Synchronized Detection of Evoked Potentials to Drive a High Information Transfer Rate
Hybrid Brain-Computer Interface Application

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Abstract  
Brain-computer interfaces (BCIs) recently have been focusing on combining various BCI modalities to form different combinations of hybrid BCIs. These paradigms are designed to elicit more than one brain potential in the form of BCI features. This research is being carried out with the objective of increasing classification accuracy and information transfer rate (ITR) based on measurement of brain potentials. This study proposed a novel hybrid BCI elicitation and measurement technique combining steady-state visually evoked potential (SSVEP) and P300 potentials to increase the ITR. The hybrid BCI also increased the number of target options compared to SSVEP paradigm for a set number of presumed frequencies of flickering. One of the hybrid BCIs used distinct colours along with distinct flickering frequencies for targets, with an aim to increase the accuracy of classification and reduction of system uncertainty parameter known as false activation rate (FAR). The results of a study in 10 volunteers established that the novel SSVEP-P300 hybrid BCI with distinct colours for target frequencies had average parameters as follows: classification accuracy of 90.76%, ITR of 81.10 bits/min and FAR of 2.99%. A comparative study of the two novel paradigms with SSVEP and P300 paradigms in the same environment was conducted. The results of the comparative study concluded that the hybrid BCI with distinct colours for various target frequencies yielded the best results and hence can be considered as a viable paradigm option for the development of an assistive device.

Keywords: SSVEP, P300, BCI, ITR, FAR.

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1. Introduction

Researchers all over the world have achieved great success in the area of brain-computer interfacing with the aim of improving quality of life for locked-in subjects and enhancing task performance for healthy subjects. Due to certain limitations such as neurologically degenerative disorders, physical disabilities, or in some cases, hazardous nature of the task, some people may not be able to communicate or accomplish a task. The assistive devices (ADs) based on various BCI models help subjects overcome the above-mentioned limitations to accomplish the tasks at hand. These ADs work on various standardised BCI markers that are detected via brain waves using different techniques, one of which is electroencephalography (EEG). After detection of BCI markers, classification algorithms are used to translate brain wave variations into machine command. The EEG features used most frequently by different research groups are broadly classified as self-regulated features consisting of slow cortical potential (SCP) [1–3], event-related synchronization (ERS) and event-related desynchronization (ERD) [4,5], as well as evoked potentials such as P300 [6] and steady-state visually evoked potential (SSVEP) [7].

P300, which is an event-related potential (ERP), is represented by a positive amplitude shift in the EEG signal delayed by a period of 300 ms from the advent of an infrequent stimulus. When subject concentrates on one infrequent target out of a pool of frequent targets, it generates a P300 shift in the EEG signal, and hence we are able to estimate the item under consideration. P300 BCIs require minimal training and have shown exceptional results in patients as well as healthy subjects [8]. P300 signal is very weak, and thus averaging techniques are used...
SSVEP, a visually evoked potential, is defined as the presence of steady-state harmonics in the EEG signal recorded over the visual cortex after the subject is exposed to flickering objects of predefined frequencies [10,12]. The visual cortex is located over the occipital region, located at the back of the human scalp. The SSVEP appears in the form of 1st, 2nd and 3rd harmonics of the fundamental flickering frequencies within the EEG with respect to the flickering stimulus [13,14]. In a stereotypical SSVEP paradigm-based BCI, the subjects fix their gaze to one of the multiple decision targets presented on a computer screen, such that each target has a unique flickering frequency. When the subject is focusing on one of the targets, the SSVEP response over that object’s frequency is most significant. Thus, the determination of the decided target can be done generally by finding the 1st harmonic frequency which has maximum power. The numbers of decisions in an SSVEP paradigm which are uniquely represented by different frequencies are limited due to the bandwidth of the frequencies that can elicit SSVEP in a subject. Hence other techniques such as phase coding or resorting to hybrid paradigms based on SSVEP are considered for the development and improvement of ADs.

