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An improved model for the use of facial stimulation in hybrid SSVEP+P300 brain-computer interfaces

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Abstract

Purpose: This research proposes a hybrid BCI that integrates Steady State Visual Evoked Potentials (SSVEP) and Event Related Potentials (P300) simultaneously. We included human facial structure into a visual stimulus to elicit stronger cortical responses in a hybrid SSVEP+P300 BCI. We also discussed the possibilities of triggering one potential with facial stimuli and another with non-facial stimuli.

Methods: To elicit SSVEP and P300 responses, non-face and neutral-face stimulus paradigms are presented. We also tested the neutral-face and flicker paradigm, in which non-face stimuli would elicit SSVEP and neutral-face stimuli would elicit P300.

Results: The results showed that the latter paradigm evoked more robust cortical potentials, leading to enhanced system accuracy and ITR. The neutral-face and flicker paradigm has an average accuracy of 91.62%, with an average system communication rate of 22.04 bits per second.

Conclusions: The author talked about visual stimulus characteristics that might change the way that multiple brain potentials are activated simultaneously and how that affects the individual potentials.

Keywords: Neutral-face stimuli; Non-face stimuli; Hybrid SSVEP+P300 BCI; Visual stimulus characteristics

1. Introduction

Brain-Computer Interface systems (BCIs) are competent to control external devices by directly measuring human cortical activity. BCIs based on electroencephalogram (EEG) are classified as motor imaginary BCI, SSVEP BCI, P300 BCI, and so on [1]. BCIs are categorized based on the kinds of brain signals used for command generation [25].

The popularity of BCIs that employ visual evoked brain signals (VEP) has increased in recent years due to their ease of usage, greater communication rate, and short training time. Steady State Visual Evoked Potentials (SSVEP) BCI and Event Related Potentials (P300) BCI are the most widely used VEP-based BCIs [1]. Recently, researchers developed hybrid BCIs by combining two or more brain signals in order to boost the capabilities of single brain signal-based BCIs [2, 25]. A hybrid SSVEP+P300 BCI is generated by combining a traditional single SSVEP BCI with a P300 BCI in either sequential or simultaneous mode [3]. Since SSVEP is in the frequency domain and P300 is in the time domain, it is possible to combine them in a way that doesn't overlap.

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A very limited number of papers have tested hybrid SSVEP+P300 BCIs. These BCIs have been found to be more accurate, durable, and communicative than single brain signal-based BCIs [4, 26]. A large range of visual stimulus paradigms have been developed and tested to elicit brain signals in VEP-based BCIs. However, the majority of them are influenced by inter-stimulus interference, a lack of user attention, and user fatigue [5]. To overcome these limitations, researchers use human faces as visual stimuli since the brain is sensitive to facial structure [6, 7]. Conventional BCIs were tested with variable facial patterns such as facial expression change, inversion, rotation, configuration, viewpoint, and movement [8, 9]. The flashing of a face stimulus elicits two additional negative event-related potentials (ERPs), N170 and N400, in the cortex. The BCI system's accuracy is improved because of these extra ERPs [10]. Kaufmann et al. (2011) [6] discovered that flashing face stimuli reduce the number of flashes needed to achieve higher accuracy. The addition of face-related N170 and N400 components helps to distinguish between target and non-target flashes [11]. Stimuli with facial expression changes elicit N170 and N400 with a larger amplitude and less latency than neutral facial structure. Therefore, it improves the system's efficiency. Rossion et al. (2011) [12] provide evidence that flickering faces at a specific frequency produces an SSVEP at the fundamental stimulation frequency that corresponds to the flashing frequency. Faces flickering at lower frequencies evoked a strong SSVEP compared to other kinds of flicker. Emotional faces enhance multicommand SSVEP BCI usability and information transfer rate (ITR) [7].

