International Journal of Human–Computer Interaction

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/hihc20

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INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
2022, VOL. 38, NO. 1, 42–52
https://doi.org/10.1080/10447318.2021.1921482

Efficient Quadcopter Flight Control Using Hybrid SSVEP + P300 Visual Brain Computer Interface

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ABSTRACT

The objective of this study was to assess the feasibility of hybrid SSVEP + P300 visual BCI systems for quad-copter flight control in physical world. Existing BCI-based quad-copter flight control has limitations of slow navigation, lower system accuracy, rigorous user training requirement and lesser number of independent control commands. So, there is need of hybrid BCI design that combines evoked SSVEP and P300 potentials to control flight direction of quad-copter movement. GUI design is developed such that user can effectively control quad-copter flight by gazing at visual stimuli buttons that produce SSVEP & P300 potentials simultaneously in human cortex. We compare the performance metrics of the proposed flight control systems with other existing BCI-based flight control as conventional SSVEP BCI and P300 BCI and commercially available keyboard flight control systems. Results proved that the proposed system outperforms the existing BCI-based flight control systems but has slightly lower performance efficiency than the commercial keyboard flight control systems. Further, the proposed quad-copter flight control system proved its suitability for patients with severe motor disabilities.

1. Introduction

Improving life quality of people with severe motor disabilities is a vital issue to be addressed. Unmanned Arial Vehicle (UAV) technology proved to have broader application prospect and can be implemented to assist for independent living of people with severe motor failure (F. Duan et al., 2015; LaFleur et al., 2013). UAV couple with other devices such as a camera or robotic arm can help with remote living requirements of such individuals such as groceries purchasing or traveling (Khan & Hong, 2017; Wang et al., 2018). Commercial controlling with UAV flight with other means such as joystick, trackball, touch screens, keyboard, head control and so on is inadequate for patients with complete motor failure (Kos'Myna et al., 2015). Hence, to completely remove physical activity dependency for UAV control there is a need of brain computer interface (BCI) based flight control (Chiuzbaian et al., 2019). Quad-copter flight control using BCI requires interpretation of user's brain potentials only, which are then converted into control commands.

In BCI systems, there is a straight interface between computer & human brain without the need of any muscular activity. There are various BCI system types based on type of cortical potentials used for processing (Fernando & Gomez-Gil, 2012). Out of them, BCI systems based on visual evoke potentials (VEPs) called visual BCI (VBCI) are most effective than other types because of their various advantages over another BCI types. VEP-based BCIs have numerous advantages compared to other BCI types as they are easy to use, has higher information transfer rate, maximum amount of accessible independent BCI commands, minimal BCI command latencies, high operating reliability, availability of Emergency exit from operations, mobility and insignificant training time (Kapgate et al., 2020). Most of current VBCI systems are made up of either Steady State Visual Evoked Potentials (SSVEP) or Event Related Potentials (P300) or both (Gruss et al., 2012). SSVEP potentials are evoked when user focuses attention on visual stimuli flickering with specified frequency and P300 is evoked by focusing attention on random flashing stimulus (oddball paradigm) (Fernando & Gomez-Gil, 2012). Recently, hybrid SSVEP + P300 BCI systems are developed to overcome limitations of conventional SSVEP BCI & P300 BCI (Bi et al., 2014). Hybrid BCIs are complex, has complicated system structure, increased metal workload, lower user satisfaction, and operational overhead. But hybrid SSVEP + P300 BCI systems are providing promising results to overcome above said limitations of Hybrid BCI systems to some extent. Hybrid SSVEP + P300 proved to be efficient than all other BCI types (Gruss et al., 2012).

Recently, many researchers focused their attention on quad-copter flight control using BCI systems (Nourmohammadi et al., 2018). Since, it could possible to obtain flexible & resilient movement in 3D real space and can be extended for substituting quad-copter with any remote mobile devices (Christensen et al., 2019). Semi-autonomous UAV navigation using BCI based on motor imaginary (MI) potentials is investigated by Shi et al. (2015). Where left/right hand imaginary movement EEG signals are used for selection of movement directions of UAV (Tezza & Andujar, 2019). However, this study was limited for indoor

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UAV control. Further, flight control of virtual helicopter in 3D real world space is done by Royer et al. (2010) by using MI potentials. LaFleur et al. (2013) control quad-copter flight successfully in physical world using sensory motor rhythms. Though, all these systems proved effective flight control but these systems needs rigorous user training for longer period.

