Improving SSVEP responses from LED stimuli through orientation analysis

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Abstract

This article focuses on different orientations of LED visual stimulus configurations which could be used to elicit Steady State Visual Evoked Potentials (SSVEP). SSVEP is extensively used in the research for various biomedical applications and require a configurable light source flickering at a constant frequency that would induce responses in corresponding frequencies in the EEG recorded over the visual cortex area of the scalp. The present study investigated the SSVEP amplitude dependence of horizontal and vertical LED visual stimulus orientations. SSVEP amplitudes were compared for five healthy subjects from five sessions of 30 seconds each and the recorded EEG signals were analysed. Individual recording sessions were carried out with horizontal and vertical orientation with 10 Hz visual stimulus for analysing the SSVEP responses and also to evaluate the viewing comfort in each orientation. The signals were processed with band-pass filtering and analysed with Fast Fourier Transform (FFT) and autoregressive spectral analysis. The sign rank statistical results showed horizontal visual stimulus gave the higher response and viewing comfort in all subjects in comparison to vertical orientation.

Keywords: LED stimulus; SSVEP; Stimulus orientation; Visual stimulus.

1. INTRODUCTION

Electroencephalogram (EEG) records the electrical signals from the brain and research in this area has grown tremendously due to the easier and cheaper procurement of EEG hardware and the availability of advanced software to analyse and interpret the data. One popular application of EEG is in the area of brain-computer interfaces (BCI), which translates the signals from brain to usable control signals without the use of any muscular movements. The need to identify and address the issues of people with disabilities have accelerated this research area even further to develop new augmentative methods and control techniques to support people with severe spinal cord injuries and other neuromuscular disorders [1].

Many brain imaging systems exist for measuring and analysing brain activity such as electrocorticogram (ECoG), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), functional near-infrared Spectroscopy (fNIRS) and electroencephalography (EEG) [1, 2, 3, 4]. Each of this technique has its own individual merits and demerits. Within this group of techniques, EEG is comparatively low cost, portable, non-invasive, easy to acquire signal and as such, is widely used by research community.

Different paradigms are used in EEG-BCI research such as P300, slow cortical potential (SCP), and steady-state visual evoked potential (SSVEP) [5, 6, 7, 8]. Among these paradigms, SSVEP has been explored widely by the research community using a visual stimulus flickering at a desired frequency [2, 8, 9, 10, 11, 12, 13]. SSVEP based BCI systems are chosen widely due to its high information transfer rate and the less training time required by the subject and also the fewer number of electrodes allows practical design. Studies have identified that low frequency flickers induce higher amplitude in SSVEP, but at the same time introduce visual fatigue for the user during prolonged usage [14]. Choice of colour and stimulus intensity can increase the comfort level of the user while gazing constantly on flickers to induce SSVEP [15].

Visual stimulus plays an important role in SSVEP based BCI's, since the choice of colours, flicker frequency and stimulus orientation influence the user as well as the amplitude of induced SSVEP. Visual stimulus hardware design here is based on red, green and blue (RGB) LED's driven by a microcontroller capable for generating ten simultaneous channels for frequencies from 7- 15 Hz but we chose to use 10 Hz stimulus here as it was used in a previous study[15] and furthermore, lower frequencies generally evoke higher responses. The choice of colour or frequency can be pre-programmed in the stand-alone hardware and can be updated from the computer, if required.

In this paper, the aim is to analyse the responses in SSVEP amplitude for different orientation of the visual stimulus which consists of 12 RGB LED's arranged in two rows. This is in line with the hypothesis that horizontal orientation of LEDs will be able to evoke a larger SSVEP response as compared to vertical orientation due to being more natural for stereotyped vision system in humans[16, 17].

The next section details the methodology, while Section three give the results and their discussion while the final section concludes the paper.

2. MATERIALS and METHODS

2.1.Experimental Setup

To investigate the effects of stimulus orientation on SSVEP, the subjects were seated 50 cm from the stimulus which was fixed at eye level. The EEG signals were recorded using Gtec g.Mobilab+ connected to g.gammabox where the active electrodes were connected. The recording device is powered by battery to avoid any power line interferences in the recorded EEG. The system communicates with the computer via a RS232 serial interface which is converted to USB standard communication for PC connectivity. Three electrodes were positioned at O_z (occipital) and F_z (frontal) with A_2 mastoid as the reference. Only one active electrode (i.e. at location O_z) was used because it simplifies the design greatly for practical purposes and the location O_z was chosen as it is known to give maximal responses to visual stimulus. The SSVEP data in channel O_z was used with reference to channel F_z but no other channel averaging was done. The visual stimulus was activated at a pre-set flicker frequency of 10 Hz and the EEG was recorded for 30 seconds. Each subject had five sessions for each orientation which consist of 150 segments of one second SSVEP signal for one subject. Five healthy subjects volunteered for this study (three females and two males) in the age group of 20 – 44. None of these subjects had any previous experience in BCI and had perfect vision or corrected vision.

