33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Revealing the Neural Response to Imperceptible Peripheral Flicker with Machine Learning

Anne K. Porbadnigk, Simon Scholler, Benjamin Blankertz, Arnd Ritz,
Matthias Born, Robert Scholl, Klaus-Robert Müller, Gabriel Curio and Matthias S. Treder

Abstract— **Lighting in modern-day devices is often discrete. The sharp onsets and offsets of light are known to induce a steady-state visually evoked potential (SSVEP) in the electroencephalogram (EEG) at low frequencies. However, it is not well-known how the brain processes visual flicker at the threshold of conscious perception and beyond. To shed more light on this, we ran an EEG study in which we asked participants (N=6) to discriminate on a behavioral level between visual stimuli in which they perceived flicker and those that they perceived as constant wave light. We found that high frequency flicker which is not perceived consciously anymore still elicits a neural response in the corresponding frequency band of EEG, contralateral to the stimulated hemifield. The main contribution of this paper is to show the benefit of machine learning techniques for investigating this effect of subconscious processing: Common Spatial Pattern (CSP) filtering in combination with classification based on Linear Discriminant Analysis (LDA) could be used to reveal the effect for additional participants and stimuli, with high statistical significance. We conclude that machine learning techniques are a valuable extension of conventional neurophysiological analysis that can substantially boost the sensitivity to subconscious effects, such as the processing of imperceptible flicker.**

I. INTRODUCTION

Understanding human perception of visual flicker is of importance both for basic research on the human visual system and for optimizing the design and manufacturing of light sources. In the past decades, artificial lighting changed from continuous to discrete (i.e., flickering) light based on LEDs. The conventional approach for assessing perception of flicker is based on behavioral data, such as subjective reports. The approach taken here, however, is to record and analyze EEG data in addition to behavioral responses. Previous EEG studies have shown that visual flicker of up to 50Hz can be perceived consciously for light sources fixated with the eye, inducing a neural response with the same dominant frequency as the stimulus frequency, the so-called steady-state visually evoked potential (SSVEP) [1], [2], [3]. It has also been shown that the sensitivity for perceiving flicker in the visual periphery is at a substantially higher level [4]. The aim of the present study was to assess whether a flickering light source in the visual periphery elicits a neural SSVEP response, even if flicker is not perceived consciously, as well as to evaluate the potential benefits of machine learning techniques for revealing this effect.

A.K. Porbadnigk, S. Scholler, B. Blankertz, K.-R. Müller and M.S. Treder are with the Machine Learning Laboratory, Berlin Institute of Technology, 10587 Berlin, Germany anne.k.porbadnigk@tu-berlin.de

K.-R. Müller is also with the Institute for Pure and Applied Mathematics, UCLA, Los Angeles CA 90095-7121, USA

A. Ritz is with Philips Research Eindhoven, The Netherlands. M. Born and R. Scholl are with Philips Research Aachen, Germany

G. Curio is with the Department of Neurology and Clinical Neurophysiology, Charité, 12200 Berlin, Germany

A. Motivation for the Use of EEG

Generally speaking, the potential benefits of neurophysiological data are manifold. First, neural data might provide a more objective measure than behavioral data, as mental processing is less influenced by subjective evaluation. Second, the compliance of participants is not necessarily required, apart from their general willingness to partake in the study. The most important aspect is the potential of neurophysiological data for revealing subconscious processing of stimuli, that is processing which is not reflected on the behavioral level. This subconscious processing might lead to lapses of concentration or growing dissatisfaction of a user over time. Thus, neurophysiological measures seem to have the potential to complement behavioral approaches at the threshold of perception, as was recently shown for marginally noisy audio stimuli [5]. The neurophysiological measure of choice needs to provide a high temporal resolution for capturing the fine-grained temporal differences in the visual signals. Additionally, it needs to be affordable and relatively mobile for potential on-site applications. All of these requirements are met by electroencephalography (EEG). In recent years, methods developed within research on EEG-based Brain Computer Interfaces (BCIs, [6]) are increasingly used for investigating questions beyond communication and control [7]. Based on such methods, this paper presents an initial approach towards applying machine learning techniques on EEG recordings in order to assess (sub)conscious processing of flicker in the visual cortex.