To improve the performance of the system as well as increase reliability, the concept of hybrid BCI was introduced. Hybrid BCI combines one BCI marker with either some other BCI markers or any other physiological signal. The objectives behind this technique are to: (i) elevate classification accuracy; (ii) increase the number of available target options in a paradigm which can elicit unique BCI features within the user’s EEG for the purpose of control and communication tasks; and (iii) reduce brain command detection and implementation time [15]. Since SSVEP-based BCIs have relatively high ITRs and require the least training time [16], most hybrid BCIs have been using SSVEP as one of the BCI markers along with either motor imagery (MI) [17–22] or electrooculogram (EOG) [23] to form various BCI applications, or P300 to form purely visually evoked BCI paradigm-based applications [24–30]. Thus, to improve the performance of the system compared to P300 BCI and also to increase the number of decision targets in the system compared to SSVEP BCI, a hybrid BCI approach is proposed in this research paper. A BCI system must contain a certain minimum number of control targets for adequate functionality [31–33]. It has also been established that for standard LCD screens with refresh rate of 60 Hz, the frequency range that shows the best SSVEP response is 5 Hz to 20 Hz [34].

In an endeavour to optimise the performance of BCI systems and reduce system uncertainty, this study proposes a novel hybrid BCI paradigm that uses 4 frequencies ranging from 8 to 14 Hz to elicit SSVEP, while the P300 marker is used as time division multiplexing (TDM) identifier. This helps the system to distinguish between two sets of decision targets of four targets each, hence doubling the number of decision targets (eight) for the presumed number of frequencies (four).
The target areas were highlighted by a circular white flash against a black background. Only four frequencies were used; i.e., 8, 10, 12 and 14 Hz. The primary targets (A, B, C, and D) were presented in the outer tier of the paradigm while the secondary targets (A₁, B₁, C₁, and D₁) were presented in the inner tier of the paradigm. Targets A & A₁ had a flickering frequency of 8 Hz, B and B₁ had a flickering frequency of 10 Hz, and so on. The target with no subscript signifies that it belongs to the primary tier; meanwhile a target with subscript “₁” signifies that it belongs to the secondary tier. The flickering access to both tiers of target items was mutually exclusive in nature. This means that for the odd time intervals (e.g., 1st, 3rd, 5th intervals) with a duration of one second, the outer tier or primary targets flickered; and for the even time intervals (e.g., 2nd, 4th, 6th intervals) with a duration of one second, the inner tier or secondary target items flickered. This TDM allocation of flickering of different tiers would use P300 as a marker to decode which tier target item has been activated and further selected by the user.

A SSVEP paradigm was used for comparison purposes. It consisted of four target items with distinct flickering frequencies of 8, 10, 12 and 14 Hz for A, B, C and D target items, respectively. The number of commands was restricted to four since only four frequencies were used (same frequencies used for hybrid BCIs). Hence, having eight target items using the SSVEP paradigm is not possible. The targets were placed at the four corners of the LCD screen. A P300 eliciting paradigm was also used, having eight target options in the form of a 2 × 4 matrix, with rows and columns flashing in a block-randomised manner. Each flash lasted 100 ms and inter-flash interval was 900 ms each. The whole paradigm was presented in 6 seconds since the paradigm has two rows and four columns and each flash is associated with 100 ms of flash and a gap of 900 ms, therefore total time = 6 × (0.1 + 0.9) seconds. The row/column containing the objects flashed by changing the circular targets to white colour against a black background. The first row showed the commands A, C₁, D₁ and B and the second row consisted of commands C, B₁, A₁ and D. The nomenclature of the targets was kept uniform for P300 and hybrid BCIs to minimize variation in accuracy caused by subject confusing the targets maintained a minimum distance of 90 mm from each other.
other. All the paradigms had target items in circular shape with a diameter of 30 mm as shown in Fig. 3(c).

