No Surprise - Fixed Sequence Event-Related Potentials for Brain-Computer Interfaces*

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Abstract— **Introduction: In the field of Brain-Computer Interfaces (BCI), the original two-class oddball paradigm has been extended to multiple stimuli with balanced probabilities and random presentation sequences. Exploiting the differences between standard and deviant ERP responses, these multi-class paradigms are suitable for communication and control.**
Methods: The present study investigates the effect of giving up the randomness of stimulation sequences in favor of a repeated, predictable pattern. Data of healthy subjects (n=10) who performed a single session with a 6-class spatial auditory ERP paradigm were analyzed offline. Their auditory evoked potentials (AEP) resulting from the potentially simpler task (using fixed sequences) are compared with the AEP evoked by pseudo-randomized stimulation sequences.
Results: Class-discriminative EEG responses between target and non-target stimuli were observed for both conditions. The binary classification error estimated for standard epochs of was comparable for both conditions (random: 24%, fixed: 25%). Expanding the standard epochs to include pre-stimulus intervals, we found that the regular structure of the fixed sequence can be exploited. Compared to the standard epoch, the MSE improves by 7%, while in the random condition an improvement could not be observed.

I. INTRODUCTION

The standard oddball paradigm makes use of a frequent standard stimulus and a rare deviant stimulus. Stimuli are typically presented as visual or auditory events within a longer stimulus sequence and in a ratio of e.g. 4:1. For a two-class attended and unattended oddball paradigm, the characteristics of event-related potential (ERP) responses of the Electroencephalogram (EEG) elicited by standard and deviant stimuli depend (among many other factors, see [6], [**?**] as entry points) on the stimulus predictability expressed by either a ordered or an irregularly repeated sequence of stimuli.

In the field of Brain-Computer Interfaces (BCI), the attended flavor of this simple paradigm has been extended to multiple stimuli with balanced probabilities but (pseudo-) random presentation sequences. Typically all stimuli are presented once during a so called iteration, before they are presented again in the subsequent iteration in a shuffled order. Exploiting the differences between standard ERP responses (for non-target stimuli) and deviant ERPs (for target stimuli) with Machine Learning methods, these multi-class paradigms are suitable for communication [5], [13], [7], [29], [22] and control [27], [19], [28], [3]. Visual ERP BCIs are applicable e.g. for motor impaired patients that can at least maintain a stable gaze direction and have eye lid control, even though the communication performance is expected to deteriorate when full gaze control is lost. Recently proposed paradigms may provide a communication channel even in this case, e.g. by using covert visual paradigms [17], [1], [29] or by exploiting the auditory modality [14], [8], [9], [12], [30], [2], [11], [25], [16], [10].

Given the recent improvements in data analysis methods [23], [4], in experimental paradigms [15], [28] and in technological improvements (e.g. user-friendly wireless dry EEG sensors [20], [18], [31], [21] or small wireless implantable surface ECoG electrodes [26]), BCIs are about to take the important step out of the lab and into realistic end-user testing scenarios. In the auditory domain, however, a multi-stimulus paradigm can have a high demand for spatially directed attention. Supporting the transition from the lab to end-user testing means, that we have to tackle this high workload. Therefore the present study investigates the effect of giving up the randomness of stimulation sequences in favor of a simple, repeated, and thus predictable pattern.

II. METHODS

A. Setup

The study has been approved by the Charité ethics committee, Berlin. After declaring written informed consent, ten healthy subjects participated in a single session EEG experiment. EEG was recorded at 1000 Hz sampling frequency from 61 equally spaced scalp positions following the extended 10-20 system using a BrainAmp amplifier. The study participants performed twelve runs with a 6-class spatial auditory ERP paradigm. Runs were separated by pauses of individual duration. The six classes were coded by six different tones (duration: 40 ms) played from six unique directions around the head of the participant. The paradigm followed the AMUSE paradigm described in [25], [24], but used a stimulus onset asynchrony (SOA) of 200 ms.