B. Machine Learning Approach

EEG data in the frequency range above 50Hz suffers from an unfavorable signal-to-noise ratio, as the human EEG spectrum follows a 1/f distribution (i.e., EEG power declines with increasing frequency). In order to improve the signal-to-noise ratio, we utilized Common Spatial Pattern (CSP) analysis [8], a powerful tool frequently used in BCIs that are based on the modulation of brain rhythms [9], [10]. Roughly speaking, CSP analysis provides spatial filters that maximize the difference in amplitude between two classes of bandpass-filtered signals. For details on the use of these spatial filters in the context of single-trial EEG analysis, refer to [11]. With regard to the classification of EEG data, conventional

978-1-4244-4122-8/11/$26.00 ©2011 IEEE

Linear Discriminant Analysis (LDA, [12]) has proven to be a suitable classification method for CSP features [11].

The performance of classifiers is commonly evaluated based on the receiver operating characteristic (ROC, [13]). In the so-called ROC curve, the true positive rate is plotted against the false positive rate [14]. The area under this curve (AUC) can then be calculated as a condensed measure of classification performance [15].

II. MATERIAL AND METHODS

A. Paradigm and Apparatus

Six right-handed participants (2 males, 4 females, mean age 26.83) performed a detection task. They were asked to differentiate on a behavioral level between flickering and non-flickering stimuli in a dark room. Throughout the experiment, participants fixated a red LED in front of them. In the left visual hemifield, stimuli were presented using an LED light source fabricated by Philips Research (Aachen, Germany) that subtended a visual angle of 20 deg, ranging from 10-30 deg. A checkerboard pattern was mounted on the light source (side length of checkers: 2cm), in order to enhance the susceptibility of the visual cortex to flicker [16]. Setup and LED light source are shown in Figure 1.

Participants indicated whether they saw flicker in the stimulus or not by pressing a button (left hand: flicker seen; right hand: no flicker seen). Concurrently, EEG data was recorded using a 64-channel actiCAP active electrode system (Brain Products, Munich, Germany). Each stimulus was presented for 2500ms with a variable stimulus onset asynchrony, as the presentation of the next stimulus was triggered by the response of the participant to the previous stimulus.

B. Stimulus Selection

As the focus of interest was on flickering stimuli at the threshold of perception, stimuli were selected based on a pre-test in order to account for individual differences between participants. For each participant, the critical flicker frequency was determined in the range between 40 and 120Hz, using the psychophysical method of ascending and descending limits. In the following, critical flicker frequency (CFF) denotes the lowest frequency for which a given participant started to miss the flicker of a stimulus to a substantial degree (more than half of the trials). Based on the results of this test, four target flicker frequencies (S1-S4) were chosen: one at a frequency reliably below the CFF (S1), one centered at the CFF (S2), and two frequencies above the CFF (S3, S4). The average detection rate in the experiment showed a steep decrease from S1 (98%) to S2 (15%), from where it levelled out (2% for S3 and S4). An overview of stimulation frequencies used in the experiment is provided in Table I. This table also shows the detection rates in the experiment for each stimulus and participant, i.e., the percentage of trials for which participants indicated that they perceived flicker. For technical reasons, the constant wave stimulus (CW) was implemented as flickering light at 500Hz which was reported correctly in 99% of the trials on average.

TABLE I

STIMULATION FREQUENCIES [HZ] AND DETECTION RATES [%] PER PARTICIPANT. FOR COLORED CELLS, A NEURAL RESPONSE TO FLICKER WAS FOUND ($p < 0.05$), SHOWN BY BOTH T-TESTS AND CSP+LDA (ORANGE) OR BY CSP+LDA ONLY (YELLOW). NOTE THAT HITS OF STIMULUS S1 WERE CONSIDERED AND MISSES OF S2-4.

Participant	S1:hit		S2:miss		S3:miss		S4:miss	
VPdbe	40Hz	100%	60Hz	1%	83Hz	0%	95Hz	0%
VPik	50Hz	99%	70Hz	40%	85Hz	0%	100Hz	0%
VPdbf	50Hz	96%	70Hz	11%	85Hz	1%	100Hz	1%
VPdbd	40Hz	98%	50Hz	28%	60Hz	0%	70Hz	0%
VPow	50Hz	99%	70Hz	9%	85Hz	8%	100Hz	8%
VPfat	50Hz	97%	70Hz	3%	85Hz	0%	100Hz	1%

Fig. 1. Setup of the experiment with LED light source. The room was not illuminated during the experiment.

In the actual experiment, the stimuli were presented to each participant in 10 blocks of 150 stimuli each (randomized order). This resulted in a total of 300 trials per participant for each of the five stimulus classes (S1-4, CW).