Li et al. (2013) [13] designed a four-command hybrid SSVEP+P300 BCI in which VEPs are elicited simultaneously by flash and flicker paradigms. Allison et al. (2014) [14] used a color change flash-flicker to evoke SSVEP and P300 simultaneously. They compared the results of the hybrid BCI to those of the traditional single P300 BCI and SSVEP BCI and found that the accuracy and bit rate of the hybrid BCI had greatly improved. Wang et al. (2015) [15] used a flash-flicker paradigm with changing shapes and found that changing shapes worked better than changing colors. Singla et al. (2018) [16] created a hybrid SSVEP+P300 BCI by combining the pictorial flash and flickering paradigms. The resultant system is simpler and more efficient. The author incorporated the human face structure into the visual stimulus to study cortical processing of facial stimuli in the hybrid SSVEP+P300 BCI. This research addressed two main questions. The first question is how VEPs are different when a stimulus is a neutral face or a non-face. The second question is how BCI performs when one VEP is elicited by a face and another by a non-face stimulus. To deal with this problem, we divided the visual stimuli of the proposed hybrid SSVEP+P300 BCI into three main groups. In the first two groups, neutral-face and non-face stimuli evoke both SSVEP and P300 (ERPs). In the third group, P300 is evoked by a neutral face, whereas SSVEP is evoked by non-facial stimuli. We also thought that facial stimuli would cause strong VEPs, which would make BCIs more accurate compared to stimuli that weren't facial.

2. Material and methods

2.1. Experimental setup and Participants

Ten healthy individuals (7 males, aged 22–28 years, mean age of 25.6 years) volunteered to participate in our experiment. There were no anomalies found in the participant's normal eyesight or their history of visual epilepsy. All of the subjects gave their written agreement, as is customary in clinical research and in accordance with acceptable professional practices. Everyone who took part in the experiment was told that they could leave at any time if they felt uncomfortable or had a visual seizure.

The external stimulus is shown on a 60 Hz LCD screen, and all of the trials are carried out in a room with the lights turned off. The distance is around 90 cm between the participant and the center of the LCD panel. During the experiment, everyone who is taking part has to stay calm and not do anything that isn't necessary.

2.2. Experimental paradigm and visual stimuli

Figure 1(a) shows the participant's LCD screen with four command buttons. Each command button is made up of twelve small circles that are spaced 30^0 apart from one another around the larger circle in the center. Small circles on each command button flicker at 7.5 Hz, 8.5 Hz, 10 Hz, and 15 Hz to elicit SSVEP. Meanwhile, large circles around each command button are flashed in a random fashion. Each large circle intensifies for 100 ms, and there is a delay of 25 ms between each successive intensification. Subjects were directed to count the number of times the target circle flashed in order to evoke ERPs. Each trail is comprised of four flashes, one for each command button (Figure 1(b)). Each flash lasts for 100 ms + 25 ms = 125 ms. This means that each set of four flashes takes 125 * 4 = 500 ms (trial time). So, 500 ms is the target-to-target interval. Hence, we need to compute ERPs between 0 and 500 ms after the stimulus began. During the experiment, both the small circles flickered and the large circle flashed at the same time, which made it possible to elicit SSVEP and P300 simultaneously. We have devised three scenarios in which the command buttons flicker and flash differently:

- In the non-face paradigm (Figure 1(c)), the large circle flashes with a red character while the small circles flicker between yellow and green.
- In the neutral-face paradigm (Figure 1(d)), the neutral face is employed for flashing and flickering.
- In the neutral face and flickering paradigm (Figure 1(e)), the large circle flashes with the neutral face to evoke P300 (ERPs) and the small circles are flickered with yellow and green to evoke SSVEP.

The human face is drawn in monochrome. Faces are sketched using basic lines and circles. The sketch of the face includes a mouth, two eye brows, a nose (drawn with a single line), and two eyes (drawn with circles). The brain cortex reacts to these pictures in a way that is similar to how it reacts to real human faces because they have the same visual qualities and convey the same semantic information (like Emoji) [17].

