DECODING SSVEP RESPONSES USING TIME DOMAIN CLASSIFICATION

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Keywords: Steady-state visual evoked potential, EEG, Decoding, Brain-computer interafce.

Abstract: In this paper, we propose a new time domain method for decoding the steady-state visual evoked potential recorded while the subject is looking at stimuli flickering with constant frequencies. Using several such stimuli, with different frequencies, a brain-computer interface can be built. We have assessed the influence of the number of electrodes on the decoding accuracy. A comparison between active wet- and bristle dry electrodes were made. The dependence between accuracy and the length of the EEG interval used for decoding was shown.

1 INTRODUCTION

Research on *brain-computer interfaces* (BCIs) has witnessed a tremendous development in recent years (see, for example, the editorial in IEEE Signal Processing Magazine (Sajda et al., 2008)), and is now widely considered as one of the most successful applications of the neurosciences. BCIs can significantly improve the quality of life of patients suffering from amyotrophic lateral sclerosis, stroke, brain/spinal cord injury, cerebral palsy, muscular dystrophy, etc.

Brain computer interfaces are either *invasive* (intra-cranial) or *noninvasive*. The first ones have electrodes implanted mostly into the premotor- or motor frontal areas (Santhanam et al., 2006) or into the parietal cortex, whereas the noninvasive ones mostly employ *electroencephalograms* (EEGs) recorded from the subject's scalp.

The noninvasive methods can be further subdivided into three groups. The first group is based on the P300 ('oddbal') *event-related potentials* in the parietal cortex which is used to differentiate between an infrequent, but preferred stimulus, versus a frequent, but non-preferred stimuli in letter spelling systems (Farwell and Donchin, 1988; Combaz et al., 2009; Manyakov et al., 2010). The second group of BCI's tries to detect imagined of right/left limb movements. This BCI uses *slow cortical potentials* (SCP) (Kübler et al., 2001; Birbaumer et al., 2000), *event-related desynchronization* (ERD) of the mu- and beta-rhythm (Pfurtscheller et al., 2000) or the *readiness potential* (bereitschaftspotential) (Blankertz et al., 2007). And the third group, which is also the subject of this study, uses the steady-state visual evoked potential (SSVEP). This type of BCI relies on the psychophysiological properties of EEG brain responses recorded from the occipital area during the periodic presentation of identical visual stimuli (flickering stimuli). When the periodic presentation is at a sufficiently high rate (>6 Hz), the individual transient visual responses overlap and become a *steady state* signal: the signal resonates at the stimulus rate and its multipliers (Luck, 2005). This means that, when the subject is looking at stimuli flickering at the frequency f_1, we can detect $f_1, 2f_1, 3f_1, \dots$ in the Fourier transform of the EEG signal recorded form the occipital pole. Since the amplitude of a typical EEG signal decreases as $1/f$ in the spectral domain, the higher harmonics become less prominent. Furthermore, the fundamental harmonic f_1 is embedded into other on-going brain activity and (recording) noise. Thus, when considering a small recording interval it is quite likely to detect an (irrelevant) increase in the amplitude at frequency f_1. To overcome this problem, averaging over several time intervals (Cheng et al., 2002), or recording over longer time intervals (Gao et al., 2006) are often used for increasing the signal-to-noise ratio in the spectral domain. Finally, in order to establish a means of direct communication from the brain to the computer, not one stimulus frequency f_1, but several frequencies are used at the same time, $f_1, \dots, f_n$, each one corresponding to a particular command one wants to communicate. The detection prob-

V. Manyakov N., Chumerin N., Combaz A., Robben A. and M. Van Hulle M..
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DOI: 10.5220/0003106103760380
In *Proceedings of the International Conference on Fuzzy Computation and 2nd International Conference on Neural Computation* (ICNC-2010), pages 376-380
ISBN: 978-989-8425-32-4

lem, therefore, becomes more complex since now, one of several possible flickering frequencies f_i need to be detected from the EEG recordings.

For decoding the SSVEP BCI paradigm, traditionally, a representation in the spectral domain of the recorded EEG signal is used, hence, a variety of methods and classifiers have been described in the literature that rely on features based on amplitudes at particular frequencies (Cheng et al., 2002; Gao et al., 2006; de Peralta Menendez et al., 2009). In spite of the reported high transfer rates, achieving a reliable and fast classification still remains problematic. This can be due to the fact that, when using a computer screen for the stimuli, we don't have a precise refreshing rate of 60 Hz [1] (in our case it is 59.83 Hz). This can cause, for example, the oscillation, produced by two consecutive frames (intended to be at 30 Hz), not to exactly correspond to the desired one, which can deteriorate the decoding based on the Fourier transform (FT), when using short intervals. Furthermore, when using too short intervals, neighboring frequencies can not be distinguished because of the limited spectral resolution. For example, $60/9 = 6.67$ Hz and $60/8 = 7.5$ Hz oscillations are indistinguishable after performing a fast FT based on a 500 ms interval (in other words, we have here a spectral resolution of 2 Hz). As was recently shown by Luo and co-workers (Luo and Sullivan, 2010), time domain classifiers yield a better performance than frequency-based ones for the SSVEP paradigm.

