ERP Signal Estimation from Single Trial EEG

Hasan Mir[1]-*IEEE Senior Member*, Indu Prasad[2]-*IEEE Student Member*, Ke Yu[2]-*IEEE Member*, Nitish Thakor[2]-*IEEE Fellow*, Hasan Al-Nashash[1,2]-*IEEE Senior Member*

***Abstract*— Non-invasive EEG recordings are subject to effects such as surface conduction, resulting in very low signal to noise ratio (SNR). The conventional approach of using signal averaging to improve the SNR cannot be used for single trial EEG estimation. As such, this paper proposes a beamforming based technique that can be used to improve the signal quality from a signal trial EEG measurement. Results on experimental data show that the proposed technique can successfully isolate the signal of interest from background processes.**

I. INTRODUCTION

In modern human computer interface environments, systems should be optimized to help humans make the "correct" decision at the right time for both healthy subjects and patients. Optimization may include maximizing safety and cognitive performance efficiency [1]. Recent advances in neuroscience have started to provide researchers with new imaging modalities to interact with the brain. Electroencephalography (EEG) is a powerful imaging modality for studying brain function. A wide body of literature exists on the uses of EEG for a variety of applications in cognitive neuroscience.

When used for measurements on human subjects, EEG signals are generally recorded with an electrode array placed on the subject's scalp. Because these measurements are non-invasive, effects such as surface conduction and attenuation result in recorded signals that have very low signal to noise ratio (SNR). The conventional manner in which the SNR (and hence signal quality) is enhanced is through signal averaging, whereby signals are recorded over a large number trial repetitions (epochs), following which these epochs are averaged in order to produce a single epoch with high SNR.

The event related potentials (ERP) P300 speller brain computer interface (BCI) based system is a good example used in a wide range of different applications to aid disabled subjects in a home setting [2]-[3]. Despite the great successes achieved by BCI researchers, there are still some major challenges that confront using the P300 BCI systems in real life applications. These challenges include the relatively low bandwidth or rate of control information (the maximum reported is 25 bits/minute) [4]. Traditionally, the speller systems which use letters or symbols require at least 5 repetitions to suppress background electroencephalograph (EEG) activity and achieve acceptable accuracy. Hence, not all BCI researchers are certain that BCI will eventually replace motor movements to improve the lives of the disabled patients. In addition, applications where response time is crucial such as military surveillance and control will certainly require the BCI system to accurately respond to single trial or stimulus inputs.

While signal averaging is a simple and effective technique to improve signal quality, its use is restricted to scenarios wherein the signal of interest can be reasonably assumed to be the same from one epoch to another. Consider, however, a scenario in which an ERP signal is recorded in response to the subject being surprised by some stimulus. If this stimulus is repeated, the subject will no longer be surprised and the resulting ERP signal will not be the same as before. In such cases, it is only possible to record the signal from a single trial, and thus signal averaging cannot be applied to improve signal quality.

Work on the subject of improving single trial EEG signal quality is rather limited. Several papers on the use of beamforming for single trial EEG have been published, but these tend to focus on signal classification rather than estimation e.g. [5]-[9]. In this paper, a technique is described that applies beamforming in order to estimate the ERP signal by improving the signal quality from a single trial EEG. Estimation of the ERP signal yields more information about its characteristics compared to classification. This information is useful for BCI and cognitive engineering applications that require a higher rate of control information. The method uses the measured data to estimate the signal correlation and array response in order to perform spatial filtering on the signal.

The rest of this paper is organized as follows: Section II describes the experimental procedure. Section III describes the beamforming technique. Section IV shows the results of applying the technique described in Section III to experimental data. Section V concludes the paper.

II. EXPERIMENTAL PROCEDURE

The experimental protocol was approved by the Institutional Review Board (IRB) at the National University of Singapore. The experimental recording system is composed

[1]Department of Electrical Engineering, American University of Sharjah, UAE (e-mail: {hmir,hnashash}@aus.edu).
[2]Singapore Institute for Neurotechnology (SINAPSE), Life Sciences Institute, National University of Singapore, Singapore (e-mail: indu.iitbbs@gmail.com, yukebme@gmail.com, sinapsedirector@gmail.com).