To eliminate user training requirements for BCI-based quad-copter flight control, some researchers proposed use of visual BCI systems instead of MI based BCI. Middendorf et al. (2000) proposed use of SSVEP-based BCI for control of flight simulator. But this study was only limited to simulator without verification in real world environment. Wang et al. (2018) conducted study in simulated 3D environment with SSVEP-based BCI with head mounted device. These systems reduced user training time significantly but results in increased user fatigue and visual discomfort.

To reduce dependency on single cortical potential or mode and improve quad-copter flight control accuracy further, some researchers proposed multimodal or hybrid systems. Kim et al. (2014) developed hybrid interface by combining EEG and eye tracking. Horki et al. (2011) developed hybrid MI BCI and SSVEP BCI for control of robotic arm. X Duan et al. (2019) developed multimodal quad-copter flight control system by combining MI, SSVEP & eye blink. Though, this system proved effective performance in physical environment, it suffered from longer user training.

Hence to overcome problems like rigorous user training, slow navigation, neural adaptation effect (user tiredness over time) and to maximize number of independent control commands and system information transfer rate (ITR); there is a need of use of hybrid BCI design, which combines SSVEP and P300 visual evoke potentials (VEPs) for quad-copter flight control. In this study, author proposes quad-copter flight control system using noninvasive hybrid visual interface which evokes SSVEP & P300 cortical potentials simultaneously. Here, we are extending the application of hybrid SSVEP + P300 VBCI system, which we have developed in (Kapgate et al., 2020) for quad-copter flight control. Quad-copter used in this study has onboard mounted camera, which provides live video feedback on LCD screen and stimulation command buttons are placed on the same screen, which creates immersive first person visual feedback system. SSVEP are evoked using color flickering stimuli and random flashing of human emotional faces evoke P300. This makes proposed system with advantages of inter stimulus interval, lesser neural adaptation effect, increased user attention, minimal/negligible user training time and maximum system accuracy and ITR (Rossion & Boremanse, 2011). The proposed system's performance metrics are compared with conventional SSVEP BCI, P300 BCI & commercial Keyboard quad-copter flight control system. Performance metrics such as speed (task completion time), accuracy, ITR, system comfort and system workload (NASA TLX) are used for comparison. To the best of our knowledge, this work is first study on the use of hybrid SSVEP + P300 visual BCI for quad-copter flight control.

2. Materials and methods

2.1. Subjects and experimental setup

Twenty six healthy participants (13 male, aged 24–35 yrs, mean 29.4 yrs) involved voluntarily in online experiments. In all experiments EEG signals were captured by EEG headsets in real time from user scalp and were processed simultaneously to generate control commands and hence referred as online experiments. All individuals participated in experiments were checked for their vision correctness and visual epilepsy. None of participants was having any type of visual abnormalities. A written consent was taken from all volunteers as per good clinical practices (GCP) certification suggestions. This work was approved by research recognition committee (RRC) of Nagpur University. All participants were instructed to avoid unnecessary movements during experiment and they were free to leave experiment at any time if they feel any visual epilepsy and discomfort. First person visual feedback was presented on LCD screen having 60 Hz refresh rate. Distance between center of LCD screen and user was kept fixed at 90 cm.

2.2. Experimental stimuli paradigm

The display screen consists of four command buttons placed on edges of screen (Figure 1a) & background of screen has live video feedback recorded by quad-copter camera. Every command button consists of twelve small circles placed at every 30° along the periphery of central large circle. Each button's small circles flickered with changing color between green and yellow at frequency of 8.5, 7.5, 10, and 15 Hz, respectively, to elicit SSVEP and central large circle flashes randomly with emotional human facial structure to evoke P300. Central large circle flashed randomly with facial structure means its intensification for fixed duration of 100 ms and there is 25 ms inter-intensification delay. One trail denotes four consecutive flashes and order of flashing is up, down, left & right. Single flash total time is 100 ms+25 ms = 125 ms hence one trial time is 125 * 4 = 500 ms (Figure 1b). We should consider P300 signal trail minimum up to 500 ms following stimulus onset as target to target interval is 500 ms. For training of classifier algorithm each user has to perform 40 trail runs of timing sequence shown in Figure 1b. In training phase, there is break of 125 ms after one single trail. Thus, each user has to perform training phase for duration of 25 second. There are three conditions with varying flashing and flickering contents as -

(1) The conventional SSVEP condition where small circles are flickering with color change between yellow and green with particular frequency as explained earlier (Figure 1c) & flashing of central large circle is ceased. This evokes only SSVEP potentials in the cortex.
(2) The conventional P300 condition where the central large circle is flashed randomly with emotional facial content (Figure 1d) & flickering of small circles is ceased. This elicits only P300 potentials (ERP) in cortex.