In this paper, we describe our time domain classifier for SSVEP signal detection, and evaluate the detection performance as a function of the recording interval, for 3 subjects. The issue of using one *vs.* several electrodes for decoding is also discussed.

2 METHODS

2.1 EEG Data Acquisition

The EEG recordings were performed using a prototype of an ultra low-power 8-channels wireless EEG system, which consists of two parts: an amplifier coupled with a wireless transmitter and a USB stick receiver. The data is transmitted with a sampling frequency of 1000 Hz for each channel. We used a brain-cap with large filling holes and sockets for active Ag/AgCl electrodes (ActiCap, Brain Products). This system was developed by IMEC[2] and built around their ultra-low power 8-channel EEG amplifier chip (Yazicioglu et al., 2009). The recordings were made with eight electrodes located on the occipital pole (covering the primary visual cortex), namely at positions Oz, O1, O2, POz, PO7, PO3, PO4, PO8, according to the international 10–20 system (see Figure 1). The reference electrode and ground were placed on the left and right mastoids.

The raw EEG signal is filtered in the 4-45 Hz frequency band, with a fourth order zero-phase digital Butterworth filter, so as to remove DC and the low frequency drifts, and to remove the 50 Hz powerline interference.

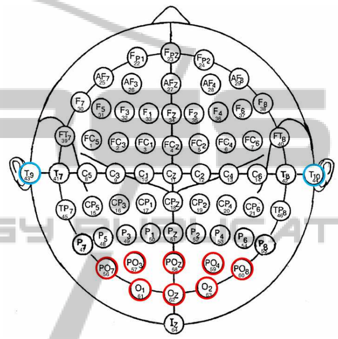

Figure 1: Electrode placement on a subject's head. Electrodes marked in red are the recording sites; those in blue are the reference and ground.

2.2 Experiment Design

Three healthy subjects (all male, aged 26–33 with average age 30, two righthanded, one lefthanded) participated in the experiments. In the beginning of the experiment, a square is shown in the center of the screen, flickering at a frequency of approximately $60/3$ Hz, for 15 seconds. After that, during 2 seconds, a blank screen is shown, and then a new square flickering at $60/4$ Hz is shown for 15 seconds, and so on. In total, 7 different flickering stimuli are presented to the subject, with frequencies corresponding to the integer divisions of 60 by $3, 4, \ldots, 9$ (note that these are equal to the lengths of flickering periods in frames). From the recorded EEG signal, the spectrogram is calculated (see, for example, Figure 2). The four most prominent frequencies are later considered for futher evaluation for a 4-command SSVEP BCI application. We choose 20, 15, 12 and 10 Hz for subject 1; 12, 60/7, 7.5, 6.67 Hz for subject 2; 10, 60/7, 7.5, 6.67 Hz for subject 3.

[1] When using light-emitting diodes (LEDs), one could precisely achieve 60 Hz, as was done in (Luo and Sullivan, 2010).

[2] Interuniversity Microelectronics Centre (IMEC), *http://www.imec.be*.

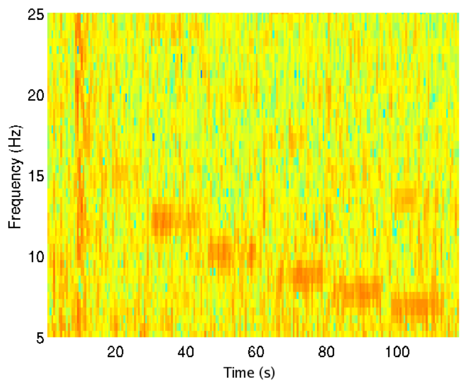

Figure 2: Spectrogram of EEG recordings from electrode Oz for subject 3, based on a 15 s visual stimulation at frequencies $60/3,\ldots,60/9$ Hz, using a 2 s interval between two consecutive stimuli. Note that not only the fundamental frequencies, but also their harmonics are visible.