2.2 Signal Acquisition

EEG signals were acquired via the eego™ Sports amplifier manufactured by ANT Neuro, with maximum sampling rate of 2048 Hz and resolution of 24 bits [Fig. 4(b)]. It has 32 channels which are referenced with respect to CPz [Fig. 4(a)]. Out of the 32 electrodes, 14 referenced channels were used in the study (mentioned in the next section). These channels were subjected to a bandpass filter with high-pass and low-pass cut off frequencies at 0.1 Hz and 40 Hz, respectively. All electrode impedances were maintained below 5 kΩ. The sampling rate used for this study was 512 samples per second. The channels used for signal acquisition were: C3, Cz, C4, P3, Pz, P4, T5, T6, F3, Fz, F4, O1, O2 and Oz [Fig. 4(a)] [35,36]

2.3 Feature Extraction

An accurate estimate of even and odd one-second intervals was required for the purpose of determining which tier of target items was being activated and further selected by the user. From the second minute of one-second recording, windows were used to isolate one-second of recording. These windows were stored in different columns of arrays. This was done for 14 referential recordings (C3, Cz, C4, P3, Pz, P4, T5, T6, F3, Fz, F4, O1, O2 and Oz) [9,12,37]. The data from these leads was restructured in the form of 512 × 480 matrix, each column of which was used for determination of P300 as well as in power spectrum density for determination of SSVEP data.

A sixth-order Butterworth bandpass filter was applied to O2, O1 and Oz for SSVEP feature extraction by filtering the EEG recordings (band frequency 5 Hz to 15 Hz). Then, fast Fourier transform and later power spectral density of each column were calculated and the corresponding columns were averaged to form the SSVEP matrix. The global maxima of each column gave the highest power frequency for the corresponding nth one-second recording.

For P300, EEG data from C3, Cz, C4, P3, Pz and P4 was filtered using sixth-order Butterworth bandpass filter (band frequency 0.1 Hz to 5 Hz). The odd columns contained the recordings of electrode potentials from these electrodes for odd-interval (1st, 3rd, 5th etc.) of recording
time (primary target items flickering), and the even columns contained the recording data from these channels for even-interval (2nd, 4th, 6th etc.) of the recording time (secondary target items flickering). Further, each window of data was normalised using peak normalisation, such that the normalising factor is the peak of the base rhythm determined in the first one minute of each trial. The process of threshold detection was used to detect the positive amplitude shift 300 ms from the advent of flash, which is also called P300 response. Eventually, a matrix of $1 \times 480$ was created, which stored the time (ms) when the pre-processed signal crossed the 0.707 value (RMS value) of the normalised amplitude if a positive shift was detected within a window of EEG data.

The final feature matrix ($F_m$) for single-step classification was a $3 \times 480$ matrix in which the columns represent 480 different feature vectors and the rows show the 3 components of each feature vector. The three components were PO, PE and S; where PO represents the value of time (ms), if a positive amplitude shift occurs during an odd one-second interval (PE is kept zero), while PE represents the value of time (ms) if a positive amplitude shift occurs during an even one-second interval (PO is kept zero); and S represents the SSVEP response ($S = 0$, if PO = PE = 0).

### 2.4 Feature Classification Models

Classification of P300-based paradigm was accomplished by using Bayesian linear discriminant analysis (BLDA). The Bayesian analysis determines the extent of regularization, which is estimated from training dataset without the need for cross-validation [38]. If the target $t$ is associated with feature matrix $x$ then:

$$t = w^T x + n$$

(1)

where $n$ is the Gaussian noise.

The probability function is defined as:

$$p(D | \beta, w) = \left( \frac{\beta}{2\pi} \right)^{N/2} e^{-\frac{1}{2} w^T \beta w}$$

(2)

where $w$ = weights used, $t$ = vector consisting targets, $X$ = matrix with each row as feature vectors, $D = f (X, t, \beta)$ and $N$ = population of the training dataset. Then:

$$p(w | \alpha) = \left( \frac{\alpha}{2\pi} \right)^{D/2} e^{-\frac{1}{2} w^T \alpha w}$$

(3)

