

Detection of Steady-State Visual Evoked Potentials Using Simulated Trains of Transient Evoked Potentials

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Abstract— In this paper, we address the problem of detecting steady-state visual evoked potentials (SSVEPs) in EEG signals by using a set of simulated trains of VEPs instead of the sine-waves basis typically used in Fourier Transform. The detection algorithm is calibrated using the subject's brain response to visual stimulation. The original contribution of the paper is that our detection method automatically takes into account all the spectral content adapted to the steady-state response in terms of harmonic localization, weights, and phase. We show that this method give better results than simple frequency analysis for SSVEP detection while requiring less features, thereby reducing the risk of overfitting the detection model.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) are communication systems that enable users to exchange information with a machine without using traditional input devices such as mouse, keyboard, buttons or levers. They allow users to send commands to a computer by reading only their brain activity – see [1] for an introduction about BCI. Neural activity is generally measured using electroencephalography (EEG), which is convenient, non-invasive, and has a high temporal resolution (in the millisecond range), making it a good choice for real-time applications. Most EEG-based BCIs are designed around a pattern recognition approach: features describing the relevant information embedded in the EEG signals are extracted and serve as inputs for a translation algorithm which convert these features into commands for the computer or machine. Various BCI systems have been designed using different EEG components as input features, including P300 evoked potentials, slow cortical potentials, motor related potentials, and visual evoked potentials (VEPs) – see [2] for references about different BCI types.

These VEPs are electric responses elicited in the visual cortex of the brain by sudden visual stimulation of the retina. Their low amplitude (about 10 μ V) makes them hard to discriminate from the rest of the recorded EEG activity in single trial scenarios. However, when the stimulation is repeated over time at a constant frequency – a procedure known as Intermittent Photic Stimulation (IPS) – the brain response becomes somehow stationary [3] and is referred to as Steady-State Visual Evoked Potentials (SSVEPs) [4]. This stationary response is known to contain precise components in the frequency domain at the stimulation frequency and its multiples (harmonics) [3].

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SSVEP-based BCIs exploit these potentials by presenting the user a set of images, checkerboards or more complicated patterns all flickering at different frequencies. Processing of EEG data collected over the occipital cortex of the subject allows for identification of the stimulation the user is attending to. Most of the time, the algorithms that identify which command is attended by the user take profit of the precise localization of SSVEP components in the frequency domain, and use the amplitudes of these spectral components as inputs of classifiers trained on a set of subjects whose SSVEPs have been recorded and processed offline.

Based on the hypothesis that SSVEPs are merely a succession of transient VEPs, we study how we can use correlation with simulated trains of VEPs in the time domain instead of the more common spectral features to detect SSVEPs. Different types of features are compared using linear discriminant analysis. When using simulated trains of VEPs for SSVEP detection on a given subject, we expect that the best results will be obtained by generating the simulated signals with the VEP recorded from that subject.

II. MATERIALS AND METHODS

EEG data used in this study has already been described in [5] (to be published) and part of this section is therefore similar to section II. of [5].

A. Subjects

Ten healthy subjects took part in the experiment. Nine were males and one female, with an average age of 24.8 (standard deviation: 3.6, range: 21-34). All had normal or corrected-to-normal vision and none of them had any history of epilepsy, migraine or any other neurological condition. The study followed the principles outlined in the Declaration of Helsinki. All participants were given explanations about the nature of the experiment and signed an informed consent form before the experiment started.

B. Experimental Conditions

EEG recordings took place in a dark room, where subjects were seated in a comfortable armchair, at about 70 cm from the screen used to display visual stimulation. The subjects were shown their EEG activity prior to the recording and explanations were given about muscular artifacts and eye blinks. They were instructed to relax and prevent excessive muscular contractions or eye movements.

C. Data Acquisition

EEG signals were continuously recorded at a sampling rate of 2 kHz using 16 active Ag/AgCl electrodes from an

actiCap system, connected to a V-Amp amplifier, both from Brain Products. The electrodes were placed according to the 10-20 system with a focus on parietal and occipital regions at positions Fp1, Fp2, F7, F3, F4, F8, C3, C4, P7, P3, Pz, P4, P8, O1, Oz and O2. Two additional electrodes were used as mass and reference for the amplifier and were located respectively at AFz and FCz.

