{(l)}(t) \tag{7}$$

IV. Results

At first the proposed method has been applied on simulated data. For the simulation we have used the age-matched control subject's average P300 and then added Gaussian noise with a signal to noise ratio of 0.5. While adding

Gaussian noise we have also introduced latency jitter from a normal distribution with mean at 248ms and standard deviation of 35ms. Estimated latency for target and non-target both estimated and shown in figure 2. The correlation coefficient of estimated latency and true latency is 0.87 and the root mean squared error is 25ms.

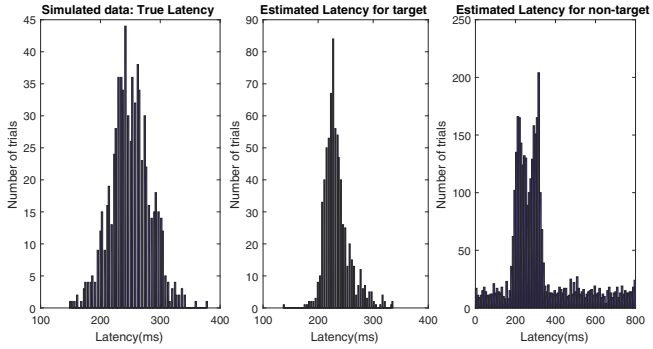


Fig. 2. Estimated P300 latency for simulated data. Latency jitter from a normal distribution with mean at 248ms and standard deviation of 35ms introduced in the simulated data.

Then the method has been applied on our data and latencies calculated using equation 6. Figure 3(a) shows the signals from 20 trials at the P300-dominant channel (Pz). P300 responses were first detected using equation 2 and then the LMS filter was applied to each detected trial to estimate the P300 latency. After applying the LMS filter, signals for the same electrode location and trials are shown in figure 3(b). Signals shown in figure 3 were acquired from a control participant.

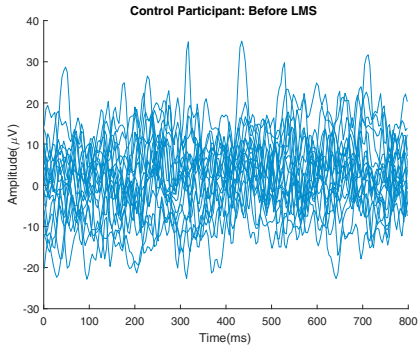
Figure 4(a) & 4(b) show 20 single trials before and after applying LMS filter, respectively. These trials are from a participant with ALS. The filtered signals are visually cleaner than their original form.

Figure 3(c) & 4(c) show estimated P300 latency for a control participant and participant with ALS, respectively. We have shown the control participant and participant with ALS side-by-side to allow comparison of their latency variation.Both participants are 45-year-old men. From these two figures, one can see that the ALS participant has more latency jitter compared to the control, and also longer mean latency than the control participant.

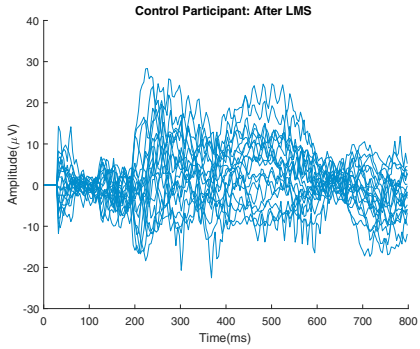
TABLE I
MEAN AND STANDARD DEVIATION (S.D) OF ESTIMATED LATENCIES FOR PARTICIPANTS WITH ALS.