Using Bayes’ rule, the computation of posterior distribution is described as:

$$p(\hat{t} | \beta, \alpha, D) = \frac{p(D | \beta, w)p(w | \alpha)}{\int p(D | \beta, w)p(w | \alpha)dw}$$

(4)

Further, the predictive distribution obtained by multiplying Eq. (4) with Eq. (2) computed for a new input vector $\hat{x}$ with a new regression target $\hat{t}$ is given by:

$$p(\hat{t} | \beta, \alpha, \hat{x}, D) = \int p(\hat{t} | \beta, w)p(w | \beta, \alpha, D)dw$$

(5)

Predictive identification of P300 peak is done by the mean and variance:

$$\mu = m^T \hat{x}$$

$$\sigma^2 = \frac{1}{\beta} + \hat{x}^T C \hat{x}$$

(6)

(7)

SSVEP paradigm was classified using canonical correlation analysis (CCA) [26,35,39–43]. A statistical algorithm based on multivariable analysis is based on correlation between datasets. If two sets of variables $X \epsilon R^{n \times d}$ & $Y \epsilon R^{n \times d}$ are to be classified such that they contain random demeaned values, then CCA would find a pair of linear transforms $w = eR^t$ and $v = eR^t$, which maximizes the correlation between $x = w^T X$ and $y = v^T Y$. The optimization is expressed as:

$$\rho = \max_{w,v} \frac{E[xy]}{\sqrt{E[x^2]E[y^2]}} = \frac{E[w^T XY^T v]}{\sqrt{E[w^T XX^T w]E[v^T YY^T v]}}$$

$$= \frac{\sqrt{\sum_{xx} w^T \sum_{yy} v}}{\sqrt{w^T \sum_{xx} w}}$$

(8)

where

$\rho$ = correlation coefficient

$\sum_{xx}$ and $\sum_{yy}$ = inter-class Covariance Matrix.

$\sum_{xy}$ = Cross set covariance matrix.

It estimates the target frequency by recognizing the hidden frequency component of the EEG by optimizing the correlation between the EEG recording channel and the SSVEP stimulus flickering rate. CCA analysis was performed on O2, O1 and O2. A power spectral density analysis was performed on the data from O2, O1 and O2 using fast Fourier transform.

The Hybrid P300-SSVEP BCI designed in this study could not be classified in terms of individual classifications for P300 and SSVEP, since the feature vector consisted of both SSVEP and P300 data. Hence a two-step classifier model was used which is described in Fig. 5. P300 feature extraction was based on BLDA, and SSVEP dominant frequency was determined using CCA. Once mean and variance from BLDA predicted the presence of P300 peak and CCA predicted SSVEP frequency with the highest power, a decision-making code was used to determine the actual target under consideration. The case rules for the determination of targets after feature classification are as follows:

Case one: when $\sigma^2$ and $\mu$ values show existence of P300, the correlation coefficient shows existence of heightened response for one of the presumed frequencies and the interval count is odd, then one of the primary targets (A, B, C and D) is identified as brain command depending on the frequency with heightened response (8 Hz, 10 Hz, 12 Hz and 14 Hz, respectively).

Case two: when $\sigma^2$ and $\mu$ values show existence of
P300, the correlation coefficient shows existence of heightened response for one of the presumed frequencies and the interval count is even, then one of the secondary targets (A1, B1, C1 and D1) is identified as brain command depending on the frequency with heightened response (8 Hz, 10 Hz, 12 Hz and 14 Hz, respectively).

Case three: when $\sigma^2$ & $\mu$ values show absence of P300, the correlation coefficient shows existence/absence of heightened response for one of the presumed frequencies and interval count is odd/even, then "Null" command is activated.

It was observed that while using the two-step classification protocol to classify user intentions for data recorded for hybrid BCI with different stimuli colours, the classification accuracy remained low. Therefore the study was continued by looking for more options of single-step classifiers to increase the average classification accuracy. The $3 \times 480$ feature matrix formed for single-step classification would serve as both training and datasets. Hence, a support vector machine (SVM) classification algorithm was used to classify the system outcomes.