2.3 Features and Classification

As a feature, we took the average response expected for each of the flickering stimuli. For this, the recorded EEG signal of length t ms was divided into $n_i = [t/f_i]$ nonoverlapping, consecutive intervals ([.] denotes the integer part of the division), where each interval is linked to the stimulus onset. For example, for 2000 ms recordings, and for a stimulus frequency of 10 Hz, we have $2000/10 = 20$ such intervals of length 100 ms ([1,100], [101 200],...). This procedure is repeated for all frequencies used in the BCI set-up, thus, for $i = 1..4$ (the actual four frequencies used for the different subjects was discussed in Sec. 2.2). After that, the average response for all such intervals, for each frequency, is computed. Such averaging is necessary because the recorded signal is a superposition of *all* ongoing brain activities. By averaging the recordings, those that are time-locked to a known event, are extracted as evoked potentials, whereas those that are not related to the stimulus presentation are averaged out. The stronger the evoked potentials, the fewer trials are needed, and *vice versa*. To illustrate this principle, Fig. 3 shows the result of averaging, for a 2 s recording interval, while the subject was looking at a stimulus flickering at a frequency of 20 Hz. It can be observed that, for the intervals used for detecting the frequencies 12 and 15 Hz, the averaged signals are close to zero, while for those used for 10 and 20 Hz, a clear average response is visible. Note that the average response does not exactly look like integer period of a sinusoid, because the 20 Hz stimulus was constructed using two consecutive frames of intensification followed by frame of no intensification. There is also some latency present in the responses since the evoked potential does not appear immediately after the stimuli onset. It could also be the case that, in the interval used for detecting the 10 Hz oscillation, the average curve consists of two periods. This is as expected, since a 20 Hz oscillation has exactly 2 whole periods in a 100 ms interval.

In order to assess the decoding performance, the EEG recordings were divided into two nonoverlapping subsets (training and testing). This division was made 10 times for every time interval of length t ms, which provides us with statistics for result comparison. Based on the training set, we built 4 classifiers based on linear discriminant analysis (LDA). Each of these classifiers was built for the averaged responses for the time intervals of the stimulus frequencies considered (see Figure 3 where, *e.g.*, 4 of such intervals are shown). These classifiers were constructed so as to discriminate the stimulus flickering frequency f_i in window i from all other flickering frequencies, and for the case when the subject does not look at the flickering stimuli at all. As a result of LDA classification (on testing data), we have four posterior probabilities p_i, which characterize the likelihood of a subject's gaze on one of the 4 stimuli flickering at different frequencies f_i. If all four probabilities p_i are smaller then 0.5, we conclude that the subject is not looking at the flickering stimuli. In all other cases, we take, as an indication of the stimulus the subject's gaze is directed, the flickering frequency f_i response that generates the largest posterior probability p_i. Since we do not take the raw EEG signal, but rather a 4-45 Hz filtered one (see above), our 1000 Hz sampling frequency is in fact largely redundant. This can lead to zero determinants of the covariance matrices in the LDA estimation. To overcome this, we downsampled our data to a lower resolution (we took only every fifth sample in the recordings), and took only those time instants, for which the p-values were smaller than 0.05 in the training data, using a Student t-test between two conditions: averaged response in interval i corresponding to the given stimulus with flickering frequency f_i versus the case when the subject is looking at an other stimulus, with another flickering frequency, or looking at no stimulus at all. This feature selection procedure, which is based on a filter approach, enables us to restrict ourselves to relevant time instants only.

All what was described above is valid only for the case when we have a single electrode. In the case of several electrodes (8 electrodes in our case), the same feature selection was performed for each electrode, but the 4 LDA classifiers were build based on pooled features from all electrodes.

