Localization of Brain Activity in Electroencephalography Data during Brain-Computer Interface Operation

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***Abstract*—A novel subspace-based technique was used to suppress spatially correlated electroencephalography (EEG) interference sources, followed by a technique that estimates the source parameters with a near maximum likelihood performance. These sources are found to correlate with event-related potentials (ERPs) and are thus hypothesized to be responsible for the N200 and P300 ERPs ellicited by operation of a brain-computer interface (BCI) speller. The source localization technique was tested on EEG data of 6 able-bodied subjects, and my analysis underlines consistencies and variation of brain activity locations both within and across subjects.**

I. Introduction

P300 speller systems, first implemented by Farwell and Donchin in 1988 [1], utilizes the relatively strong response seen as primarily N200 and P300 ERPs following an unexpected stimulus. Today's state-of-the-art P300 spellers can reach information transfer rates (ITR) of over 3 bits/s, allowing a user to spell 12.75 characters/minute [2].

The P300 is related to simple cognitive processes, such as decision making and working memory. It arises whenever an individual has to discriminate between sensory stimuli and can be visualized by averaging many trials of EEG data, time-locked to the stimulus, using something called the oddball paradigm first described by Donchin in 1978 [3]. Johnson et al. [4], [5] predicted that the P300 arises from multiple different neural generators by analyzing P300 and forming a "triarchic" model. Each of these generators would be responsible for their own neural processes. They said (in 1993) that our understanding for how to ellicit the P300 is far superior to what this ERP really means, and that the functions of the P300 may be much more complex than previously thought. The idea that the P300 can be split up into subcomponents has since been generally accepted. The two most important, or only, of these subcomponents are P3a and P3b.

The P300 ERP and its origin has been a research interest for a long time. However, success in localizing the actual sources for this cognitive function has been very limited. P300 has been defined as a positive ERP component with a maximum at C_Z or P_Z electrode (central part of parietal lobe) between 300 ms and 1 s after stimulus [5]. This quite wide definition may be one reason to the fact that many studies show quite different results for where activity actually originates from. Bledowski et al. [6] also found that many people have tried to localize P300 generating nuclei, with varying success. They found that there are significant discrepancies between results and explained it with the fact that there is no unique solution to the EEG inverse problem, which states that there are always multiple solutions for what dipole sources underly any particular EEG data.

P300, or the ERP response in general does not look the same between individuals. It has been shown however, that monozygotic twins have very similar P300s, and genetically close individuals in general have similar ERPs [7], [8]. Still, even within the same individual, ERPs will vary based on such seemingly small changes as ultradian rythms (natural processes in the brain that recur in cycles of around 90 minutes) [9]. Ravden and Polich found visual P300 habituation when measuring consequent 10-minute trial blocks: P300 amplitude decreased over time at electrodes F_Z and C_Z, possibly reflecting a biological variance in arousal state over time.

Based on neurophysiological results, experimental findings and personality ERP variation, Polich hypothesized [10] that the P300 and the underlying subprocesses functional mechanism may involve inhibition of on-going processes where the first action is reallocation of attentional resources (P3a, frontally located) which may cause subsequent promotion of temporal-parietal located memory storage functions (P3b). The exact type of stimulus will determine what the resulting P300 ERP will look like, as the two subcomponents are very much over-lapping each other in time.

II. Methods

A. Data acquisition

Subjects participated in a BCI speller experiment very similar to [2], with the difference that potentials were measured at 15 electrodes instead of 8. During an experiment a subject typically did three offline "training" sessions and three online "spelling" sessions at three different interface speeds. During one offline training session, the subject is asked to pay attention to one of the characters in a 6×7-letter matrix, where 7 letters at a time then flashes randomly for 30 seconds. The interval between flashes is 170, 240 or 400 ms, determined by the interface speed parameter. This procedure is repeated with attention being paid to 10 different characters, or "oddballs". The collected data teaches the BCI computer what the subject's response to an oddball flash looks like. This data will is also what is used for localization of brain activity as the many trials allow us to extract nice ERPs.

In the consequent online session, the subject is asked to spell a sentence:

The quick brown fox jumps over the lazy dog*

(* to exit the interface) a 44 character English-language pangram, to demonstrate that he or she has obtained purposeful control of the BCI. If the subject is unable to spell the sentence, the corresponding training session is discarded. Additionally, some "control" state data immediately preceding and following an oddball will discarded, due to overlap in data acquisition and extensive oddball responses. Lastly, the data for each electrode is adjusted with respect to impedance, by dividing with the measured value for that sensor.

Six subjects participated in the experiments, depending on subject availability they completed 1-3 sessions at typically all three interface speeds each time.