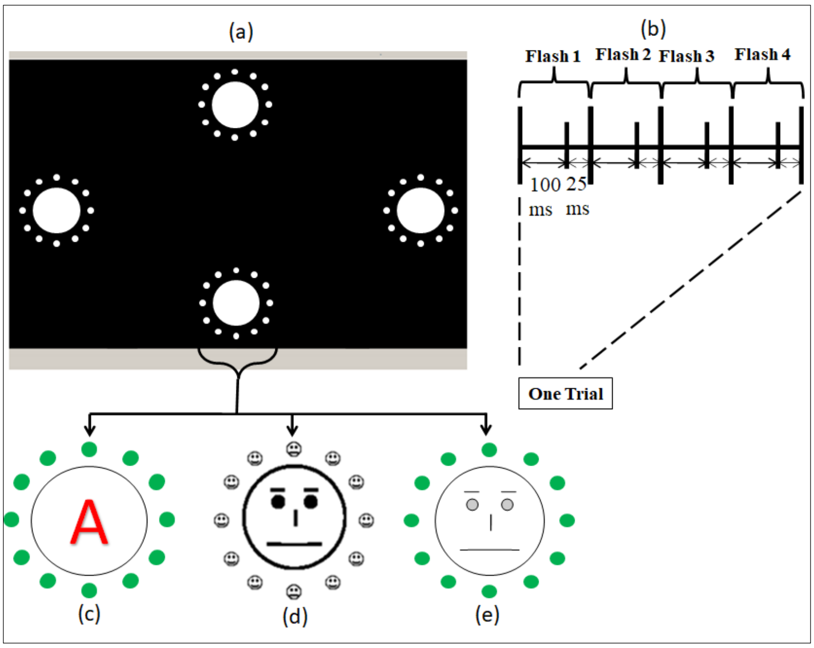

Figure 1 Experiment Paradigms (a) the user-viewable display (b) the trial time series (c) the non-face paradigm (d) the neutral-face paradigm (e) the neutral-face and flicker paradigm

2.3. EEG recording

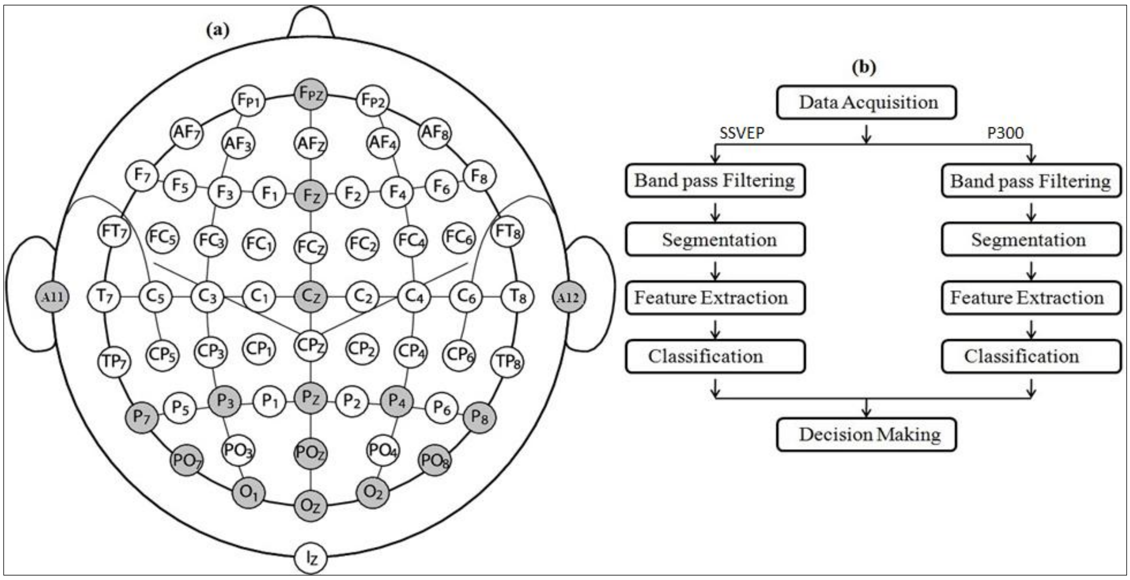

Figure 2 (a) The electrode placement is shown in grey. (b) A flowchart of how EEG signals are pre-processed and classified.