Each run contained twelve trials of approx. 16 s duration, which alternated between the two conditions (see below). Altogether, each subject performed 144 trials. From trial to trial, the target tone, which was indicated to the subject prior to the trial start by three cues, was changed. During a trial, 11 to 13 iterations of the set of six tones were played. During each iteration (with duration $6 * 200\,\text{ms} = 1200\,\text{ms}$), each of the tones was played once. Subjects were asked to mentally count the number of target appearances during each trial and report the number after the trial had finished. If correct, this

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number corresponded to the number of iterations (11 to 13) played. While the experimenter provided immediate feedback about the counting performance, no online feedback by the BCI system was given.

B. Two Conditions: Randomized and Fixed Sequence

Depending on the condition, the sequence of six tones was either pseudo-randomized from iteration to iteration (condition **rand**), or randomized for the first iteration only, and then kept fix for all 11 to 13 iterations of a trial. But even in the **rand** condition, the pseudo-randomization took care that neighboring iterations would not end and start with the same tone. Thus two target stimuli were always separated by at least one non-target stimulus. In the **fix** condition, target tones were separated by exactly five non-target tones, while in the **rand** condition only the *expected* number of non-target tones was five. In condition **fix**, subjects had a chance to recognize the regular pattern of stimuli after the second iteration had finished. As previous experiments have shown that the spatially directed attention is generally not easy to establish for the first tones after an inter-trial pause, the stimulus marker of the first two iterations of each trial (12 stimuli) have been discarded from further analysis, and only the stimulus markers of nine to eleven full iterations have been kept for each trial. As in the last step (see below), epochs started as early as -2400 ms relative to the stimulus marker, this removal guaranteed, that an epoch would not start prematurely (e.g. in the inter-trial pause or cue period).

Overall, the experimental setup corresponds to a typical calibration phase of a BCI session, except for the two conditions applied.

C. Analysis Methods

The collected data were analyzed offline. After high-pass filtering the continuous EEG data with a cut-off frequency of 0.2 Hz, it was low-pass filtered with a cut-off frequency of 30 Hz and down-sampled to 100 Hz sampling frequency. Starting with a standard epoch interval of [0–1000] ms relative to a stimulus, the analyzed epochs were enlarged in 12 steps by additional pre-stimulus intervals of 200 ms duration for each step. The largest analyzed epochs thus were located at [-2400–1000] ms around a stimulus. After removing approx. 50 to 300 outlier epochs based on a simple variance and amplitude criterion, approx. 4200 epochs remained for each condition. Thus, approx. 700 target epochs and 3500 non-target epochs were available for further analysis.

In the first part of the analysis, the average ERP responses for targets and non-targets of both conditions were obtained. Further more, the signed r^2 value as an indicator for class separability was calculated.

For classification of the smallest epochs ([0–1000] ms), the following set S of intervals (milliseconds relative to the stimulus onset) was utilized: $S =$ [60 100; 100 140; 140 180; 180 220; 220 260; 260 300; 300 400; 400 500; 500 600; 600 700; 700 800; 800 1000]. For any enlarged epochs, two copies of S, time-shifted by -1200 ms and -2400 ms were supplied in addition. Only those of the overall $3 * 12$ intervals, which overlapped with the (growing) epochs were used. The EEG amplitude values were averaged within each interval, but for each channel separately. As a result, the smallest analyzed epochs of [0–1000] ms were represented by 12 features per channel only, while the largest epochs of [-2400–1000] ms were represented by 36 features per channel.

The time structure of class-discriminant information contained in an epoch is in addition analyzed by a sliding window of 50 ms width. Classification is done separately for steps of 10 ms width. In this case, only a single feature per channel was extracted.

Classification was always performed with a Fisher Linear Discriminant Analysis (FDA), that had been regularized with shrinkage of the class covariance matrices. Due to the applied regularization, even the maximum number of $61 * 36 = 2196$ features lead to stable classification results. All reported error values have been estimated by averaging the outcome of a 5-fold cross-validation that on top was shuffled randomly for another 5 times. Errors represent class-wise balanced errors with a chance level of 50 %.