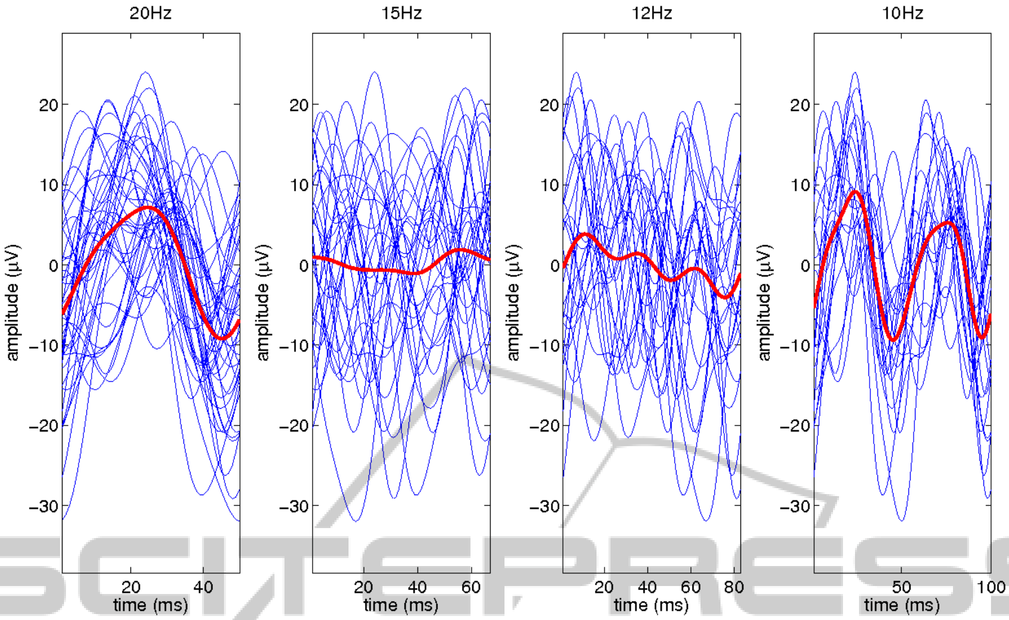

Figure 3: Individual traces of EEG activity (blue) and their averages (red), time locked to the stimuli onset. Each individual trace shows changes in electrode Oz for subject 1. The lengths of the shown traces correspond to the durations of the flickering periods of 3, 4, 5 and frames (from left to right panel), and with a screen refreshing rate of 59.83 Hz. The subject was looking to the stimulus flickering at ≈ 20 Hz (period equal to 3 frames). One observes that, in the left panel, we obtain one complete period for the average trace, and in the right panel, two complete periods, while in the other panels, the average trace is almost flat.

3 RESULTS

After constructing the classifiers on the training data, they can be applied to test data of all 3 subjects. We obtained the results shown in Figure 4, plotted as a function of the interval length t. It can be seen that a 1 second interval is sufficient to make a decision with high accuracy for all subjects, and for a BCI application with four different frequencies (+ also distinguishing the case where the subject is not looking at any stimuli). This shows that the proposed time domain BCI is able to achieve a performance with a high information transfer rate (Pierce, 1980).

We have also verified the dependency of the decoding accuracy on the number of electrodes used for decoding. As was expected, the highest accuracy for a single electrode design is obtained for the electrodes placed along the central line (Oz or POz). Taking all eight electrodes together generates a significantly better performance than the case of only a single electrode. Finally, for EEG recordings with an interval length above 1.5 sec, there is no difference in decoding performance.

We have also tested bristle dry electrodes (MedCat) instead of active wet ones (ActiCap, Brain Products). Dry electrodes enable the preparation time of

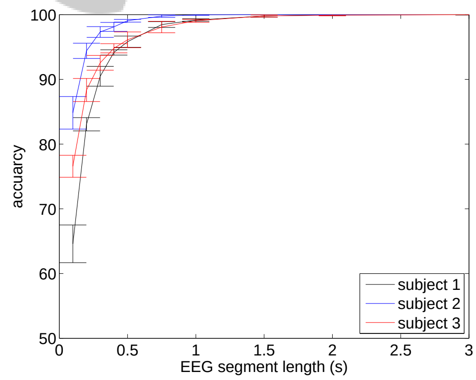

Figure 4: Decoding accuracy (vertical axis) as a function of the length of the EEG interval used for averaging (horizontal axis).

the subject to be reduced to the absolute minimum, since one does not require any gel or scraping away of dead skin cells: the EEG cap is put on and one is ready for recording, all in a few seconds. But on the other hand, they have a large impedance, which leads to weak signals and inferior decoding results. Given the positions O1 and O2 for the dry electrodes, we estimated the decoding accuracy as a function of the EEG recoding length, and compared with the accuracy obtained with the active electrodes, for the same electrode locations. We found that, to achieve the same accuracy as with the active wet electrodes, we have to at least consider a 4 times longer EEG intervals. Nevertheless, we still believe that this to be an encouraging result for a dry electrode SSVEP BCI application.

ACKNOWLEDGEMENTS

NVM is supported by the European Commission (IST-2004-027017), NC is supported by the European Commission (IST-2007-217077), AC is supported by a specialization grant from the Agentschap voor Innovatie door Wetenschap en Technologie (IWT) (Flemish Agency for Innovation through Science and Technology), MMVH is supported by research grants received from the Excellence Financing program (EF 2005) and the CREA Financing program (CREA/07/027) of the K.U.Leuven, the Belgian Fund for Scientific Research – Flanders (G.0234.04 and G.0588.09), the Interuniversity Attraction Poles Programme – Belgian Science Policy (IUAP P6/054), the Flemish Regional Ministry of Education (Belgium) (GOA 10/019), and the European Commission (IST-2004-027017 and IST-2007-217077). This work is also supported by a SWIFT grant from the King Baudouin Foundation of Belgium for developing patient BCI applications (2009).

The authors wish to thank Refet Firat Yazicioglu, Tom Torfs, and Chris Van Hoof, from the Interuniversity Microelectronics Centre (IMEC) in Leuven, for providing us with the wireless EEG system and for their support.

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