EEG signals were sampled at 250 Hz and recorded using a 16-channel OpenBCI headset with an ADS 1299 amplifier (manufactured by Texas Instruments). Electrodes were positioned on the scalp according to the 10–20 international system (Figure 2(a)) at POz, Fz, Pz, Cz, P3, P7, P4, P8, PO7, PO8, Oz, O1, and O2. Electrodes are referenced at A12 and A11 average and grounded at FPz. The channels P7, P8, P3, P4, Fz, Cz, Pz, and Oz are taken into consideration for P300 detection, while the channels Oz, O1, O2, PO8, PO7, and POz are selected for SSVEP detection. Conducting liquid is put between the electrodes and the scalp to reduce resistance.

2.4. Feature extraction procedure

We employed two different preprocessing procedures for each signal (SSVEP and P300) in this study (Figure 2(b)).

2.4.1. P300

EEG filtering between 0.1 Hz and 12 Hz is accomplished with the help of a sixth-order Butterworth band pass filter. After that, the sample rate of the filtered EEG is lowered from 250 Hz to 50 Hz. A signal segment from 0 to 800 ms was taken from the data after the start of each flash.

2.4.2. SSVEP

In order to properly analyze SSVEP data, it is necessary to combine the readings from several electrodes at the same time [21, 22]. Therefore, in order to achieve the best possible discrimination between the various conditions, we have used the Common Spatial Patterns (CSP) approach as a spatial filter. A Butterworth band pass filter of the sixth order is used to filter EEG between 5 and 30 Hz.

2.5. Classification

Linear Discriminant Analysis with Probabilistic Multi-class classification [18, 19] is employed for the classification of brain potentials among varying command buttons. Let ‘k’ is a number of classes, ‘n’ number of features, and ‘m’ correspond to a number of data vectors. Then every input feature vector can be characterized as ‘$x \in R^n$’. A discriminant function used for classification of input feature vector ‘x’ amongst classes ‘i’ and ‘j’ is given by -

$$D_{i,j}(x) = w_{i,j}^T \times x + b_{i,j} \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where

- Bias term $b_{i,j}$ of discriminant function$D_{i,j}(x)$ is given as $b_{i,j} = -w_{i,j}^T \times \mu_{i,j}$
- Weights Vector $w_{i,j} = \sum_{i,j}^{-1}(\mu_j - \mu_i)$
- Every class pair’s average covariance matrices calculated as

$$\sum_{i,j} = \frac{C_i + C_j}{2} \text{ for } j > i \in (1,2,-----,k) \quad \ldots\ldots\ldots(2)$$

4) The average mean vector of each class pair is $\mu_{i,j} = \frac{\mu_i + \mu_j}{2}$

The probability of assignment of ‘x’ to class ‘i’ is

$$Q_{i,j}\left(\frac{i}{x}\right) = \sigma(D_{i,j}(x)) \quad \ldots\ldots\ldots\ldots\ldots(3)$$

where

$$\sigma(D_{i,j}(x)) = \frac{1}{1+\exp(-D_{i,j}(x))} \quad \ldots\ldots\ldots\ldots \quad (4)$$

Then the probability of allocation of input feature vector ‘x’ among all classes is calculated as vector P -

$$P_i(x) = \frac{\sum_{j\neq i} Q_{i,j}\left(\frac{i}{x}\right)}{\sum_k \sum_{j\neq k} Q_{i,j}\left(\frac{k}{x}\right)} \quad \ldots\ldots\ldots\ldots\ldots(5)$$

$\bar{k} = \max_i P_i(x)$

Where, $\bar{k}$ is uppermost probability class number, therefore classifier allots 'x' to most probable class.

2.6 ITR calculation -

ITR (communication rate) of the proposed system is calculated by-

$$B = \log_2(N) + Acc * \log_2(Acc) + (1 - Acc) * \log_2\{\frac{1-Acc}{N-1}\} \text{ ………………….. } (6)$$

$$ITR = B * \langle\frac{60}{t}\rangle \quad \text{……………….. } (7)$$

Where Accthe classification accuracy, t is is the time required to recognize each target, N is the target item number, and B is the single target ITR.