B. Analysis

Null-space projection (NP) [11] is a method used to mitigate interfering sources (i.e. organized or systematic noise) in EEG data, and relies on the presence of control state data which is used to create a subspace that is orthogonal to the noise and that the activity state data then can be projected onto. The method requires knowledge of, or rather an estimation of, how many interfering sources, N_I are present. This number was found as the number of singular values of control data needed to satisfy a power ratio of .99, meaning 99% of the energy in the signal can be recovered by N_I sources. These interfering sources are not assumed to be static, but are assumed to be essentially the same in control and activity data.

Recently, a localization method originally developed for direction finding [12] has been adapted to find highly correlated sources in EEG [13], [14]. It is called noise subspace fitting (NSF), and is asymptotically equivalent to maximum-likelihood approaches, but is much faster because dipole location and moment estimations are decoupled.

NSF was developed with the intention that a period of interest (in time) would already be available or loosely defined and localization would then be done with data from that time window. I found however, that using only one sample in time and localizing sources for all available time samples, was quite efficient. It can be shown that this does not violate the data model or calculations of the NSF method.

Accompanied to the single sample NSF I developed an automatic cluster finder. We hypothesized that consecutive single sources located in close euclidean proximity to each other was a sign of a "true" source. (Remember that NSF always will give some location for the number of sources you are trying to find, but that it relies on the user to specify how many true sources there are, which in some cases can be 0.) The basic requirement for the cluster finder is that a "source" must have a dipole moment of about 1/5 or more of that of the strongest dipole in the dataset. Then, the actual cluster finder relied on two simple euclidean distance requirements:

1) Two consequent sources must not be separated with more than a certain distance, and
2) At least 5 consecutive sources must satisfy (1).

By feeding the cluster finder algorithm with all the consecutive locations from single sample NSF, locations and time frames for sources of activity in the dataset are found.

III. Results & Discussion

Shown below is the result for subject B, session 3, medium speed, which has been chosen among other similar plots for its clarity and representativeness. Three clusters can be seen, color-coded relating to their latency with respect to the stimulus. The first, green cluster at $200 - 245$ ms is, even though no N200 is seen in the occipital data, most likely evidence of information processing in the occipital lobe. The next cluster, $255 - 320$ ms post-stimulus, matches perfectly to the P300 ERP, seen in central electrodes and we can hypothesize that the neural generator for the P300 in this subject and dataset was located centrally/parietally. A later cluster, $350 - 390$ ms, is also seen, which may be some later cognitive processing going on, or just an artifact from data. The dipole moment (source strength) seen as circle sizes here, are small in comparison to those in the preceding two clusters, which may point towards it just being a coincidence.

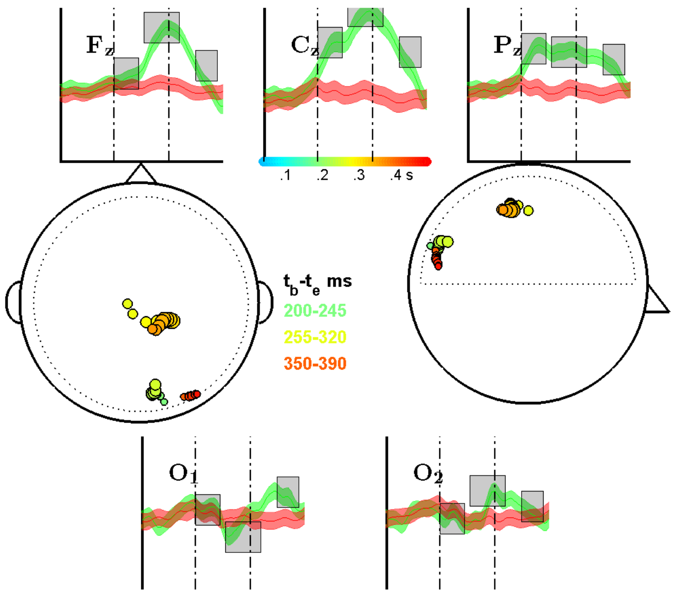

Figure 1. In the middle are sources ($200 - 245$, $255 - 320$ and $350 - 390$ ms) for subject B, session 3, medium speed as found by NSF as described in this paper. Their latency with respect to stimulus is color coded. Inset are plots for the three central electrodes (top, left to right: F_Z, C_Z, P_Z) and the occiptial electrodes (bottom left: O_1, right: O_2). "Activity" data is colored green and control data is red. Shaded is the activity data corresponding to the time windows for the sources.

In total, 6 subjects performed the experiment whereof 4 could be distinguished as "proficient" users in that they could spell the test sentence in online mode without major problems. The data from these subjects was also much clearer and unambiguous, and the results from localization are shown below.