A photodiode connected directly to the EEG amplifier auxiliary input allowed synchronization between the EEG recordings and the visual stimulation. The BPW-21R photodiode was chosen for its sensitivity to visible light (420-675 nm) and its theoretical response time of about 3 μ s, lower than any other time scale in our setup.

D. Stimulation

The presented stimuli were flickering black and white checkerboards composed of a 10 by 10 grid of squares, for a total stimulus size of 500 by 500 pixels, corresponding approximately to 11° by 11° of the visual field. During experiments, subjects were asked to keep their gaze on a 40 pixels red fixation cross located at the center of the display, at the intersection of four checkerboards.

Stimulations were designed using PsychToolBox-3 [6][7] on MATLAB and displayed on a Samsung S23A750D screen with a refresh rate of 120 Hz. In the rest of the paper, a stimulation with 2 reversals per second will be referred to as a 2 Hz stimulation. Photodiode measurements allowed us to check that the contrast of stimulations decreased by less than 1% between low frequency and high frequency stimulations (up to 60 Hz). Furthermore, the stimulation frequency had no noticeable variations over time at a 2 kHz sampling rate.

E. Recording Procedure

Each experiment consisted in the recording of 2 minutes of resting state with eyes open, 2 minutes of resting state with eyes closed, a total of 5 minutes of VEPs (at a 2 Hz frequency) and 3 sets of SSVEPs, composed of 20 different stimulation frequencies, each presented during 15s in a randomized order, for a total of 45s of SSVEP signal per frequency. The total stimulation time was 20 minutes.

The sequences were displayed in the following order:

- 1 min resting state with eyes open
- 1 min resting state with eyes closed
- 5 sequences of 30 s of VEP recording (2 Hz)
- 20 sequences of SSVEP recording of 15 s each
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- 20 sequences of SSVEP recording of 15 s each
- 1 min resting state with eyes open
- 1 min resting state with eyes closed
- 5 sequences of 30s of VEP recording (2Hz)

Between each sequence, the subject was able to rest for as long as desired, and controlled the beginning of the next

sequence with a button. After the button was pressed, a 3s countdown preceded the beginning of the sequence.

SSVEPs were recorded at the following frequencies (in reversals per second): 1, 1.5, 2, 2.5, 3, 4, 5, 6, 7.05, 8, 9.23, 10, 12, 13.33, 15, 17.14, 20, 24, 30 and 40.

F. Signal Processing

Analyses were performed using MATLAB® 2013a, with the signal processing toolbox. The recorded EEG signals were filtered between 0.5 Hz and 90 Hz, and a notch filter was applied in real time by the amplifier to remove the 50 Hz component due to the power grid. Before any analysis was performed, all data were downsampled from 2 kHz to 1.8 kHz using MATLAB's resample function. Thanks to this procedure, all inter-stimuli durations for all previously mentioned frequencies corresponded to integer numbers of points in the downsampled signals. This allowed for precise segmentation of SSVEPs and precise estimation of frequencies using Fast Fourier Transforms (FFTs). Both filtering and downsampling were applied on the raw signal before any segmentation to avoid border effects.

G. Simulations

For a given frequency, SSVEPs were simulated for each subject by generating trains of individual VEPs. VEP was computed for each subject by averaging of 600 trials lasting 0.5 s. Delay between two successive waveforms was taken equal to the desired SSVEP period. When this delay was shorter than the length of the VEP, the waveforms were summed in the overlapping area. Fig. 1 illustrates the principle of this simulation and shows examples of SSVEPs simulated at different frequencies.