III. RESULTS

A. Basic Electrophysiology of Event-Related Potentials

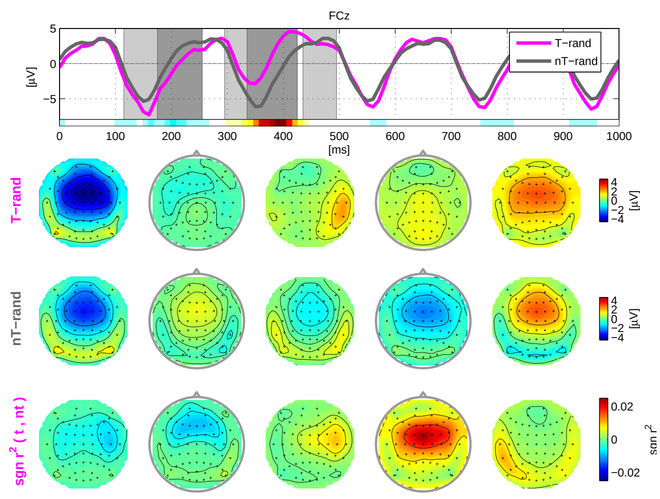

Fig. 1. Overview ERP plots for condition **rand** for subject no. 2. The top row depicts the average time course of target (T) and non-target (nT) responses for channel FCz. The horizontal colored bar visualizes signed r^2 values for each time bin as an indicator for class discriminability. Rows two and three depict scalp plots of average activity in five selected time intervals (see gray shades in the top row). The bottom row shows the distribution of class discriminative information for these five intervals over the scalp.

Examples of the ERP responses of both conditions are depicted in Fig. 1 (**rand**) and Fig. 2 (**fix**). The plots are based on the recordings from subject no. 2, who revealed a rather representative ERP activity. Up to a slightly different scaling and selection of intervals, the plots provide the same view on the data of both conditions. Clearly the average time courses are dominated by the stimulus SOA of 200 ms. The large number of averaged epochs lead to a very regular rhythmic activity, which is mainly carried by early components

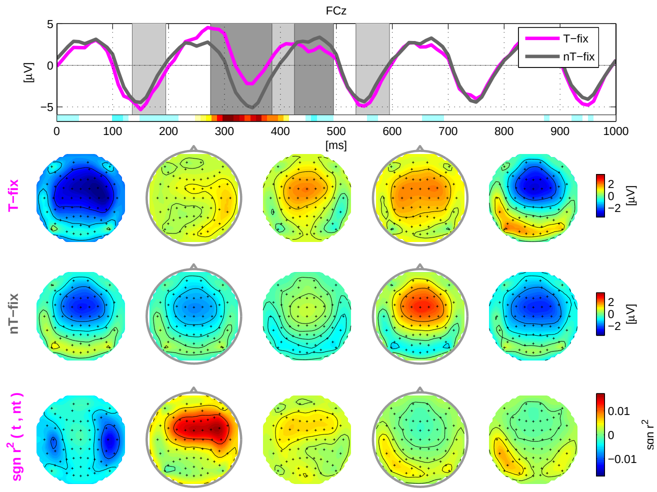

Fig. 2. Overview ERP plots for condition **fix** for subject no. 2. For an explanation see Fig. 1.

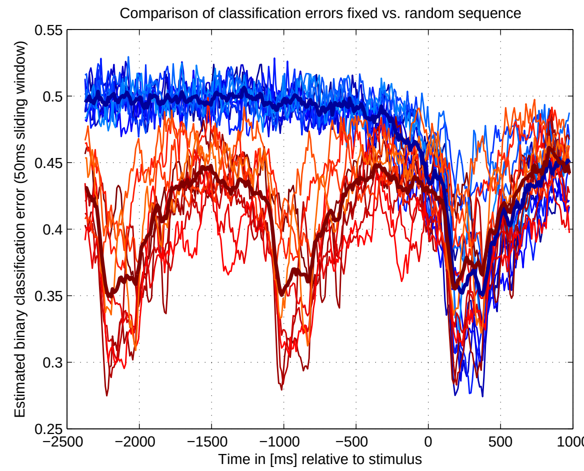

Fig. 3. MSE estimated in a sliding window of 50 ms width in steps of 10 ms for ten subjects and two conditions. Errors for condition **rand** are plotted in blue colors, while errors for condition **fix** are plotted in red colors. Thin lines represent the errors of single subjects and thick lines represent the grand averages.