For stimulus orientation design, the stimulus was rotated 90^0 clockwise each time the orientation required changing. So, in effect, the stimulus orientation could be horizontal flicker or vertical flicker according to the requirement.

2.2.Visual Stimulus

The visual stimulus for this study was designed using high power RGB LED's arranged in two lines of six LED each fixed on transparent acrylic board with equal spacing of 1 inch. Figure 1 shows the horizontal and vertical orientation of the lighted visual stimulus. Acrylic board can be rotated freely for any desired orientation for SSVEP EEG recording and in this study, the board was just rotated for either horizontal or vertical stimulus. Various studies identified the use of LEDs for visual stimulus as better than conventional approach of generating flickers on computer screen which is depended on the refresh rate of the screen and could vary with time causing frequency variations in the flickers [18, 19, 20].

Figure 1: Horizontal and vertical visual stimulus

The RGB LED stimuli were controlled by a microcontroller board based on open source Arduino for different frequency flickers. Since these RGB LEDs require more current and fast on/off transitions, a high current MOSFET driver adapter is used for constant current and this ensures the uniform brightness for the flickers as shown in Figure 2. Since SSVEP studies require different frequencies of flicker in the range of 6 Hz to 50 Hz, the visual stimulus is programmed with ten different frequencies for simultaneous use (though we only used 10 Hz in the experiment in this paper). All the programmed frequencies were verified using a digital oscilloscope at the LED end so as to ensure the precision for the flickers and the error in frequency was below 0.012 Hz at room temperature.

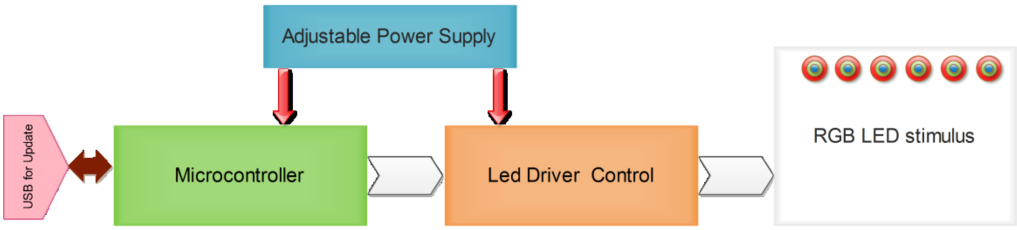

Figure 2: Functional block diagram for visual stimulus

The code inside the controller is completely customisable and uses a look up concept so any electronics novice BCI researcher could amend the changes and update through the computer without any requirement for special hardware.

The visual stimulus is capable of producing three primary colours: red, green and blue and thousands of other colours by the combining the primary colours. In this research, we used green for generating the flickers to investigate the influence of stimulus orientation in SSVEP). The colour green was used because we have shown in a previous paper[15] that this colour gave the highest response when compared to other colours. The hardware platform is completely reusable and customisable for realising many combinations of visual flickers and frequencies and at the same time could be built with off-shelf components costing less than £100.

2.3.Data Acquisition

Minimal numbers of electrodes were used to record the EEG using the portable bio-signal acquisition system from g.tec. Three electrodes used in this study were positioned at highlighted locations as shown in Figure 3. EEG cap fitted with active electrodes at these locations with electrode conductive gel were used on all subjects.

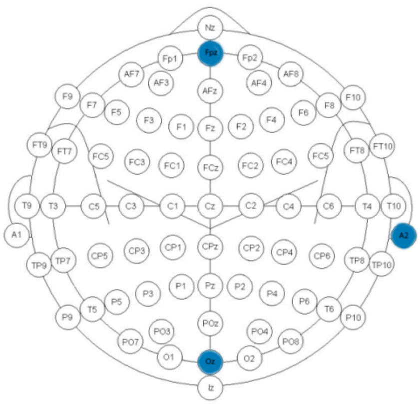

Figure 3: Electrode positions used for data collection

This setup did not require any pre-conditioning of the scalp. The subjects were introduced to BCI with short presentations describing the experiment. Each recording session lasted for 30 seconds and subjects were given a rest period of one minute before the next session started. Previous study showed that a break of one minute was sufficient to neutralise the effect of the 30 seconds flicker [15]. All subjects were verbally informed five seconds before the start of a session to initiate gazing at the stimulus and continue gazing for 30 seconds. The sequence of recording for each subject was for 30 seconds in horizontal orientation followed by 30 seconds vertical with a break of one minute in between. This was alternated to avoid any habituation effects on one particular orientation. Five sessions for both orientations were recorded. After activating the visual stimulus, EEG data were recorded with a sampling frequency of 256 Hz. Each session from each subject took approximately 14 minutes to complete all sessions of horizontal and vertical orientation.