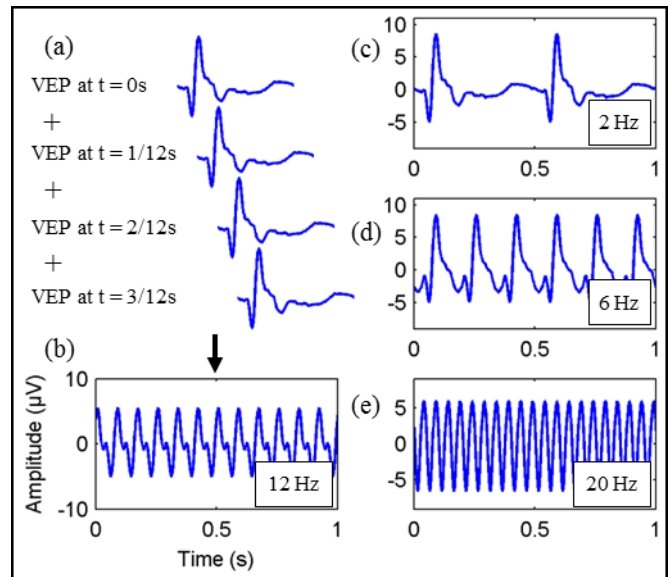


Figure 1. Simulation of SSVEPs using transient VEPs. (a) Principles of the simulation: in order to generate a SSVEP signal at a given frequency f , VEPs are concatenated in the time domain with a delay between two consecutive VEPs equal to the period of the stimulation ($1/f$). (b) Result of the simulation procedure at 12 Hz presented in (a) in the time domain. (c), (d), (e) SSVEPs simulated at other frequencies (2 Hz, 6 Hz and 20 Hz)

H. Classification

Using MATLAB's linear discriminant analysis (LDA) function, we built a classifier which takes as input a set of features extracted from an EEG epoch recorded during SSVEP stimulation at one of the 20 frequencies mentioned in II. E. The classifier is trained to evaluate the frequency of the IPS during which the recording was performed (20 classes classifier). We evaluated the performances of the classifier as the percentage of well-classified epochs. We used two different approaches for cutting our data into training and test sets. First, we randomly segmented our database into 100 small sets of equal size. We evaluated the accuracy of the classifier on each small set while all other sets were used for training (leave 1% out). Performances were then averaged on all test sets. The other approach consists in training the classifier using all but one subject and to use data from the last subject as the train set. This was done for all subjects, and performances were averaged (leave one subject out). All classification tests were performed for different epoch length, ranging from 1 s to 15 s.

I. Features used for Classification

Three types of features were used as inputs of the classifier. The first one is the spectral amplitude taken at each stimulation frequency (for a total of 20 features), which was estimated using MATLAB's FFT algorithm on time windows corresponding to multiples of the stimulation period, so that stimulation frequency and its harmonics would fall precisely on points of the resulting frequency axis. The second type consists in a signal-to-background ratio (SBR) in the spectral domain, which is easily computed by dividing the previously mentioned spectral amplitude by the average amplitude in a 1 Hz radius around the stimulation frequency. Both FFT amplitudes and SBR were extracted at the first 10 harmonics of each frequency. The third type of features is the maximum of the cross-correlation function between the EEG epoch and simulated SSVEPs at each of the 20 stimulation frequencies. Unless specified otherwise, the simulated signals are generated for each subject using their own VEP in order to estimate the cross-correlation. All features were extracted from the Oz channel, located over the visual cortex.

III. RESULTS

A. Classification using one set of features

Fig. 2 shows the classification accuracies obtained with a single set of features (calculated for each stimulation frequency therefore containing 20 features). Accuracy is computed for different epoch lengths, and in the two conditions described in II. H.

We observe that the correlation score is the best feature to classify epochs for all epoch lengths and in both conditions. Classification using FFT amplitudes and FFT signal-to-background ratios as input features give very similar results, with FFT amplitudes giving slightly better results than FFT SBR for epoch lengths below 6 s and FFT SBR doing slightly better for epoch lengths above 6 s. Classification accuracy using these spectral features

decreases as the order of the harmonic taken into account increases. Accuracies are always better in the leave 1% out condition (Fig. 2a) than in the leave one subject out condition (Fig. 2b), but these do not differ by more than 4%.