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of a 62 channel EEG, one channel ECG and one channel EOG. A total of 15 normal male and female subjects with no previous nervous system or psychiatric disorders and not on medications were invited to participate in the experiments. The experiments were carried out in a quiet room with a controlled level of luminance. After signing the consent form, the participating subject is seated such that the distance between the eyes and the monitor is approximately 57 cm, corresponding to a visual angle of 40 x 30 degrees. The EEG, ECG and EOG were recorded from each subject while performing an experimental task designed around the odd-ball paradigm. Each experiment lasted approximately 90 minutes including subject preparation, trials, and breaks. During that time, the subject was exposed to different cognitive workload levels. If the subject fell asleep during the experiment, the experiment was terminated and a new appointment was scheduled. In each experiment, the subject was presented with approximately 210 repetitive sequences of visual stimuli. The image was also randomly drawn from a database containing different object and human face images. Following the disappearance of the image, the subject was instructed to respond as fast as possible by pressing on the computer keyboard the letter 'Q' for a target sequence and 'P' for a non-target sequence. A maximum window of 3000 ms was allowed for the subject's response. The target sequence was that which contained only a human face image. Out of the 210 different stimuli images, there were only 30 images used for target sequences.

III. SIGNAL ESTIMATION

Consider an EEG array with N electrodes. Let $\mathbf{v}(\theta)\in\Re^N$ denote the array response to a source originating at location θ. Furthermore, denote the desired signal as s_n which originates from θ_t, denote the signals u_{mn} originating from locations θ_m, $m = 1\ldots M$, as other unwanted processes, and denote $\mathbf{w}_n \in\Re^N$ as additive white noise. The measured signal $\mathbf{x}_n \in\Re^N$ can be described as:

$$\begin{aligned}\mathbf{x}_n &= s_n\mathbf{v}(\theta_t) + \sum_{m=1}^{M} u_{mn}\mathbf{v}(\theta_m) + \mathbf{w}_n \\ &= \mathbf{x}_{sn} + \mathbf{x}_{in}\end{aligned}$$

where $\mathbf{x}_{sn}$ represents the desired signal vector and $\mathbf{x}_{in}$ represents unwanted processes and noise.

The goal is to determine a spatial filter vector $\mathbf{h}\in\Re^N$ that minimizes the effect of signals emanating from any location other than that of the desired signal. Mathematically, this can be written as the Lagrangian:

$$L = \mathbf{h}^+\mathbf{R}_i\mathbf{h} + \lambda\left(\mathbf{h}^+\mathbf{v}(\theta_t) - 1\right) \tag{1}$$

where $\mathbf{R}_i\in\Re^{N\times 1}$ represents the autocorrelation matrix of $\mathbf{x}_{in}$. Note that the constraint term is necessary to avoid the trivial solution $\mathbf{h} = \mathbf{0}$. Solving (1) yields the solution:

$$\mathbf{h} = \frac{\mathbf{R}_i^{-1}\mathbf{v}(\theta_t)}{\mathbf{v}^+(\theta_t)\mathbf{R}_i^{-1}\mathbf{v}(\theta_t)} \tag{2}$$

(2) is known in the array processing literature as the minimum variance distortionless response (MVDR) beamformer [10].

Unfortunately, the MVDR beamformer cannot be directly applied to single trial EEG. The main reasons for this are:

- Since $\mathbf{x}_{in}$ is not directly available, $\mathbf{R}_i$ cannot be computed. Note that the pre-stimulus region cannot be used as an interference training region since it does not reflect post-stimulus interference statistics.
- The EEG array response and source location may not be known and hence $\mathbf{v}(\theta_t)$ cannot be computed.

In order to overcome these obstacles, consider first Figure 1 which shows a typical epoch of all 62 simultaneously recorded EEG signals (the different lines represent the individual channels).

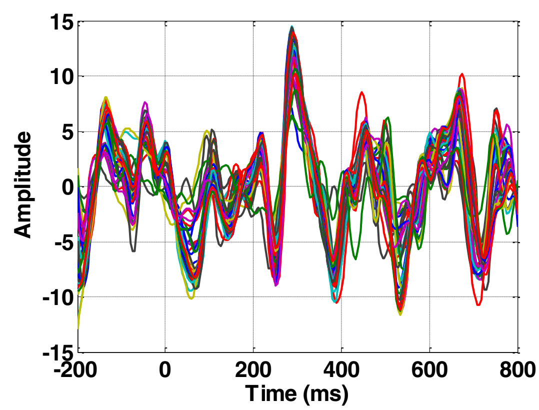

Fig 1. Typical single-trial EEG (epoch) obtained from 62 channel system

The P300 peak is quite pronounced and clearly visible. It is thus assumed that samples from around this peak are due primarily to the desired source. Consequently, they can be used to obtain an estimate of $\mathbf{v}(\theta_t)$. Moreover, it is possible to show that the same beamformer in (2) results by simply replacing $\mathbf{R}_i$ with $\mathbf{R}_x = \mathrm{E}\{\mathbf{x}_n\mathbf{x}_n^+\}$, which is easily estimated directly from N data snapshots as $\hat{\mathbf{R}}_x = \frac{1}{N}\sum_{n=0}^{N-1}\mathbf{x}_n\mathbf{x}_n^+$.