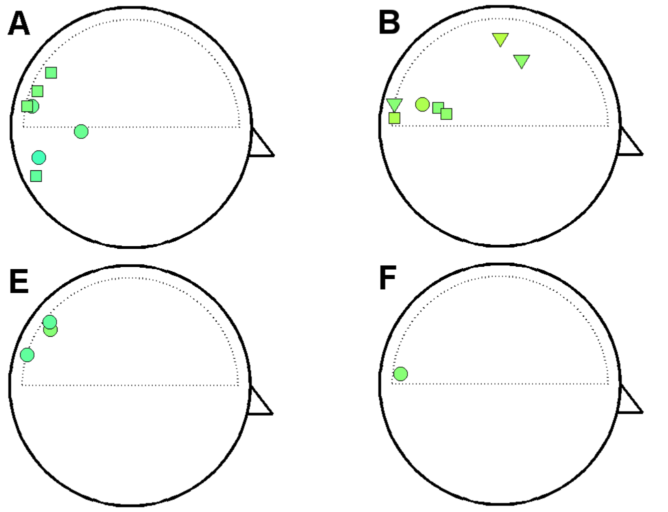

Figure 2. Different sessions (experimental days) are denoted by circle, square and triangle.

The shown locations were found by using data from the whole time window for each N200 related cluster that was found by the automatic cluster finder. For example, the cluster seen at 200 – 245 in figure 1 will here be represented by a single dot (or triangle rather) in the back of the head.

For subject A a total of 7 datasets was available and a cluster hypothesized to be responsible for the N200 was found in each of them (7/7), numbers for subject B with same notation was 7/9, subject C 3/3 and subject D 1/1. Corresponding numbers for discarded subjects C and D would be, respectively, 2/3 and 0/1.

Results for the later P300 peak were less consistent and are not shown here. More on why the P300 is hard to localize can be read in a recent Master's thesis [15].

IV. Conclusions

I found, using the described methods that there seem to be clusters of activity that highly correlate with ERPs found in EEG, and additionally, they are located in reasonable areas of the brain based on literature. More interestingly, the NP-NSF single sample-clustering method found similar clusters in datasets that had no apparent ERPs, which speaks for the power of this method.

NP-NSF shows promise in being used to localize brain activity when dual-condition datasets are available.

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References

[1] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and Clinical Neurophysiology*, vol. 70, no. 6, pp. 510 – 523, 1988.

[2] P. Wang, C. King, A. Do, and Z. Nenadic, "Pushing the communication speed limit of a noninvasive bci speller." (submitted).

[3] E. Donchin, W. Ritter, and C. McCallum, *Cognitive psychophysiology: the endogenous components of the ERP. In: Brain Event-Related Potentials in Man.*, E. Callaway, P. Tueting, and S. Koslow, Eds. Academic Press, New York, 1978.

[4] R. Johnson Jr, "A triarchic model of p300 amplitude." *Psychophysiology*, vol. 23, no. 4, pp. 367–384, Jul 1986.

[5] R. JohnsonJr, "On the neural generators of the p300 component of the event-related potential." *Psychophysiology*, vol. 30, no. 1, pp. 90–97, Jan 1993.

[6] C. Bledowski, D. Prvulovic, K. Hoechstetter, M. Scherg, M. Wibral, R. Goebel, and D. E. J. Linden, "Localizing p300 generators in visual target and distractor processing: a combined event-related potential and functional magnetic resonance imaging study." *J Neurosci*, vol. 24, no. 42, pp. 9353–9360, Oct 2004.

[7] S. O'Connor, S. Morzorati, J. Christian, and T.-K. Li, "Heritable features of the auditory oddball event-related potential: peaks, latencies, morphology and topography," *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, vol. 92, no. 2, pp. 115 – 125, 1994.

[8] J. Polich and T. Burns, "P300 from identical twins," *Neuropsychologia*, vol. 25, no. 1, Part 2, pp. 299 – 304, 1987.

[9] D. Ravden and J. Polich, "On p300 measurement stability: habituation, intra-trial block variation, and ultradian rhythms," *Biological Psychology*, vol. 51, no. 1, pp. 59 – 76, 1999.

[10] J. Polich, "Updating p300: An integrative theory of p3a and p3b," *Clinical Neurophysiology*, vol. 118, no. 10, pp. 2128 – 2148, 2007. [Online]. Available: we'replayingyouintheeurocup

[11] S.-C. Wu, A. Swindlehurst, P. Wang, and Z. Nenadic, "Mitigating interference and highly correlated sources in eeg localization." (in revision).

[12] P. Stoica and K. C. Sharman, "Maximum likelihood methods for direction-of-arrival estimation," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 38, no. 7, pp. 1132–1143, 1990.

[13] R. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Transactions on Antennas and Propagation*, vol. 34, no. 3, pp. 276–280, 1986.

[14] J. C. Mosher, P. S. Lewis, and R. M. Leahy, "Multiple dipole modeling and localization from spatio-temporal meg data," *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 6, pp. 541–557, 1992.

[15] O. Hjärtquist, "Localization of brain activity in electroencephalography data during brain-computer interface operation," Master's thesis, Lund University, 2011.