For using SVM in cases of linearly separable data, a matrix of hyperplanes was formed by finding the dot product of input variables:

$$\text{H}_{ij} = y_i y_j k(x_i, x_j) = x_i x_j^T$$ (9)

Family functions, also known as kernel functions, may be expressed as $k(x_i, x_j) = x_i^T x_j$, which represent a linear kernel. A generic kernel may be defined as variants of (10), such that it is expressed as inner products of two feature vectors. It signifies that if the functions were to be plotted in a higher dimensional space with respect to a non-linear feature mapping function $x \rightarrow \varphi(x)$, then the dot products of the input vectors mapped onto the feature space can be predicted without explicitly calculating $\varphi$ [44].

The kernel can be estimated as:

$$k(x_i, x_j) = e^{-\frac{(x_i-x_j)^2}{\sigma^2}}$$ (10)

If a dataset is not linearly separable in a two-dimensional data space, then it might be linearly separable in the non-linear feature space, which may be defined implicitly by a radial basis kernel. Two of the more popular kernels used as classification or regression kernels are the polynomial kernel and sigmoidal kernel, respectively defined by:

$$k(x_i, x_j) = (x_i x_j + a)^b$$ (11)
$$k(x_i, x_j) = \tanh(ax_i x_j + b)$$ (12)

such that constants a and b define characteristics of the kernel. For our application, we decided to use the linear ($b=1$) and quadratic ($b=2$) kernel functions as expressed in Eq. 11 as kernel functions. To explain the working of the SVM classifier, we discuss Trial-3 of subject s5, during which the subject was exposed to hybrid BCI paradigm with distinct colours. During the trial for the interval, when the subject was trying to evoke the "C" target, one of the feature vector achieved was as follows:

$$F_{m123} = \begin{bmatrix} 341.9 \\ 0 \\ 12.1804 \end{bmatrix}$$ (14)

where, $F_{m123}$ represents the $123^{rd}$ column vector of $F_M$. The first row shows P300 peak RMS value at 341.9 ms from the interval change, indicating that a primary target is under consideration. The second row shows a "0" value indicating that secondary target tiers are inactive. Row three indicates a maxima of power spectral density distribution at 12.1804 Hz for the current window. This feature vector was correctly identified as target "C".

### 2.5 Information Transfer Rate

ITR is a credible performance index when it comes to evaluating the communicative performance of a BCI-based system [9]. In an experiment with N number of possible commands/outcomes, with equal probability of occurrence, such that the accuracy (Acc) of the system that the intended command is correctly predicted is invariant and also every wrong selection has the same probability of occurrence, the ITR (bits/min) can be calculated as:

$$B = \log_2 N + \text{Acc} \log_2 \text{Acc} + (1-\text{Acc}) \log_2 \frac{1-\text{Acc}}{N-1}$$ (15)
where \( N \) is the total number of possible outcomes; Acc is the value of accuracy shown by the system to correctly classify an outcome; \( B \) is the number of bits consumed during correct determination one target; \( t \) is the cost in time required to determine one target.

3. Results

The timeline of the trials is shown in Fig. 6. Four trials were conducted. During each trial, the subject was exposed to one of the four paradigms, which was selected randomly. The random selection was such that each subject was exposed to each paradigm only once. During each trial of 10-minute duration, data was recorded for a period of eight minutes. The remaining two minutes were used for baseline determination and resting. The period of eight minutes was equally divided into eight intervals of one minute each, since three out of four paradigms had a maximum of eight targets. During each interval, the subject was asked to focus on a new target. For uniformity of the experiment, the trial in which the subject was exposed to SSVEP paradigm also had eight intervals, even though the maximum number of targets available was only four (each target was presented in two intervals). Filtered and windowed EEG data (after normalization) from 60 target flashes during odd and even one-minute intervals for all subjects were averaged. The same was done for 60 such instances for non-target flashes. The averaged target P300 waveform over \( C_z \) location for 10 subjects as well as non-target waveform are shown in Fig. 7. The positive shift in potential for target detec-