2.4. Signal Processing

This section explains the signal processing techniques applied to identify the difference in response for the stimulus orientations. The 30 seconds of EEG data were filtered with a band-pass Elliptic filter. The filter parameters used were 9-11 Hz pass band, maximum 0.1 dB ripple in pass-band and minimum attenuation of 30 dB in stop-band. Filter order of four was chosen because it gave sufficient suppression in the stopband. The data was then segmented into one second length of EEG segments for analysis. One second length of EEG was chosen because Fast Fourier Transform (FFT) requires a number of cycles in order to be accurate and one second of EEG would have about ten cycles using 10 Hz stimulus.

The two methods used to obtain the frequency content were FFT and autoregressive spectral analysis (AR). All the spectral estimation was performed using MATLAB® version 8.3 on 32 bit Windows platform.

For FFT analysis, the frequency resolution was 0.5 Hz because the one second EEG data was padded with one second length of zeros before analysis (the padding was useful to increase the frequency resolution). The maximum spectral amplitude of the filtered SSVEP data for all the 150 segments were computed and stored for statistical investigation. This was repeated with all five subjects' data in horizontal and vertical orientation.

AR spectral method is a popular linear feature extraction method used when there are limited numbers of parameters. This model, also known as parametric method, involves selection of the correct model order and model parameters from the available data. The model evaluation is represented by Equation 1.

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \quad (1)$$

where p is the model order, $x(n)$ is the data of the signal at the sampled point n, a_k is the real valued AR coefficients and $e(n)$ represents the white noise error tern independent of past samples.

AR modelling assumes that a data point is closely related to the previous few data points. Techniques like Yule-Walker, Burg's algorithm and Levinson-Durbin algorithm have been used to estimate the AR parameters. In our study, we used Burg's algorithm since it is more accurate for small data sets as well as the data points are used directly instead of autocorrelation function which is generally erroneous for small data segments. Furthermore, Burg's method uses more data points simultaneously by minimising not only a forward error but also a backward error. Using these AR parameters, the spectral content is obtained by using Equation 2.

$$S(f) = \frac{\sigma^2}{|1 - \sum_{k=1}^{p} a_k e^{-i2\pi fkT}|^2} \quad (2)$$

where $S(f)$ is the magnitude at frequency f, σ^2 is the variance of the error term and T is the sampling period. Akaike Information Criterion (AIC) is normally used to select the AR model order [21]. But in this paper, order two was used as the SSVEP is pseudo-sinusoidal with one major frequency content, which will be the same as the flickering LED frequency. Therefore, order two would be sufficient. Furthermore, the error variances for the AR model were found to be very close to zero when using any order above two.

Similar to FFT analysis, the maximum spectral amplitude of the filtered SSVEP data for all the 150 segments were computed using the AR method and stored for statistical investigation. This was repeated with all five subjects' data in horizontal and vertical orientation.

Statistical estimation was performed on the data for 150 segments from all five sessions from horizontal and vertical orientation as well as 30 segments from each session. This analysis was applied for all the data from the subjects to statistically show the difference of stimulus orientation effect in SSVEP.

The statistical analysis was performed using sign rank method, which is a nonparametric test for two paired samples to check the null hypothesis. The test returns a *p*-value which determines the acceptance of the hypothesis. The stored data was statistically analysed with sign rank using 150 values from both orientations as well as using sessional data of 30 values from both vertical and horizontal orientations.

3. Results and Discussions

As previously mentioned, the two orientations were tested for the difference in performance using SSVEP. To statistically compare the spectral output from FFT and AR methods, sign rank comparison was employed with a significance value (alpha) set to 0.1. Two orientations were compared with 150 data segments as well as sessional data of 30 segments. The set of values compared were from the same subjects in all five sessions to identify the influence of the orientation on SSVEP response. Tables 1 and 2 show the mean and standard deviation values for the obtained FFT and AR spectral values. Table 3 shows the FFT data analysis for 150 segments using sign rank for horizontal and vertical SSVEP EEG data.