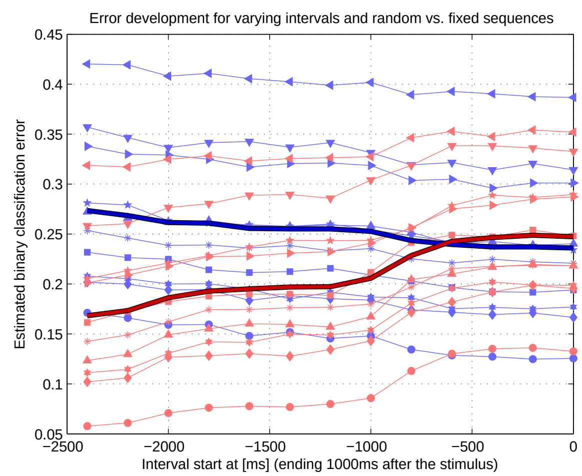

Fig. 4. Estimated MSE for ten subjects, different lengths of the analyzed epochs and two conditions. The x axis indicates the start point of the analyzed intervals, while the end was kept constant at 1000 ms post stimulus. Errors for condition **rand** are plotted in blue colors, while errors for condition **fix** are plotted in red colors. Thin lines represent the errors of single subjects and thick lines represent the grand averages. Corresponding curves of a subject can be identified by a common marker.

(N1/P2) of non-targets, but is also present in the epochs of non-target responses due to subsequent non-target stimuli.

For target stimuli, however, the figures reveal a changed ERP response in both conditions. The r^2-plots in the lower rows show two main class-discriminative intervals in both conditions. An early negativity around 150 ms after stimulus onset is stronger for the target stimuli than for non-targets. This negativity can be best be exploited at fronto-lateral sensor positions. For simplicity it will be referred to as N1 component. A later positivity around 250 to 350 ms is observed for target stimuli, which will be referred to as P3 component.

Please observe, that for this subject the absolute amplitudes of the late positive potential, the exact locations on the scalp as well as their discriminative time intervals (350 ms to 430 ms for **rand**, and 250 ms to 330 ms for **fix**) vary between conditions. The same is true for the earlier discriminative N1 components.

B. Classification

The time structure of class-discriminant information contained over all channels is depicted in Fig. 3. It contains the classification errors of a small sliding window which is lead over the largest epoch. The rhythmic structure of the red lines in 3 show, that class-discriminant information in condition **fix** (expressed by differences between target and non-target ERP responses) is forming a pattern that repeats each iteration. In contrary, the blue lines of condition **rand** quickly approach the chance level of 50 % error, when the epochs are enlarged to pre-stimulus intervals.

The absolute classification errors of both conditions are compared in Fig. 4. With growing analysis intervals, the random stimulus sequences show an increased error. A potential explanation for this increase is the enlargement of the feature dimensionality. Adding 24 non-discriminative (noisy) features to the meaningful 12 features per channel, the FDA performs slightly worse – despite of the regularization.

The potential reduction of the binary classification loss is visualized in Fig. 5. Observe, that the binary classification error of the randomized standard paradigm (epoched [0–1000] ms) can be reduced by 7 % when fixed stimulation sequences are applied and exploited epoch intervals are enlarged to include two full predecessor iterations.

IV. DISCUSSION

Our finding, that fixed stimulation sequences elicit class-discriminative ERP responses comparable to randomized sequences will enlarge the toolbox of ERP setups for future BCI designs. It has to be tested, though, if the advantage observed for extended time intervals with fix sequences

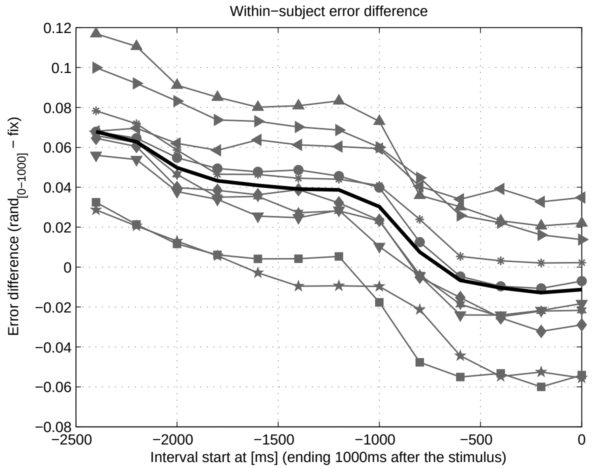

Fig. 5. The MSE error in condition **rand** for the smallest epoch [0–1000] ms is compared with the MSE of condition **fix** for different interval sizes. The x axis indicates the start point of the analyzed intervals of condition **fix**, while the end was kept constant at 1000 ms post stimulus. Thin lines represent the error differences of single subjects and the thick line represents the grand average.