\[
ITR = B \times \frac{60}{t} \tag{16}
\]
tion and the absence of positive shift for non-target detection are distinctly visible. To visualise SSVEP visual response, the filtered and windowed epochs were subject to fast Fourier transform and power spectrum density analysis. The averaged waveforms, using moving average smoothing filter, over 60 similar outcomes for each for the four frequencies used (8, 10, 12 and 14 Hz) are shown in Fig. 8. After construction of the feature matrices for all 10 subjects, a 10-fold nested cross validation process was used to train and test the quadratic SVM classifier. These tools were applied to the extracted feature matrix on MATLAB platform. The cross-validated data from each subject was plotted in a vector space. The vector space with classified feature vectors using a trained quadratic SVM classifier from subject s5 is shown in Fig. 9. The vector space is a 3-dimensional vector space with PO, PE and S as three dimensions (each component of a feature vector).

The classification accuracy and the ITR for each subject with respect to the four different paradigms are given in Table 1. Also, comparison of the FAR for all four stimuli is provided in Table 2. Comparison of classification accuracy of hybrid BCI using two-step and single-step classifiers is shown in Table 3.

Fig. 8 Spectral density averaged over 60 outcomes for the same frequency for 10 subjects. Averaged spectral densities (dB) for 8, 10, 12 and 14 Hz are shown in (a), (b), (c) and (d), respectively.

Fig. 9 Test results from subject s5’s testing set for the trained quadratic SVM, showing very minimal classification error as each class has generally the same colour vector plots in vector space. PO represents the value of time (ms) when a positive amplitude shift occurs during odd one-second interval. PE represents the value of time (ms) when a positive amplitude shift occurs during even one-second interval. S represents the SSVEP response.
4. Discussion

The results of the study conducted are summarised in Table 1 and Table 2, in which the four paradigm options are compared on the basis of classification accuracy, ITR and FAR. One of the most significant advantages of using the proposed novel hybrid BCIs is that we can increase the number of available commands/outcomes by an nth multiple just by adding n tiers of commands, where the flashing access to each tier is time-division multiplexed. The placement of targets within different tiers is very important to maximise accuracy. Various layouts were tried and tested for the hybrid BCIs, but the current arrangement was the one showing optimal coverage of the entire LCD screen with a minimum distance of 150 mm from neighbouring targets. Our results showed that both novel paradigms had better classification accuracy (90.76% and 83.47% for distinct colours and white colour hybrid BCIs, respectively) than P300 (79.36%) but lower classification accuracy than the SSVEP (93.78%). However, the average ITR of hybrid BCIs (81.10 and 75.09 bits/min) was much higher than both SSVEP and P300 (36.26 bits/min and 23.24 bits/min, respectively).

### Table 1  Comparison of accuracy and ITR in individual subjects for all four paradigms.

| Subjects | Distinct Colour Novel Hybrid BCI | Novel Hybrid BCI (White Coloured Targets) | SSVEP BCI | P300 BCI |
|----------|----------------------------------|------------------------------------------|-----------|----------|
|          | Acc. (%) | ITR (bits/min) | Acc. (%) | ITR (bits/min) | Acc. (%) | ITR (bits/min) | Acc. (%) | ITR (bits/min) |
| s1       | 94.12    | 83.86         | 88.41    | 79.09         | 98.45    | 38.84         | 76.25    | 38.84         |
| s2       | 89.71    | 80.12         | 87.91    | 78.70         | 88.75    | 33.73         | 86.5     | 33.73         |
| s3       | 83.61    | 75.50         | 81.23    | 73.84         | 92.35    | 35.44         | 80.12    | 35.44         |
| s4       | 93.69    | 83.48         | 83.14    | 75.17         | 96.44    | 37.62         | 79.12    | 37.62         |
| s5       | 95.45    | 85.09         | 89.65    | 80.07         | 98.41    | 38.82         | 89.23    | 38.82         |
| s6       | 89.64    | 80.07         | 83.73    | 75.59         | 91.58    | 35.06         | 72.35    | 35.06         |
| s7       | 92.81    | 82.71         | 78.69    | 72.14         | 95.65    | 37.17         | 83.89    | 37.17         |
| s8       | 85.37    | 76.78         | 77.28    | 71.23         | 89.45    | 34.05         | 73.45    | 34.05         |
| s9       | 91.17    | 81.32         | 81.45    | 73.99         | 93.14    | 35.83         | 87.31    | 35.83         |
| s10      | 92.06    | 82.07         | 83.21    | 75.22         | 93.65    | 36.10         | 65.41    | 36.10         |
| **Average** | 90.76 ± 3.80 | 81.10 ± 3.1  | 83.47 ± 4.1 | 75.50 ± 3.0 | 93.78 ± 3.41 | 36.26 ± 1.8 | 79.36 ± 7.6 | 23.52 ± 1.6 |