Table 1 - Mean and standard deviation values for 30 seconds FFT amplitudes in five sessions for vertical and horizontal stimuli

Subject										
Session	S1		S2		S3		S4		S5	
	Horizontal		Horizontal		Horizontal		Horizontal		Horizontal	
	Mean	SD	Mean	SD	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
1	1.9e-3	1.5e-4	2.0e-3	1.8e-4	2.8e-3	1.1e-3	5.8e-4	2.1e-4	7.3e-4	2.1e-4
2	2.0e-3	1.8e-4	1.7e-3	1.6e-4	3.0e-3	9.9e-4	4.8e-4	1.4e-4	1.1e-3	1.5e-4
3	1.7e-3	1.6e-4	2.0e-3	2.7e-4	2.5e-3	9.2e-4	5.9e-4	1.5e-4	1.7e-3	3.1e-4
4	1.9e-3	2.1e-4	1.9e-3	2.1e-4	2.6e-3	1.2e-3	6.1e-4	2.0e-4	1.8e-3	1.7e-4
5	2.0e-3	2.7e-4	1.7e-3	2.2e-4	1.2e-3	1.0e-3	6.8e-4	2.0e-4	1.9e-3	1.5e-4
Subject										
Session	S1		S2		S3		S4		S5	
	Vertical		Vertical		Vertical		Vertical		Vertical	
	Mean	SD	Mean	SD	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
1	1.0e-3	1.4e-4	1.3e-3	2.0e-4	2.7e-3	1.2e-3	2.4e-4	1.0e-4	7.3e-4	3.4e-4
2	1.6e-3	1.4e-4	1.1e-3	2.8e-4	2.2e-3	9.2e-4	3.1e-4	9.5e-5	8.8e-4	2.5e-4
3	9.1e-4	2.1e-4	1.6e-3	2.5e-4	2.2e-3	9.1e-4	2.4e-4	9.3e-5	1.4e-3	2.3e-4
4	1.1e-3	3.1e-4	1.2e-3	1.9e-4	2.1e-3	9.4e-4	2.4e-4	1.1e-4	1.4e-3	3.0e-4
5	1.1e-3	2.5e-4	1.8e-3	2.2e-4	2.2e-3	9.4e-4	2.4e-4	7.8e-5	1.3e-3	2.8e-4

Table 2 - Mean and standard deviation values for 30 seconds of AR spectral analysis in five sessions for vertical and horizontal stimuli

Subject										
Session	S1		S2		S3		S4		S5	
	Horizontal		Horizontal		Horizontal		Horizontal		Horizontal	
	Mean	SD	Mean	SD	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
1	2.1e-8	5.2e-8	7.6e-10	5.0e-10	2.4e-8	1.8e-8	4.0e-10	6.4e-10	4.1e-9	1.0e-8
2	7.6e-10	5.0e-10	1.7e-8	3.9e-8	2.8e-8	1.5e-8	1.1e-09	2.9e-9	1.2e-8	3.0e-8
3	1.7e-8	3.9e-8	6.8e-9	1.6e-8	2.0e-8	1.3e-8	1.6e-09	4.5e-9	1.50e-8	2.8e-8
4	6.8e-9	1.6e-8	1.1e-8	2.4e-8	2.1e-8	1.6e-8	1.4e-09	2.8e-9	8.0e-9	3.0e-8
5	1.1e-8	2.4e-8	3.0e-08	6.1e-8	2.5e-8	1.3e-8	9.7e-10	2.8e-9	2.1e-8	5.2e-8
Subject										
Session	S1		S2		S3		S4		S5	
	Vertical		Vertical		Vertical		Vertical		Vertical	
	Mean	SD	Mean	SD	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
1	1.9e-9	3.0e-9	4.9e-9	1.7e-8	2.3e-8	1.5e-8	5.7e-11	7.4e-11	1.6e-9	3.1e-9
2	2.3e-9	4.0e-9	2.5e-9	4.7e-9	1.6e-8	1.9e-8	3.8e-10	8.8e-10	2.4e-9	6.6e-9
3	1.1e-9	2.9e-9	5.9e-9	9.4e-9	1.4e-8	1.5e-8	1.6e-10	3.6e-10	3.9e-9	8.6e-9
4	1.9e-9	3.3e-9	3.7e-9	7.1e-9	1.5e-8	1.8e-8	1.9e-10	7.2e-10	2.9e-9	5.0e-9
5	1.0e-9	2.3e-9	2.8e-9	6.1e-9	1.4e-8	1.4e-8	1.1e-10	2.8e-10	4.6e-9	1.0e-8

Table 3 - Signrank significance (p-value) results comparing 150 segments of FFT amplitudes for vertical and horizontal LED stimuli

Subject									
S1		S2		S3		S4		S5	
Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis
2.9e-26	H>V	3.9e-3	H>V	1.3e-5	H>V	1.1e-24	H>V	1.0e-15	H>V

Table 4 - Signrank significance (p-value) results comparing 30 seconds FFT amplitudes in five sessions for vertical and horizontal LED stimuli.