2.6. Experimental procedure

Participants performed 12 sessions. Each command button was targeted once per session. Participants counted the number of flashes of a large circle on the corresponding target command button to evoke P300. In each session, there were 6 trials (figure 2(b)). Therefore, we collected (4 targets/trial × 6 trial/session × 12 sessions) 288 target P300 data epochs and (3 non-targets × 4 × 6 × 12) 864 non-target P300 data epochs. Round is the process of choosing one target, i.e., any one of the four command buttons. In each round, the participant focused on the flickering of small circles on the command button for 9.5 sec. Participants performed 12 sessions, where each session consisted of 8 rounds. The author considered a window length of 4 seconds and a step size of 0.5 seconds to calculate data epochs. Hence, the total number of SSVEP data epochs are 1152 ((((9.5 - 4) / 0.5) + 1) × 8 × 12).

2.7. Statistical analysis

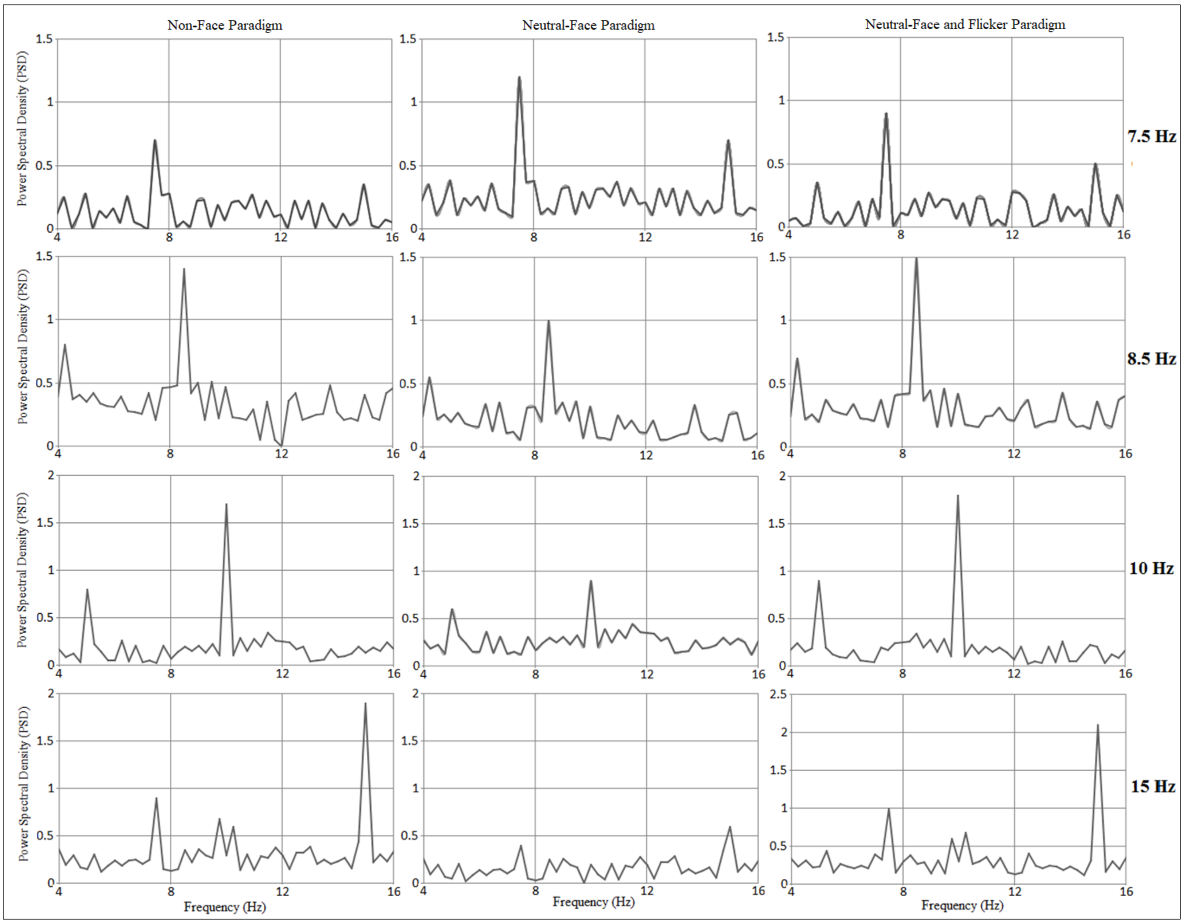

Figure 3 Average Power Spectral Density (PSD) of the channels used for SSVEP detection. PSD is shown for a range of frequencies from 4 to 16 Hz

The ANOVA statistical technique is used to compare the proposed system's accuracy and ITR. According to ANOVA's requirements, data is tested for normal distribution (one-sample Kolmogorov-Smirnov test) and sphericity (Mauchly's test). Independent variables were the non-face paradigm, the neutral-face paradigm, and the neutral face and flicker paradigm. Post-hoc analysis is performed with the use of the Tuckey-Kramer tests.