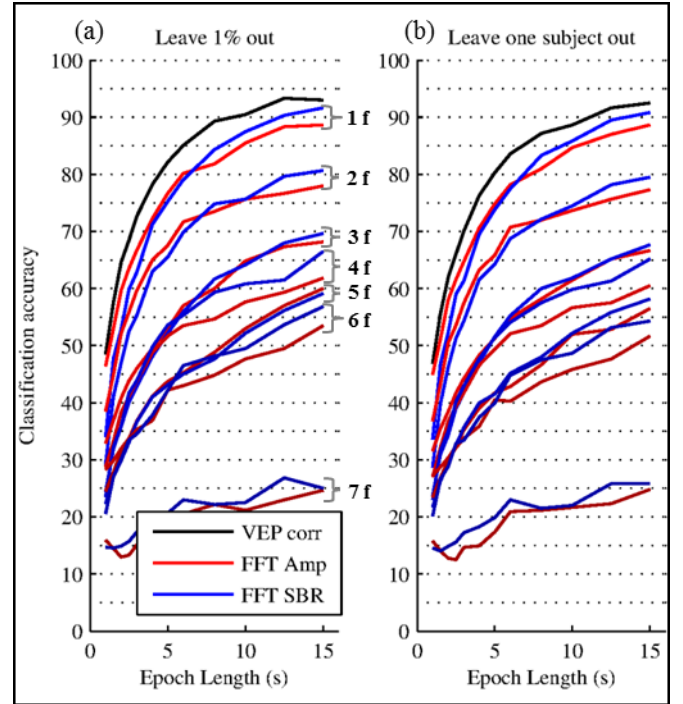


Figure 2. Classification accuracy with a single set of features. (a) Using the leave 1% out learning approach. (b) Using the leave one subject out learning approach. Black lines: accuracy using correlation scores with simulated trains of VEPs. Red lines: accuracy using the FFT amplitudes taken at the stimulation frequency (1 f) and its harmonics (2 f, 3 f...). Blue lines: same as red but using FFT signal-to-background ratio.

B. Classification using multiple harmonics

Fig. 3 shows the classification accuracies obtained when increasing the number of harmonics taken into account simultaneously by the classifier. Fig. 3a and 3b compares the results obtained using the proposed correlation score with those obtained using respectively FFT amplitudes and SBR at the stimulation frequency and its harmonics. Only the accuracies obtained with the leave one subject out method are displayed, since this situation is the most likely to happen in real SSVEP-based BCI training and test scenarios.

We observe that classification accuracy increases when we add the 2nd and 3rd harmonics as input features to the classifier as compared to when using only spectral features at the fundamental frequency. Addition of higher order harmonics does not improve the classification results significantly.

Spectral amplitude-based classification (Fig. 3a) using 3 or more harmonics give similar accuracies as correlation-based classification for epochs shorter than 6 s, while not being as accurate for longer epochs. The opposite effect can be observed on Fig. 3b, which shows that spectral SBR-based classification gives smaller accuracies for epochs below 6 s than correlation-based classification, but reaches equal or even slightly superior accuracies for longer epochs.

