A Real-Time Brain-Computer Interface Based on Steady-State Visual Evoked Potentials

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Abstract

Steady-state visual evoked potential (SSVEP)-based BCIs take advantage of the stereotypical response to flicker in the visual cortex. They offer the possibility of high performance non-invasively and with minimal training time. A real-time SSVEP BCI system was developed and tested on 14 control subjects. While inter-subject variability existed, the results were promising, proving that the stimulation frequency of gaze can be detected in under five seconds. This detection can be made even when nine or more flickering stimuli are simultaneously present.

1 Introduction

In recent years, many attempts have been made to establish a direct brain-computer interface (BCI) which circumvents traditional motor pathways for communication and control [1]. Such an interface could restore lost function in the severely paralyzed, such as those affected by ALS, stroke, or spinal cord injury. BCI research and development is an interdisciplinary endeavor, involving neuroscience, psychology, engineering, mathematics, computer science, and clinical rehabilitation. A key goal of such research is identifying the best possible signal features, whether evoked potentials, spontaneous rhythms, or single-neuron firing rates. Numerous invasive and non-invasive approaches are currently in development [2]-[6].
The steady-state visual evoked response appears to be a promising approach because training time should be negligible and high detection speeds are possible [8]. Recent studies in SSVEP-based BCIs have sought to distinguish between two [2] or four [8] possible selections presented simultaneously on a computer screen. The aim of the present study was to increase the number of selections and to evaluate whether information transfer rates from such a system would compare favorably with other BCI approaches.

2 Materials and Methods

2.1 System overview

The stimulation was performed using a 750MHz Dell Notebook connected to a Nokia (Multigraph 445X pro) 21 inches monitor. Its refresh rate and resolution were 85Hz and 1024x768 pixels, respectively. The subject, sitting at approximately 50 centimeters away from the screen was presented nine flickering (120 pixels) blocks at different frequencies. Chosen according to physiological results and to avoid harmonics interaction, the 9 blocks were respectively flickering at (in Hz):

11.087	21.250	12.750	8.927	12.140
7.080	17.000	5.000	7.727	

Acquisition was done using a Nuamps (40 channels DC EEG amplifier, connected to a second laptop computer (Toshiba, 650MHz). A normal 64 channels cap was used, the ears were linked and connected to the ground. The channel O2 (10-20 system) was used for the detection.
Both stimulation and acquisition systems were programmed in C++ using DirectX (stimulation) and a DLL provided by Neuroscan systems (acquisition).

2.2 Stimulation

The DirectX multimedia library was used to ensure a good stimulation quality, which was tested using a luxmeter. Only the subharmonics of the screen refresh rate can be obtained on a CRT Screen. For an 85Hz monitor, one can obtain 85Hz, 42.5Hz, 21.25Hz and so on, which is not acceptale for a keyboard based BCI. A technique, based on combinaisons of these basic frequencies was then developped to increase the number of possible items. The stimulation parameters were optimized in order to obtain a clear signal from the recording channels. The flickering blocks were white, with a small light gray square in the middle in order to keep accomodation. They were placed close to each other to approach real conditions of a screen keyboard.

2.3 Real Time Detection

A real-time system needs to be fed continuous data from the EEG recordings. For this purpose, we used a data exchange library (`DataXchg.DLL` provided by Neuroscan 4.2) which enables external programs to access data on-line. A custom acquisition program was written to access data from the DLL and send it to the detection algorithm. The data portion of each buffer contained multiplexed data points from each channel.

The detection algorithms used in SSVEP analysis are usually quite simple due to the fact that a strong peak in the power spectrum can be seen at the frequency of stimulation. Sampled at 1000Hz, the signal was processed using a bank of filters based method centered at the stimulation frequencies. In order to minimize the number of false detections, three levels of detection were implemented. These rules were defined as follows:

D1 = the frequency with highest power.

D2 = D1 if above a threshold, defined as ten times the mean power of all frequencies.

D3 = D2 if it occurred twice consecutively.