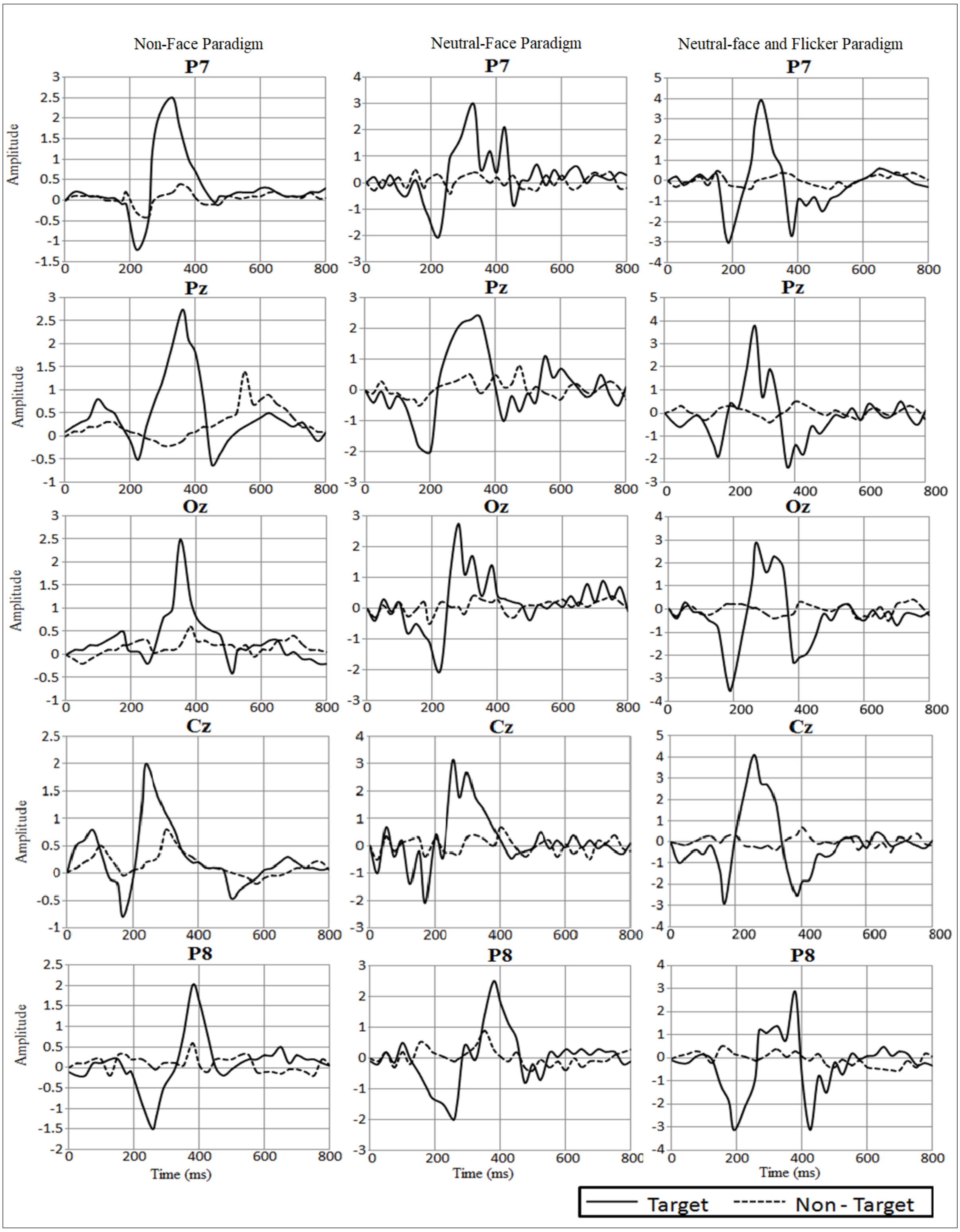

Figure 4 The average ERP waveform at Pz, Cz, Oz, P7, and P8 evoked by all paradigms

3. Results

3.1. SSVEP PSD and P300 waveform analysis

We plot the power spectral density (PSD) that was computed using the fast fourier transform (FFT) with the average data that was gathered from all SSVEP channels (O1, O2, Oz, PO7, PO8, and POz) (Figure 3). For all paradigms, SSVEPs are evoked with higher power at the fundamental stimulation frequencies (and a small boost at the second harmonic frequencies). In the non-face paradigm, as well as the neutral-face and flicker paradigm, it was shown that the SSVEP responses were less distinct at lower frequencies (7.5 Hz & 8.5 Hz) than they were at higher frequencies (10 Hz & 15 Hz). On the other hand, in paradigms in which faces are flashed to induce SSVEP, such as the neutral-face paradigm, SSVEP responses are more distinguishable at lower frequencies than at higher frequencies. Neutral-face