IV. RESULTS

Multiple trials (epochs) of EEG data were collected as described in Section II. For reference, the result of using conventional signal averaging over 30 epochs is shown in Figure 2. The method described in the previous section was then used to compute and apply the beamforming vector for a single epoch of EEG data.

Figures 3-6 shows typical examples from different single epochs which demonstrate the capability of the proposed method in estimating the ERP signal on a single trial basis. In each figure, the left pane shows the raw multi-channel data, whereas the right pane shows the single trial result after beamforming. The right pane shows the result of using the MVDR beamformer in bold. For the purpose of comparison, the quiescent solution, which corresponds to simple uniformly weighted spatial averaging, is also included in the right pane. It is clear in all cases that the MVDR beamformer significantly suppresses other signals compared to spatial averaging. Moreover, the resulting signal is close to the time averaged signal in Figure 2. Thus, the proposed beamforming method can provide signal quality from a single trial that approaches that of a signal obtained from time averaging multiple trials.

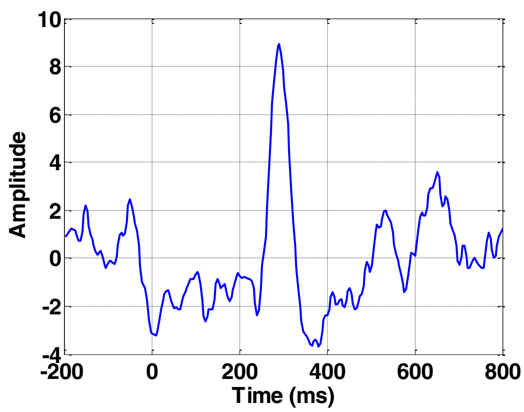

Fig 2. EEG signal averaged over 30 epochs

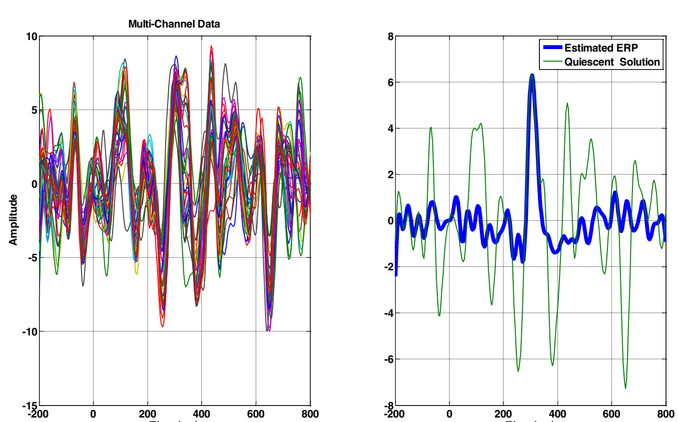

Fig 3. Raw and beamformed data for Epoch 5

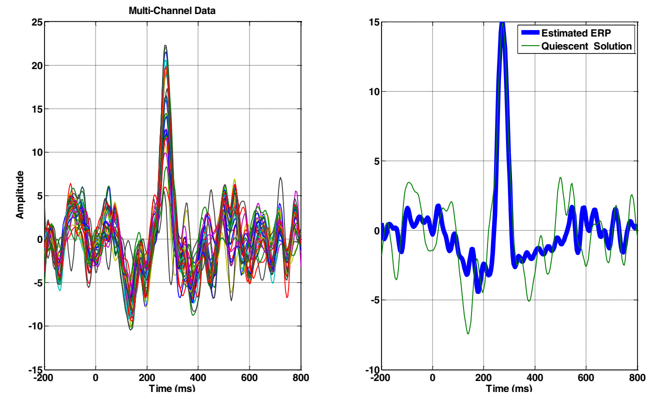

Fig 4. Raw and beamformed data for Epoch 8

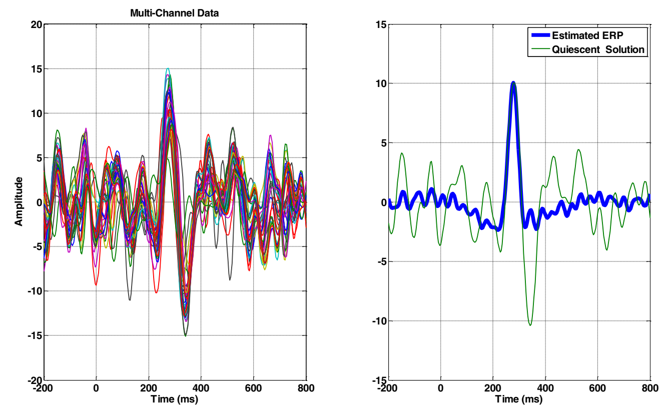

Fig 5. Raw and beamformed data for Epoch 17

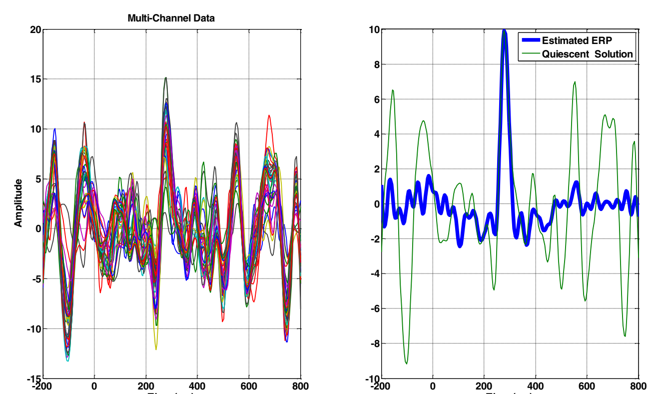

Fig 6. Raw and beamformed data for Epoch 28

V. CONCLUSION

Phenomena such as surface conduction and attenuation cause non-invasive EEG recordings to have low signal to noise ratio (SNR). For single trial EEG, this condition cannot be remedied using conventional signal averaging. In this paper, the EEG array response was estimated directly from a single epoch of data in order to compute an MVDR beamformer. Application of the resulting beamformer to experimental data shows that the proposed technique can yield a signal quality from a single epoch that is similar to the quality of a signal obtained from time averaging a large number of epochs. Future work will focus on studying the dynamic variations of the ERP signal characteristics (including amplitude and latency) across all trials.