Subjects	K143	K145	K146	K147	K152	K155	K156	K158	K159	K160
Mean (ms)	324.8	583.3	307.2	251.2	237.5	293.9	232.7	280.3	477.3	301.7
S.D (ms)	53.04	51.68	45.63	42.16	38.96	38.00	40.14	36.10	48.38	40.29

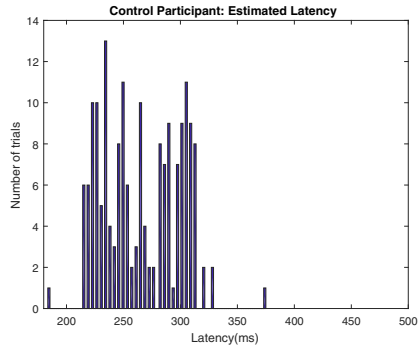
Table I shows the means and standard deviations of the estimated latencies after using the LMS filter. The standard deviations of the latency are an indicator of latency jitter for the participant, which may serve as an indicator of the participant's performance in P300 speller BCIs paradigm [14]. Latency jitter hurts classifier performance and it has been shown previously that correcting latency differences can help classifier performance [16], [19].



(a) Single trials detected as containing a P300 response.



(b) Single trials after applying LMS filter on trials shown in (a).



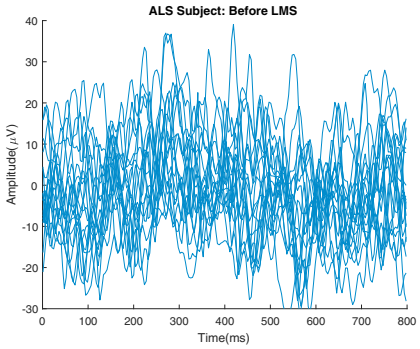
(c) Estimated P300 latency.

Fig. 3. P300 responses from an age- and gender-matched control participant. a) and b) are 20 representative trials before (a) and after (b) applying LMS filter. c) shows a histogram of all estimated latencies from the data file.

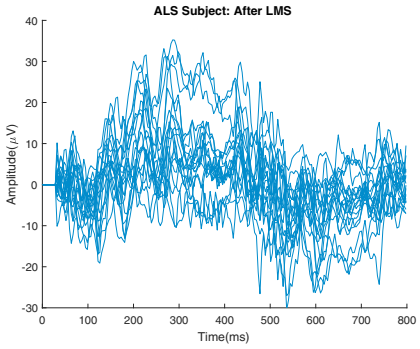
V. CONCLUSION

In this work, we have proposed a method to estimate P300 latency and amplitudes in a speller BCI paradigm. Our method uses an LMS filter for estimating P300 ERPs, and the filter requires a reference or example of the signal to be estimated. Here, the average ERPs from a training session, where the target characters were known, was used as the reference.

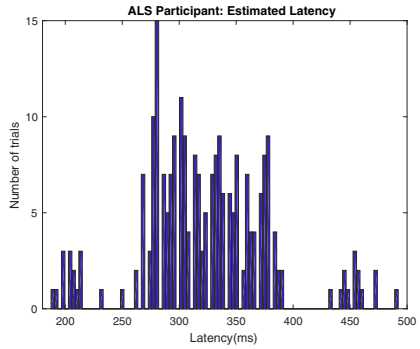
The method has been applied on real data. However, the performance is not compared with existing methods and still under development. Our goal was to investigate the efficacy



(a) Single trials detected as containing a P300 response.



(b) Single trials after applying LMS filter on trials shown in (a).



(c) Estimated P300 latency.

Fig. 4. P300 responses from a participant with ALS. a) and b) are 20 representative trials before (a) and after (b) applying LMS filter. c) shows a histogram of all estimated latencies from the data file.

of LMS adaptive filtering to estimate the latency of the P300 potential. From the above results, it is convincing that LMS filter worked as expected and LMS is able to help extract the P300-related components.

Further analysis is required to test the efficacy of this method, which will include testing the method on simulated ERPs where ground truth can be established. However, the proposed technique showed some potential and allowed us to analyze the variability of P300 latency for participants with ALS. The mean estimated latency for all participants with ALS, shown in table I, are within the expected range for P300 latency given the age of the participants. This fact lends additional evidence that the method is performing as expected. Most importantly, this method could be applicable to the estimation of other forms of ERP, with the choice of suitable reference, and is thus not limited to only P300 ERPs.

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