and flicker paradigms provide clear SSVEP signals at all frequencies. As a result, we have the presumption that face flicker may be more likely to impair SSVEP responses than color change flicker. The average ERP waveform can be seen in figure 4, which was captured at P7, Pz, Oz, Cz, and P8. Non-face paradigm and neutral-face paradigm have bigger non-target interfaces than neutral-face and flicker paradigm.

Table 1 The accuracy and ITR (bits/min) for every paradigm

Sub.	Non-Face Paradigm		Neutral-Face Paradigm		Neutral-Face and Flicker Paradigm	
	Acc	ITR	Acc	ITR	Acc	ITR
S1	86.3	18.1	86.3	18.1	88.8	19.7
S2	78.8	13.8	86.3	18.1	93.8	23.5
S3	87.5	18.9	83.4	16.3	88.8	19.7
S4	83.4	16.3	78.8	13.8	97.5	26.9
S5	73.8	11.3	73.8	11.3	83.4	16.3
S6	83.4	16.3	88.8	19.7	95	24.5
S7	93.8	23.5	73.8	11.3	88.8	19.7
S8	67.5	8.6	88.8	19.7	93.8	23.5
S9	78.8	13.8	67.5	8.6	97.5	26.9
S10	88.8	19.7	93.8	23.5	88.8	19.7
Avg.	82.21	16.03	82.13	16.04	91.62	22.04
Std. Dev.	7.7	4.3	8.3	4.6	4.5	3.5