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References

[1] A. Nijholt and D. Heylen, Editorial, *Int. J. Autonomous and Adaptive Communications Systems*, vol. 6, no. 1, pp. 1-8, 2013.

[2] S. Kleih, T. Kaufmann, C. Zickler, S. Halder, F. Leotta, F. Cincotti, F. Aloise, A. Riccio, C. Herbert, D. Mattia, and A. Kübler, “Out of the frying pan into the fire–the P300 based BCI faces real world challenges,” *Prog. Brain Res.*, pp. 27–46, 2011.

[3] C. Duncan, RJ. Barry, J. Connolly, C. Fischer, P. Michie, R. Näätänen, J. Polich, I. Reinvang, and C. Van Petten, “Event-related potentials in clinical research: Guidelines for eliciting, recording, and quantifying mismatch negativity, P300, and N400,” *Clinical Neurophysiology*, vol. 120, pp. 1883-1908, Nov. 2009.

[4] J. Karat and J. Vanderdonckt, *Human-Computer Interaction Series*, Springer-Verlag, London, 2010.

[5] Y. Li, G. Dong, X. Gao, S. Gao, M. Ge, and W. Yan, "Single trial EEG classification during finger movement task by using hidden Markov models," *International IEEE/EMBS Conference on Neural Engineering.,* pp.625-628, Mar. 2005.

[6] X. Song, S-C. Yoon, and V. Perera, “Adaptive Common Spatial Pattern for single-trial EEG classification in multisubject BCI,” *International IEEE/EMBS Conference on Neural Engineering.*, pp. 411-414, Nov. 2013.

[7] S. Samdin, C-M. Ting, S-H. Salleh, A. Ariff, and A. Mohd Noor, “Linear dynamic models for classification of single-trial EEG," *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),* pp. 4827-4830, Jul. 2013.

[8] A. Marathe, A. Ries, and K. McDowell, “Sliding HDCA: Single-Trial EEG Classification to Overcome and Quantify Temporal Variability,” *IEEE Trans. on Neural Systems and Rehab. Engr*, vol. 22, pp.201-211, Mar. 2014.

[9] H. Wang, “Multiclass Filters by a Weighted Pairwise Criterion for EEG Single-Trial Classification,” *IEEE Trans. Biomedical Engr*, vol.58, pp.1412-1420, May 2011.

[10] H. Van Trees, *Optimum Array Processing*, Wiley, New York, 2002.