transfers into the online BCI use. In typical online setups, a decision is based on the agglomeration of evidence over several iterations. This technique is applicable even for randomized sequences, and may exploit sequential information in a similar way than with epoch enlargement for fixed sequences.

REFERENCES

[1] Laura Acqualagna and Benjamin Blankertz. A gaze independent speller based on rapid serial visual presentation. In *Conf Proc IEEE Eng Med Biol Soc*, volume 2011, pages 4560–4563, 2011.

[2] A. Belitski, J. Farquhar, and P. Desain. P300 audio-visual speller. *J Neural Eng*, 8(2):025022, 2011.

[3] Benjamin Blankertz, Michael Tangermann, and Klaus-Robert Müller. BCI applications for the general population. In J. R. Wolpaw and E. W. Wolpaw, editors, *Brain-Computer Interfaces – Principles and Practice*, pages 363–372. Oxford University Press, New York, 2012.

[4] Sven Dähne, Johannes Höhne, and Michael Tangermann. Adaptive classification improves control performance in ERP-based BCIs. In *Proceedings of the 5th International BCI Conference*, pages 92–95, Graz, 2011.

[5] L.A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol*, 70:510–523, 1988.

[6] Craig Gonsalvez and John Polich. P300 amplitude is determined by target-to-target interval. *Psychophysiology*, 39(03):388–396, 2002.

[7] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger. How many people are able to control a P300-based brain-computer interface (BCI)? *Neurosci Lett*, 462:94–98, Oct 2009.

[8] Jing Guo, Shangkai Gao, and Bo Hong. An auditory brain-computer interface using active mental response. *IEEE Trans Neural Syst Rehabil Eng*, 18(3):230 –235, june 2010.

[9] S. Halder, M. Rea, R. Andreoni, F. Nijboer, E. M. Hammer, S. C. Kleih, N. Birbaumer, and A. Kübler. An auditory oddball brain-computer interface for binary choices. *Clin Neurophysiol*, 121(4):516–523, Apr 2010.

[10] J. Hill and B. Schölkopf. An online braincomputer interface based on shifting attention to concurrent streams of auditory stimuli. *jneuraleng*, 9(2):026011, 2012.

[11] Johannes Höhne, Konrad Krenzlin, Sven Dähne, and Michael Tangermann. Natural stimuli improve auditory BCIs with respect to ergonomics and performance. *J Neural Eng*, 2012. in press.

[12] Johannes Höhne, Martijn Schreuder, Benjamin Blankertz, and Michael Tangermann. A novel 9-class auditory ERP paradigm driving a predictive text entry system. *Front Neuroscience*, 5:99, 2011.

[13] B. Hong, F. Guo, T. Liu, X. Gao, and S. Gao. N200-speller using motion-onset visual response. *Clin Neurophysiol*, 120:1658–1666, Sep 2009.

[14] S. Kanoh, K. Miyamoto, and T. Yoshinobu. A brain-computer interface (BCI) system based on auditory stream segregation. In *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of theIEEE*, pages 642–645, Vancouver BC, 2008. IEEE.

[15] T. Kaufmann, SM Schulz, C. Grünzinger, and A. Kübler. Flashing characters with famous faces improves ERP-based brain–computer interface performance. *jneuraleng*, 8:056016 (10pp), 2011.

[16] Do-Won Kim, Han-Jeong Hwang, Jeong-Hwan Lim, Yong-Ho Lee, Ki-Young Jung, and Chang-Hwan Im. Classification of selective attention to auditory stimuli: Toward vision-free brain-computer interfacing. *J Neurosci Methods*, 197(1):180 – 185, 2011.