2.4 Experimental task

The experimental task was simply to look at the block dictated by the computer. The block order was chosen at random to be:

Trial 1: 5, 6, 9, 1, 4, 2, 8, 3, 7

Trial 2: 4, 1, 5, 7, 6, 9, 2, 8, 3

The two trials were consecutive and without break. The subject was to look at the block until a new number was indicated by the computer. A new number was indicated as soon as the desired one was detected, or after ten attempted detections if the desired detection was not made. The two trials were repeated in three different experiments with varying bin sizes and FFT points. The first two experiments were performed using bins of 512 and 1024 milliseconds respectively and a FFT based on 1024 points. For the third experiment, the bin size was 2048 ms and the FFT used 2048 points. A fourth experiment (bin size=1024 ms, NFFT=1024) was performed where the subject maintained gaze at the desired block for exactly ten attempted detections. Percentages were calculated for the number of correct detections made out of the ten attempts.

The varying bin sizes were chosen to test the physiological difference among subjects of time needed for the signal to develop sufficiently. The two FFT sizes were chosen to test the benefit of a better localized frequency transform.

3 Results

3.1 System performance

It is of utmost importance that a working BCI minimizes the number of false detections at the expense of increasing the number of no detections. Thus, it becomes more difficult for a subject to select the desired block, but the subject suffers less the need to undo selections that were not meant to be made.

The following terms must be defined:

True Positive (TP): The system detected a block and the user was looking at that block.

False Positive (FP): The system detected a block and the user was looking at a different block or not looking at a block.

True Negative (TN): The system decided not to detect and the user was not looking at any block.

False Negative (FN): The system decided not to detect but the user was looking at a block.

As stated before, the first objective is to minimize the number of False Positives, since they force the user to correct errors. The next objective is to maximize the number of True Positives. The following table displays the results obtained from 11 subjects in the fourth experiment (Bin Size=1024ms). The number of occurrences for each of these terms has been summed.

	Negative	Positive
True	99	681
False	1241	69

This table is an interesting source of information to judge the system quality. The ratio of correct decisions to incorrect ones ($\frac{TN+TP}{FN+FP}$) was relatively low (approx. 60 correct decisions for every 40 incorrect ones), but this was due to a high number of False Negatives. This was the result of the stringent detection rules (D3), since it was preferable not to detect than to detect something wrong. When a detection was made, the percentage correct was ($100 * \frac{681}{681+69}$) 91%.

The following figure shows these values for all the subjects in decreasing order of accuracy. The number of True Negatives and False Positives do not change significantly, but the two other values seem linked. Subjects with good results have a high amount of True Positives, whereas subjects with poorer results had a high amount of False Negatives. This high number was due to the fact that the rules (D2) were too strict for these subjects. The number of False Positives was still low for these subjects.

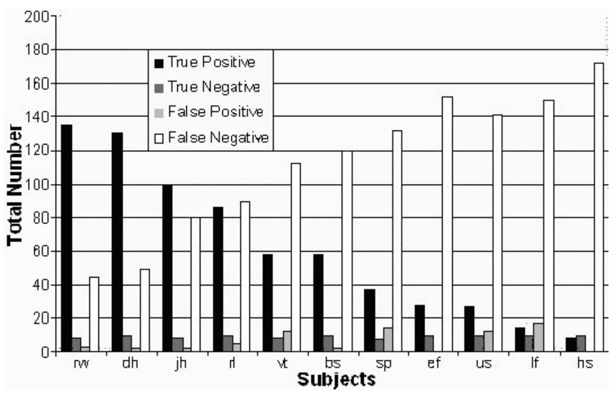

Figure 1: System evaluation for all subjects.

3.2 Detection Speed and frequencies

As might be expected, there was considerable variability in the detection performance for each frequency. A general trend appears to exist among the nine stimulation frequencies. The highest stimulation frequencies took the longest to detect and were in many cases not detected. Time to detection increases with increasing stimulation frequency for the higher frequencies used. Conversely, 7.727 Hz and 8.927 Hz resulted in the fastest detections for all experiments. The lowest stimulation frequencies used, 5 Hz and 7.08 Hz, took slightly longer to detect. The figure implies that there was an optimum range for this system around the middle of the low frequency region defined by Regan [7].

For 62% of the subjects, the median is positioned at less than 4 seconds. Taking the most suitable bin size for each subject would result in a mean detection time below 5 seconds(4.2s) in every case.

4 Conclusions

Despite considerable room for improvement, this project confirmed that a working Brain Computer Interface can be created using Steady State Visual Evoked Potentials. The time needed to correctly select a block from among nine is around 4 seconds and the percentage of correct detections equals 91%. The detection time needed and the number of detectable blocks satisfies the needs for a usable system. The work should now be continued with actual paralyzed patients to confirm that performance is still acceptable.

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