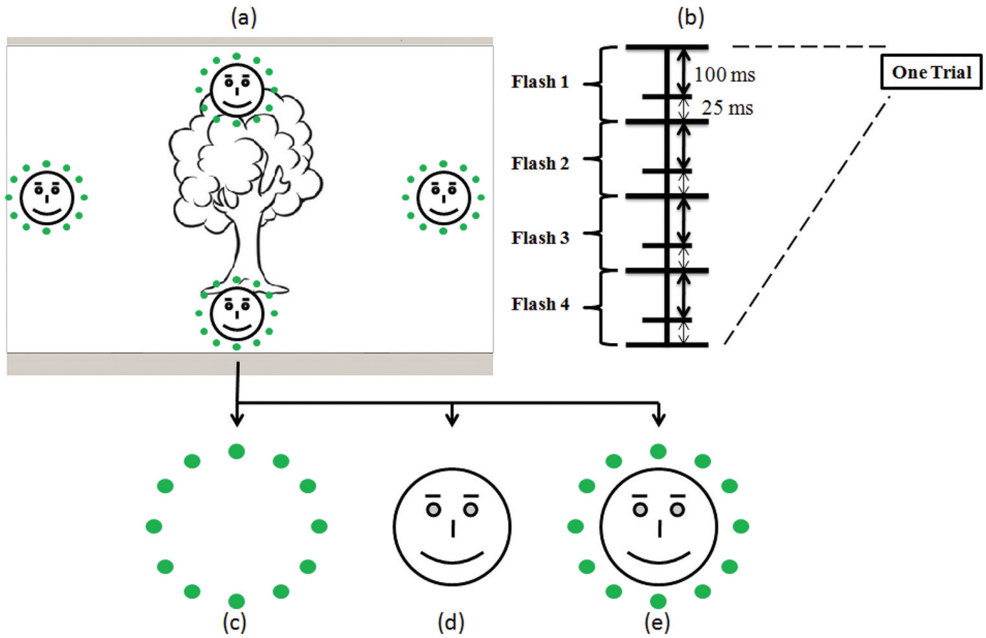

Figure 1. Experimental paradigm (a) display screen shown to user (b) Time series for single trial (c) SSVEP paradigm (d) P300 paradigm (e) hybrid SSVEP + P300 paradigm.

(3) For hybrid SSVEP+P300 condition, both small circles are flickering with specified frequency (yellow ↔ green) & central large circle flash randomly with emotional facial content (Figure 1e). This evokes both SSVEP & P300 potentials simultaneously in human cortex.

Earlier studies proved human face evoke stronger P300 potentials (Bakardjian et al., 2011; Kaufmann et al., 2011; Kellicut-Jones & Sellers, 2018; Vakli et al., 2014). The facial structure used in our study to evoke P300 is drawn in monochrome using simple lines & circles drawings of human face. As these images are having semantic information & properties similar to the real human face, the cortical responses evoked using these images are similar to responses evoked during real human faces like Emojies (Weissman et al., 2018).

2.3. Experimental procedure and layout

Matrice 100 (DJI) quad-copter with onboard camera is used in these experiments due to its open source platform making it suitable for scientific research. The experimental layout is shown in Figure 2, where quad-copter is connected to laptop over Wi-Fi. The video recorded by quad-copter camera is sent over Wi-Fi to laptop as a real time stream. User wearing EEG headset is sited on comfortable chair & concentrate on command buttons to control flight direction of quad-copter. Left, right, top, down command buttons represent respective quad-copter flight direction as left movement, right movement, forward and backward. This experiment is conducted only to evaluate suitability of hybrid SSVEP + P300 BCI for drone flight control hence use of other control commands are out of scope of this study Experiments were carried out on vacant land i.e. outside of laboratory. User controls quad-