C. Preprocessing and Classification

We investigated whether flicker in a stimulus was processed in the visual cortex of a participant or not. For each trial, we extracted the power in the EEG frequency band corresponding to stimulation frequency. This is based on the assumption that neural processing of flicker increases power relative to a baseline. As baseline, we used the power in the corresponding frequency band in the EEG data recorded during presentation of the constant wave stimulus (CW).

For assessing the neurophysiological data, t-values were then calculated for each electrode site, comparing log power of the flicker trials to log power in the CW trials. It is important to note that only correct rejects of CW were considered. These were compared with S1 trials where flicker was correctly recognized (hits), as well as with trials of stimulus class S2-4, where flicker was missed.

With regard to classification, the signal was first band-pass filtered for a given frequency, using a Butterworth filter of order 5 with a passband of width 2Hz around the frequency of interest. Then, we trained a classifier to distinguish between trials where flicker was present in a given stimulus class but not reported (S2-4, misses) and those

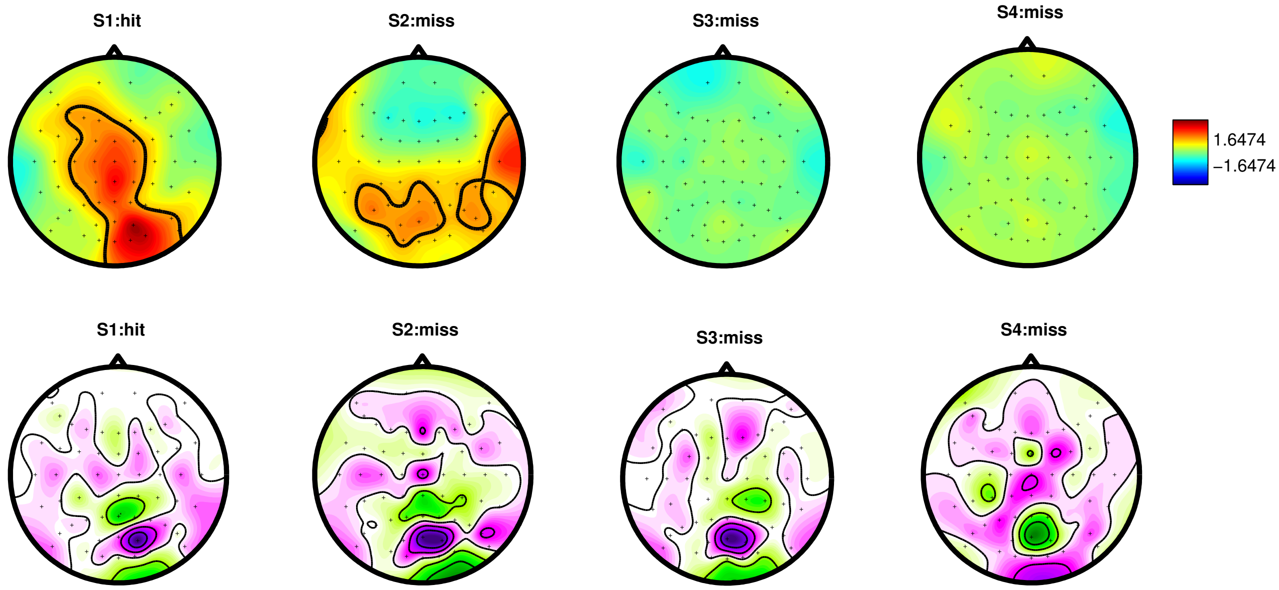

Fig. 2. T-scaled scalp maps and CSP filters for participant VPdbd (top view on the head with nose pointing upwards). Correct rejects of CW are compared with hits of S1 and misses of S2-4, respectively. *Top*: T-values plotted as scalp maps. Significant results are encircled by bold black curves ($p < 0.05$). *Bottom*: CSP filters extracted from the EEG data and then used for training the LDA-based classifiers (note that the algebraic sign of the filters can be neglected in this context).

where participants correctly recognized that it was absent (CW, correct rejects). For training and testing, 20-fold cross validation with LDA was used. The training data was first preprocessed by applying CSP in order to improve the signal-to-noise ratio, as well as to find filters that maximize the amplitude difference between two classes of interest [11]. Data was considered in the interval [500 2500ms] post-stimulus, using recordings from all electrode sites except those frontal to the F-row.