### Table 2  Comparison of FAR in individual subjects for all four interfaces.

| Subject | Distinct Colour Novel Hybrid BCI | Novel Hybrid BCI (White Coloured) | SSVEP BCI | P300 BCI |
|---------|---------------------------------|----------------------------------|-----------|----------|
|         | FAR (%) | FAR (%) | FAR (%) | FAR (%) |
| s1      | 2.26    | 5.41    | 1.93    | 6.13    |
| s2      | 3.91    | 8.34    | 2.89    | 4.72    |
| s3      | 3.84    | 12.89   | 3.87    | 6.12    |
| s4      | 3.37    | 10.25   | 2.96    | 7.02    |
| s5      | 1.68    | 7.12    | 1.12    | 3.67    |
| s6      | 4.17    | 6.09    | 3.89    | 6.91    |
| s7      | 2.53    | 6.53    | 2.03    | 6.41    |
| s8      | 2.36    | 7.73    | 3.21    | 4.17    |
| s9      | 2.72    | 4.83    | 1.93    | 13.14   |
| s10     | 3.12    | 7.67    | 2.89    | 13.24   |
| **Average** | 2.99 ± 0.8 | 7.68 ± 2.3 | 2.73 ± 0.9 | 7.15 ± 3.3 |
tion accuracy for ten subjects (s1–s10) using the two-step classifier and the single-step SVM classifier for hybrid BCI with different stimuli colours is shown in Table 3. The results in Table 3 suggest that it is beneficial to use a single-step classifier as higher accuracy of classification can be achieved.

Further, the FAR comparison conducted during the study revealed that of the two hybrid BCIs, the one using distinct coloured targets gave remarkably lower FAR (2.99%) compared to the white coloured targets (7.68%). This is due to the fact that different coloured targets provide different contrast settings, providing different strengths of SSVEP signal. This finding is in accordance with recent studies which indicates that stimulus colour influences the SSVEP response of the subject [45]. When taking into account the already existing BCIs, P300-based paradigm showed the worst FAR, whereas the FAR of distinct coloured hybrid BCI and the SSVEP BCI were comparable. The execution time, or better known as reaction time, taken by the hybrid BCI with distinct colours for each command ranged from 2.54 s to 2.62 s. For hybrid paradigm to be used in a practical BCI-based AD, further study needs to reduce this reaction time to under 2 s.

5. Conclusion

The results showed that the P300 and SSVEP modalities had good intra-participant reliability and that the novel hybrid BCI-based system showed good performance according to the criteria proposed by Wolpaw et al. 2002 [9]. The study also concluded that the novel paradigms may have been marginally underperforming compared to the SSVEP paradigm in terms of classification accuracy. However, synchronised measurement and detection of P300 and SSVEP in the hybrid paradigm gives it an advantage over the SSVEP in terms of ITR. The average ITR recorded for the novel hybrid paradigms was more than two-fold higher compared to the average ITR for the SSVEP BCI. Hence, the novel distinct colour hybrid BCI paradigm serves as a better paradigm option for practical BCI application with the purpose of rehabilitation for locked-in subjects.

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