	Subject									
Session	S1		S2		S3		S4		S5	
	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis
1	1.7e-9	H>V	7.6e-1	NS	7.8e-1	NS	2.8e-6	H>V	8.6e-1	NS
2	6.3e-9	H>V	3.7e-2	H>V	3.0e-3	H>V	2.2e-4	H>V	2.4e-4	H>V
3	1.7e-9	H>V	7.8e-2	H>V	2.3e-1	NS	3.9e-6	H>V	4.2e-4	H>V
4	1.7e-9	H>V	1.8e-1	NS	3.6e-3	H>V	2.9e-6	H>V	1.6e-5	H>V
5	1.7e-6	H>V	8.2e-5	H>V	5.0e-3	H>V	1.7e-6	H>V	1.7e-6	H>V

As can be seen from Table 3, for all subjects S1 to S5, the horizontal orientation gave better results than vertical for SSVEP EEG when 150 segments of data were analysed. Table 4 shows the 30 segments of FFT data analysis for each session using sign rank where significance of horizontal stimulus is better 80% of the time as compared to vertical orientation. The rest 20% of the cases did not indicate any significance (denoted as NS).

Table 5 shows the AR spectral analysis using Burg's method and statistically comparing the data using rank sum for 150 segments in horizontal and vertical orientation. Again, the results show that horizontal orientation is significantly better than vertical orientation for all the subjects. Table 6 shows the results for 30 segments from each session and horizontal orientation is 68% more prominent when compared with vertical orientation.

Table 5 - Signrank significance (p-value) results comparing 150 segments with AR spectral analysis for vertical and horizontal LED stimuli.

Subject									
S1		S2		S3		S4		S5	
Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis
9.4e-3	H>V	1.6e-4	H>V	1.8e-4	H>V	6.0e-14	H>V	1.7e-2	H>V

Table 6 – Signrank significance (p-value) results comparing 30 seconds AR spectral analysis in five sessions for vertical and horizontal LED stimuli.

	Subject									
Session	S1		S2		S3		S4		S5	
	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis	Significance	Hypothesis
1	5.7e-3	H>V	2.1e-1	NS	8.1e-1	NS	2.2e-4	H>V	3.9e-1	NS
2	2.1e-5	H>V	1.4e-2	H>V	8.7e-3	H>V	1.5e-2	H>V	7.6e-1	NS
3	1.0e-4	H>V	9.9e-2	H>V	1.1e-1	NS	3.6e-4	H>V	1.2e-2	H>V
4	3.7e-1	NS	2.2e-2	H>V	9.8e-3	H>V	3.7e-4	H>V	6.4e-1	NS
5	1.0e-3	H>V	1.86e-6	H>V	5.0e-3	H>V	1.2e-4	H>V	6.0e-1	NS

In general, it can be observed that SSVEP performance is better for horizontal stimulus orientation when compared to vertical orientation, which confirms previous research findings for other applications[16,17]. Also, all five participants commented that horizontal stimulus orientation was more comfortable than vertical. Therefore, visual fatigue will be reduced in horizontal orientation when used for longer periods than in vertical orientation and this would improve the usage of SSVEP for applications such as BCI.

4. Conclusion

In this study, we have investigated the influence of different visual stimulus orientation on the performance of SSVEP EEG. Since it was a pilot study, only one electrode in the occipital area (Oz) was used with one specific frequency and the results are specific to that frequency and channel. The channel Oz was used because it is generally know that this area of the brain gives significant visual responses. The participants in this study felt horizontal orientation were easier to concentrate as compared to vertical orientation. The data processed using FFT and AR spectral methods when compared statistically using sign rank proved horizontal visual stimulus to evoke higher SSVEP response than vertical stimulus and this confirmed the ease of concentration for horizontal stimulus by the participants. Furthermore all subjects were comfortable using horizontally oriented stimulus and this would reduce the visual fatigue (less strain for the eyes) for prolonged usage in SSVEP EEG based applications such as BCI. In order to implement an actual BCI, several LED arrays flickering at different frequencies simultaneous would need to be classified. So, future studies would include the usage of more frequency combinations for SSVEP analysis. The improved SSVEP setup could also proof to be useful for various other medical applications related to vision such as diagnosing issues with vision system for infants.

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