III. RESULTS

A. Neurophysiology

As a first step, spectral power was calculated for the target frequency and compared to that of the CW stimulus in the same frequency band using t-tests. As expected, we found that occipital electrode sites contralateral to the stimulated hemifield showed enhanced spectral power at the target frequencies. For half of the participants, this even held true for frequencies that were not perceived consciously anymore (S2 misses). The t-scaled scalp maps for participant VPdbd are depicted exemplarily in the top row of Figure 2.

B. Classification

We then used a machine learning approach typically taken in BCI research, first filtering the (training) data using CSP and then applying an LDA based classifier. Our aim was to assess in how far these methods would help in revealing more cases of subconscious processing: a modulation of power in the frequency band of stimulation, even if a participant reports not to perceive flicker. For each participant and stimulus class, we trained a classifier to discriminate between those trials where flicker was present, but not reported (S2-4, misses) and those where flicker was absent and correctly reported as such (CW, correct rejects). It is crucial to note that these trials are indistinguishable on a behavioral level, suggesting that the stimuli were perceived in the same way.

Our machine learning approach was successful not only in confirming the initial findings based on t-values, but also in detecting subconscious processing for additional participants and stimuli. The added value is visualized in Table I: The effects found with t-tests are marked in orange, all of which could be confirmed with our machine learning approach. Marked in yellow are those additional conditions for which we found statistically significant results that could not be revealed using t-tests.

Classification performance based on AUC values is visualized in Figure 3. Remarkably, we could not only considerably extend the sensitivity to subconscious processing. The results of the machine learning approach are also highly statistically significant for four out of six participants for missed flicker in stimulus S2 ($p < 0.01$). For participant VPdbd, AUC values at level $p < 0.01$ were reached even for stimuli S3 and S4. This might be explained by the fact that frequencies S3 and S4 were rather low for this participant compared to the others (cf. Table I, based on a pre-test).

As a sanity check, we used the same methods to compare the neural response elicited by CW and by stimulus S1, where flicker was invariably recognized easily by participants (mean detection rate: 98%). For both classes, we only considered trials where participants reported the absence (CW) or presence (S1) of flicker correctly. We found statistically significant effects for all participants, except VPfat.

Surprisingly, classification between S2 misses versus CW was oftentimes more successful than for S1 hits versus CW. This was probably caused by the use of 50Hz as S1 stimulus

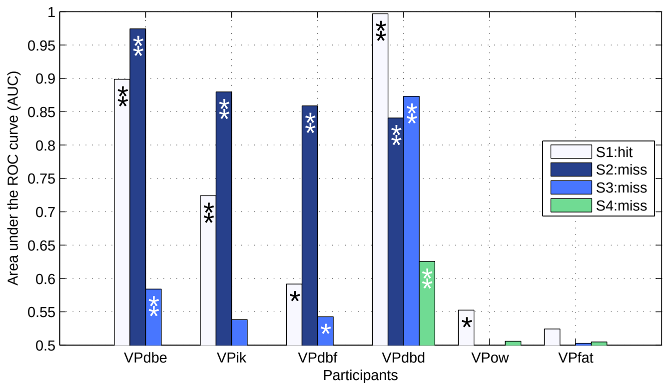

Fig. 3. AUC values for all participants, resulting from classification with LDA, based on the spectral power in the stimulation frequency (CSP filtering of the training data, 20-fold crossvalidation). Correct rejects of CW are compared to hits of S1 hits and misses of S2-4. Significance at levels $p < 0.05$ and $p < 0.01$ is marked with one and two stars, respectively.

for most participants (see Table I), which may have been contaminated with line noise. Tellingly, for both participants where this was not the case, AUC values for S1 hits were close to those of S2 misses (VPdbe) or higher (VPdbd).

Finally, it is important to note that the morphology of the CSP filters used for training the classifiers is neurophysiologically plausible. This is shown exemplarily for participant VPdbd in Figure 2. It can be seen that the morphology of the t-scaled plots of S1 and S2 (top row of the Figure) is reflected well in the corresponding CSP filters (bottom row). More importantly, the filters show a high similarity across conditions (the difference in algebraic signs can be ignored in this context). This supports our assumption that flicker was processed even for stimuli S3 and S4, for which subconscious processing could only be revealed with our machine learning approach, but not by using t-tests.