3.2. Accuracy and ITR

ANOVA is utilized to compare the system accuracy and the ITR for each participant across all paradigms. The results of pairwise comparison showed that there was a statistically insignificant difference between the non-face paradigm and the neutral-face paradigm in terms of accuracy ($F(1,18) = 0.0005$, $p = 0.98$) and ITR ($F(1,18) = 0$, $p = 0.99$). There is a significant difference between the neutral-face and flicker paradigm and the non-face paradigm in terms of accuracy ($F(1,18) = 10.9$, $p = 0.0039$) and ITR ($F(1,18) = 11.5$, $p = 0.0032$), as well as between the neutral-face and flicker paradigm and the neutral-face paradigm in terms of accuracy ($F(1,18) = 9.9$, $p = 0.0055$) and ITR ($F(1,18) = 10.4$, $p = 0.0045$). Among all the paradigms, we observed that the neutral-face and flicker paradigm has improved efficiency in terms of accuracy ($F(2,27) = 5.95$, $p = 0.0072$) and ITR ($F(2,27) = 6.78$, $p = 0.0041$) (Table 1). This shows that the neutral-face and flicker paradigm works much better than any other paradigm tested so far.

4. Discussions

The main goal of this research is to find out what happens to the strength of VEPs when facial content is added to a visual stimulus in a hybrid SSVEP+P300 BCI. As the hybrid SSVEP+P300 BCI consists of two kinds of VEPs, namely SSVEP and ERPs(P300), the facial influence on VEPs is examined independently.

When both the SSVEP and P300 signals are triggered by facial stimuli, PSD shows that the SSVEP responses are less strong. This is different from paradigms in which only one signal is triggered by a face and the other signal is triggered by something other than a face. This occurs because flashing faces, which evoke P300, produce a damaging interface for SSVEP. This is accomplished by evoking SSVEP with an unstable broader range of frequencies [20]. So, in the neutral-face and flicker paradigm, the SSVEP signals were stronger than in other paradigms.

Studies in the past have shown that facial stimuli give stronger P300 responses as well as extra information in the form of N170 and N400 ERP responses [23]. This increases the accuracy and bit rate of facial stimuli BCI systems compared to non-face stimuli. N170 and N400 both refer to a negative potential that is observed at 170 ms and 400 ms after the beginning of a face-related stimulus, respectively. N400 refers to the information that is semantically connected to faces. In the waveform analysis shown in Figure 4, the neutral-face paradigm represents P300 with a greater amplitude and a shorter delay, and it also produces amplified N170 potentials. The non-face paradigm did not produce these effects. When compared to previous paradigms, the neutral-face and flicker paradigm produces superior results, as seen by higher ERPs (namely N170, P300, and N400 amplitude) and decreased latency. Additionally, the amplitude of non-target ERPs is significantly reduced. This is due to the fact that the person is not aware of the changes occurring in nearby pictures while they are concentrating on the target image. As a second consequence, this leads to a reduction in interference from adjacent stimuli, a decrease in user fatigue, and an increase in user attention [24]. In terms of interference caused by non-targets, the non-face paradigm displays greater levels of non-target interference (dotted line), while both facial paradigms have less interference from non-targets. It is possible that the user would become less attentive if they were confronted with a greater number of non-target interferences; as a result, the system's accuracy might suffer. In our research, the neutral-face and flicker paradigm showed superior accuracy than other paradigms ($F(2,27) = 5.95$, $p = 0.0072$), corroborating the previously described ERP waveform analysis.

5. Conclusion

This study proposes three paradigms: the non-face paradigm; the neutral-face paradigm; and the neutral-face and flicker paradigm. All paradigms have been evaluated and compared in terms of cortical signal strength, accuracy, and ITR. Results indicate that the neutral-face and flicker paradigm fared better than the other two paradigms in every aspect. In the neutral-face and flicker paradigm, SSVEP responses are elicited by color change flicker while P300 responses are elicited by flashing the human face. This adjustment reduces non-target interference, resulting in improved system accuracy. Future efforts will concentrate on evaluating the stimuli with different face orientations, inversions, and combinations in a hybrid SSVEP+P300 BCI.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

No author has a potential conflict of interest.

Statement of ethical approval

All of the procedures done in this study that involved human participants were in line with the ethical standards of the Srinivas University research committee, the 1964 Helsinki declaration and its later changes, or other ethical standards that were similar.

Statement of informed consent

In accordance with the recommendations of the Good Clinical Practices (GCP) accreditation, written permission was obtained from each participant.

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