[17] Y Liu, Z Zhou, and D Hu. Gaze independent brain-computer speller with covert visual search tasks. *Clin Neurophysiol*, 122(6):1127–1136, 2011.

[18] A. Luo and T. J. Sullivan. A user-friendly SSVEP-based brain-computer interface using a time-domain classifier. *J Neural Eng*, 7:26010, Apr 2010.

[19] Jana I. Münssinger, Sebastian Halder, Sonja C Kleih, Adrian Furdea, Valerio Raco, Adi Hösle, and Andrea Kübler. Brain painting: first evaluation of a new brain-computer interface application with als patients and healthy volunteers. *Front Neuroscience*, 4(0), 2010.

[20] Florin Popescu, Siamac Fazli, Yakob Badower, Benjamin Blankertz, and Klaus-R. Müller. Single trial classification of motor imagination using 6 dry EEG electrodes. *PLoS ONE*, 2(7), 2007.

[21] J Saab, B Battes, and M Grosse-Wentrup. Simultaneous eeg recordings with dry and wet electrodes in motor-imagery. pages 312–315, Graz, Austria, 9 2011. Verlag der Technischen Universität Graz.

[22] Sulamith Schaeff, Matthias Treder, Bastian Venthur, and Benjamin Blankertz. Motion-based ERP spellers in a covert attention paradigm. In *Neurosci Lett*, volume 500, page e11, Aug 2011.

[23] Martijn Schreuder, Johannes Höhne, Matthias Sebastian Treder, Benjamin Blankertz, and Michael Tangermann. Performance optimization of ERP-based BCIs using dynamic stopping. In *Conf Proc IEEE Eng Med Biol Soc*, pages 4580–4583, 2011.

[24] Martijn Schreuder, Angela Riccio, Febo Cincotti, Monica Risetti, Benjamin Blankertz, Michael Tangermann, and Donatella Mattia. Putting AMUSE to work: an end-user study. *Int J Bioelectromagnetism*, 13(3):139–140, 2011.

[25] Martijn Schreuder, Thomas Rost, and Michael Tangermann. Listen, you are writing! Speeding up online spelling with a dynamic auditory BCI. *Front Neuroscience*, 5:112, 2011.

[26] Martin Schuettler, Fabian Kohler, Juan S. Ordonez, and Thomas Stieglitz. Hermetic electronic packaging of an implantable brain-machine-interface with transcutaneous optical data communication. In *Conf Proc IEEE Eng Med Biol Soc*, volume 2012, page (submitted), 2012.

[27] Michael Tangermann, Matthias Krauledat, Konrad Grzeska, Max Sagebaum, Benjamin Blankertz, Carmen Vidaurre, and Klaus-Robert Müller. Playing pinball with non-invasive BCI. In Daphne Koller, Dale Schuurmans, Yoshua Bengio, and Léon Bottou, editors, *Advances in Neural Information Processing Systems 21, December 8-11, 2008*, pages 1641–1648. MIT Press, Vancouver, BC, Canada, 2009.

[28] Michael Tangermann, Martijn Schreuder, Sven Dähne, Johannes Höhne, Sebastian Regler, Andrew Ramsay, Melissa Quek, John Williamson, and Roderick Murray-Smith. Optimized stimulation events for a visual ERP BCI. *Int J Bioelectromagnetism*, 13(3):119–120, 2011.

[29] Matthias Sebastian Treder, Nico Maurice Schmidt, and Benjamin Blankertz. Gaze-independent brain-computer interfaces based on covert attention and feature attention. *J Neural Eng*, 8(6):066003, 2011. Open Access.

[30] R.J. Vlek, R.S. Schaefer, C.C.A.M. Gielen, J.D.R. Farquhar, and P. Desain. Sequenced subjective accents for brain-computer interfaces. *J Neural Eng*, 8(3):036002, 2011.

[31] Thorsten Oliver Zander, Moritz Lehne, Klas Ihme, Sabine Jatzev, Joao Correia, Christian Kothe, Bernd Picht, and Femke Nijboer. A dry eeg-system for scientific research and brain-computer interfaces. *Frontiers in Neuroscience*, 5(0), 2011.