IV. CONCLUSIONS

In this EEG study, we investigated how the visual cortex processes high-frequency visual flicker at the threshold of perception. The main novelty of this paper lies in showing how advanced machine learning techniques can be used for revealing these neural correlates of flicker, even if it is only processed subconsciously. From a neurophysiological point of view, the results show that the spectral power at the stimulation frequencies is enhanced compared to stimulation with constant wave light (contralateral to the stimulated hemifield). Remarkably, this neural response to high-frequency flicker can be found with t-tests for half of the participants, even when they report not to perceive flicker anymore (S2 misses). We succeeded in substantially extending these findings by applying a machine learning approach typically used for BCIs, namely by filtering the EEG data spatially with CSP and then using classification based on LDA. Not only did this approach verify the neurophysiological findings. It also revealed this effect of subconscious processing for additional participants and stimuli, as summarized in Table I. Therefore, our conclusion is two-fold. First, even though participants reported to perceive a flickering stimulus at the threshold of perception as being temporally uniform, flicker is still processed subconsciously in the majority of participants and trials. Second, even though this effect is hidden for the naked eye in most cases, it can be robustly revealed by applying advanced machine learning techniques (CSP filtering and LDA). On the one hand, these results substantiate EEG as an investigative tool that allows to tap perceptual processes on a subconscious level, in particular when combined with advanced machine learning techniques. On the other hand, these findings are relevant to manufacturers of light sources, as they imply that it is advisable to use frequencies substantially above the behavioral perception threshold in order to minimize the possibility of provoking (subconscious) effects.

V. ACKNOWLEDGMENTS

This work was supported by Philips Research (Aachen, Germany) and the Bundesministerium für Bildung und Forschung (BMBF), FKZ 01GQ0850 and 01IB001A.

REFERENCES

[1] S. Shady, D. MacLeod, and H. Fisher, "Adaptation from invisible flicker," *Proc Natl Acad Sci USA*, vol. 101(14), pp. 5170–5173, 2004.
[2] D. Carmel and N. L. G. Rees, "Conscious awareness of flicker in humans involves frontal and parietal cortex," *Curr Biol*, vol. 16, pp. 907–911, 2006.
[3] C. Herrmann, "Human EEG responses to 1-100Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," *Exp Brain Res*, vol. 137(3-4), pp. 346–353, 2001.
[4] E. Hartmann, B. Lachenmayr, and H. Brettel, "The peripheral critical flicker frequency," *Vision Res*, vol. 19(9), pp. 1019–1023, 1979.
[5] A. Porbadnigk, J.-N. Antons, B. Blankertz, M. Treder, R. Schleicher, S. Möller, and G. Curio, "Using ERPs for assessing the (sub)conscious perception of noise," *In Conf Proc IEEE Eng Med Biol Soc*, vol. 1, pp. 2690–2693, 2010.
[6] G. Dornhege, J. del R. Millán, T. Hinterberger, D. McFarland, and K.-R. Müller, Eds., *Toward Brain-Computer Interfacing*. Cambridge, MA: MIT Press, 2007.
[7] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. Ramsey, I. Sturm, G. Curio, and K.-R. Müller, "The Berlin Brain-Computer Interface: Non-medical uses of BCI technology," *Front Neuroscience*, vol. 4, p. 198, 2010.
[8] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd ed. San Diego: Academic Press, 1990.
[9] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans Rehabil Eng*, vol. 8, no. 4, pp. 441–446, 2000.
[10] B. Blankertz, K.-R. Müller, D. Krusienski, G. Schalk, J. R. Wolpaw, A. Schlögl, G. Pfurtscheller, J. del R. Millán, M. Schröder, and N. Birbaumer, "The BCI competition III: Validating alternative approachs to actual BCI problems," *IEEE Trans Neural Syst Rehabil Eng*, vol. 14, no. 2, pp. 153–159, 2006. [Online]. Available: http://dx.doi.org/10.1109/TNSRE.2006.875642
[11] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K.-R. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," *IEEE Signal Process Mag*, vol. 25, no. 1, pp. 41–56, Jan. 2008.
[12] R. Duda, P.E.Hart, and D.G.Stork, *Pattern classification*, 2nd ed. John Wiley & Sons, 2001.
[13] M. D. Green and J. A. Swets, *Signal detection theory and psychophysics*. Huntington, NY: Krieger, 1966.
[14] T. Fawcett, "An introduction to ROC analysis," *Pattern recognition letters*, vol. 27, no. 88, pp. 861–874, 2006.
[15] A. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognition*, vol. 30, no. 7, pp. 1145–1159, 1997.
[16] M. Harter, "Evoked cortical responses to checkerboard patterns: Effect of check-size as a function of retinal eccentricity," *Vision Research*, vol. 10:12, pp. 1365–1376, 1970.