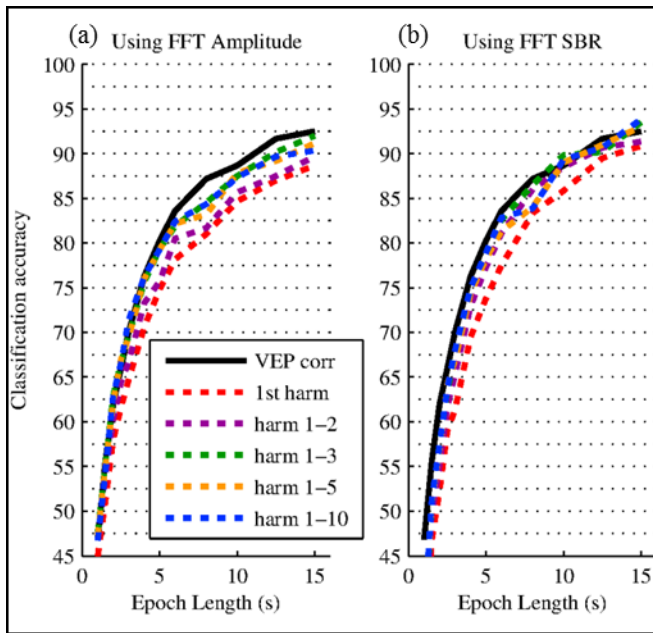


Figure 3. Classification accuracy using multiple harmonics. (a) Results with FFT amplitudes. (b) Results with FFT signal-to-background ratio. Black lines: accuracy using correlation features (20 features). Colored dashed lines: accuracy using multiple harmonics (total number of features is $20 \times$ number of harmonics).

C. Influence of the VEP used for stimulation

Simulated SSVEP signals can be generated using different VEPs. In the previous sections, correlation features were computed for each subject using their own VEP to generate simulated signals. Table 1 summarizes the results obtained when correlation features are not computed with each subject's individual VEP, but with one subject's VEP for the whole dataset.

	Epoch Length (s)											
	1	1.5	2	2.5	3	4	5	6	8	10	12.5	15
Own VEP (%)	46.8	55.6	62.0	66.0	70.0	76.3	80.3	83.6	87.2	88.7	91.7	92.5
Best VEP (%)	47.9	56.1	62.8	66.6	69.9	76.2	80.2	83.4	86.2	88.0	91.3	91.7
Average for all VEPs (%)	46.4	54.3	60.9	64.7	68.1	73.8	77.7	81.1	83.7	86.1	89.1	90.1
Best feature	VEP 5	VEP 5	VEP 5	VEP 5	Own VEP	Own VEP	Own VEP	Own VEP	Own VEP	Own VEP	Own VEP	Own VEP
# of VEPs better than own	4	1	2	1	0	0	0	0	0	0	0	0

Table 1. Classification results obtained when using different VEPs to simulate SSVEPs. **Own VEP:** classification accuracy obtained using correlation coefficients with the signals simulated from a subject's own VEP. **Best VEP:** best classification accuracy obtained using a single VEP to classify all subjects. **Average for all VEPs:** average classification accuracy obtained using each VEP to classify the dataset. **Best feature:** VEP giving the best classification results. **# of VEPs better than own:** number of VEPs giving better results when used for all subjects than using his own VEP for each subject.

IV. DISCUSSION

On Fig. 3, we observed that the accuracy of the classifier built using the proposed correlation feature is close to the

limit reached when using several harmonics of spectral features. This could indicate that correlation with a simulated train of VEPs and frequency decomposition of SSVEPs convey the same information. Of course, it is logical that a periodic signal in the time domain holds the same information as its frequency representation, but the interesting thing here is that the signal taken as reference is not a genuine SSVEP signal but a simulated SSVEP signal formed by adding VEPs in the time domain. This supports the idea that SSVEPs are indeed formed of a succession of transient VEPs, even at frequency higher than 6 Hz when consecutive VEPs start to overlap one with another.

One advantage of using a single correlation feature instead of multiple features computed for different harmonics is linked with the problem of SSVEP detection in a context where several stimulation frequencies are presented at the same time (i.e. in a SSVEP-based BCI) and contain common harmonics. Indeed, two flickering patterns can generate activity at the same frequency but with a different phase. Estimation of the spectral density will fail to make the difference between such contributions, whereas correlation with a time domain signal takes into account both magnitude and phase of the different components of the SSVEP signal in a single feature. Using fewer features also makes it easier to train the classifier and to avoid overfitting issues.

For epochs longer than 3 s, results in Table 1 confirmed our hypothesis that classification works better when comparing one subject's experimental SSVEPs with simulated signals obtained from the same subject's VEP. However, results obtained on epochs shorter than 3 s show that some properties of VEPs may make them better candidates for simulating signals used for SSVEP detection. We have yet to identify what made subject 5's VEP the best waveform in such context.

It can be noted that this study only takes into account one electrode (Oz), whereas VEP can be recorded at several locations on the scalp, allowing for multi-electrode simulation and cross-correlation which may increase the classification accuracies presented here.

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