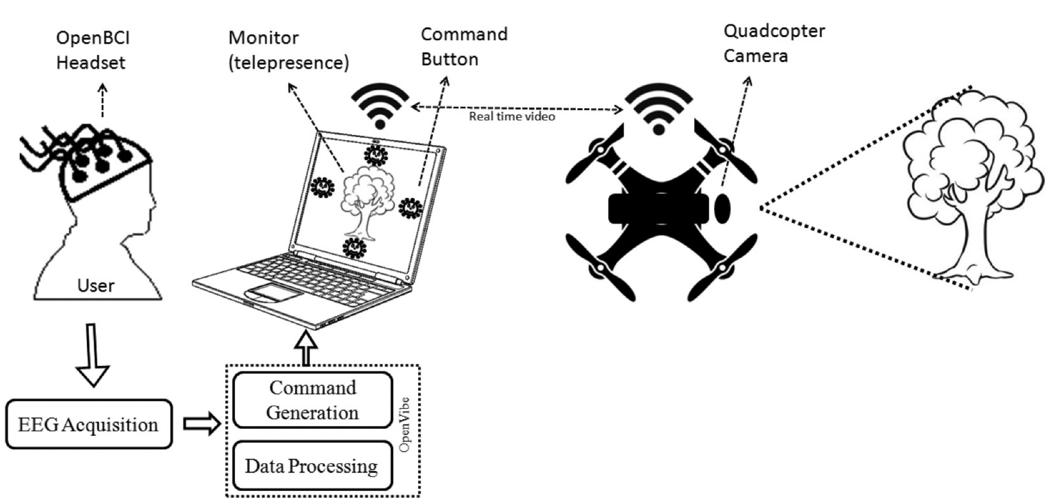

Figure 2. Architecture of proposed hybrid SSVEP + P300 VBCI based quad-copter flight control.

copter flight direction using telepresence environment. Openvibe open-source framework is used for implementation and development of proposed system.

In first experiment, user has to fly quad-copter in random zigzag pattern at certain height. This is performed in order to familiarize users with real-time flight control using BCI. The second experiment is complex to testify the performance of proposed system. Users were asked to control quad-copter flight to pass through two gates successfully following S-shaped route. The quad-copter is moved from initial position, which is 2 m away from gate A as shown in Figure 3 through 4 m distanced gates to final position. The gates were barriered so that quad-copter could not fly above top of the gate. Each user has to perform above task with conventional SSVEP BCI, conventional P300 BCI, hybrid SSVEP + P300 BCI and commercial keyboard flight control. Randomized orders of tasks of SSVEP, P300, keyboard and SSVEP + P300 were presented to participants to avoid biases. Keyboard-based flight control of drone was implemented using Matlab-simulink supported package. The light intensity and noise calculated at external physical environment was approx 4000 lx and 70 db, respectively.

2.4. EEG acquisition

16 channel OpenBCI headset is used for EEG signal recording from human scalp. The electrodes are placed on the human scalp with an application of conducting liquid in-between to minimize impedance. 10–20 international system (Figure 4b) is followed for the selection of locations for electrodes placement. The locations are POz, Oz, Pz, Cz, Fz, P8, P7, P4, P3, PO8, PO7, O2 & O1. Whereas FPz is used for ground & average of, A12 & A11 is used for reference.

2.5. Feature extraction procedures

In our study, we are eliciting two cortical potentials SSVEP & P300, by using external visual stimulus. Therefore, we follow different pre-processing procedures for each type of potentials:

P300 – Acquired EEG signal is filtered between 0.1 Hz and 12 Hz using sixth order Butterworth band pass filter. Then, down sampling of the filtered signal is performed from 250 Hz to 50 Hz. After each stimulus onset, a signal segment from 0 ms to 800 ms is extracted from whole EEG data.

SSVEP – EEG signals are first band pass filtered between 5 Hz & 30 Hz. SSVEP potentials are occur at alpha and beta rhythms in EEG signals. Alpha occurs at 8– 13 Hz and beta occurs at 14– 26 Hz. Hence filtering is applied between 5 and 30 Hz. The data length used for SSVEP detection is in between 0 and 500 ms. Interpretation of SSVEP signals from raw EEG requires clubbing of information from several electrodes at once. So, common spatial patterns (CSP) spatial filter is used for minimizing discrimination among different conditions. CSP increases the variance of one class while minimizes the variance of other class (Ramoser et al., 2000). In this study one vs. rest variant of CSP algorithm is used for multi-class paradigm (Dornhege et al., 2006). In one vs. rest CSP algorithm k-class problem is partitioned into k independent binary classes and each class is differentiated against the remaining classes. The normalized spatial covariance matrix is characterized as:

$$C_{\text{class}} = \frac{AA^{T}}{\text{trace}\left(AA^{T}\right)} \tag{1}$$

Where A is [N x S] matrix where N is the number of channels and S is the number of samples. The composite covariance calculated as –

$$C_{\text{com}} = \sum\nolimits_{\text{class}-1} C_{\text{class}} \tag{2}$$

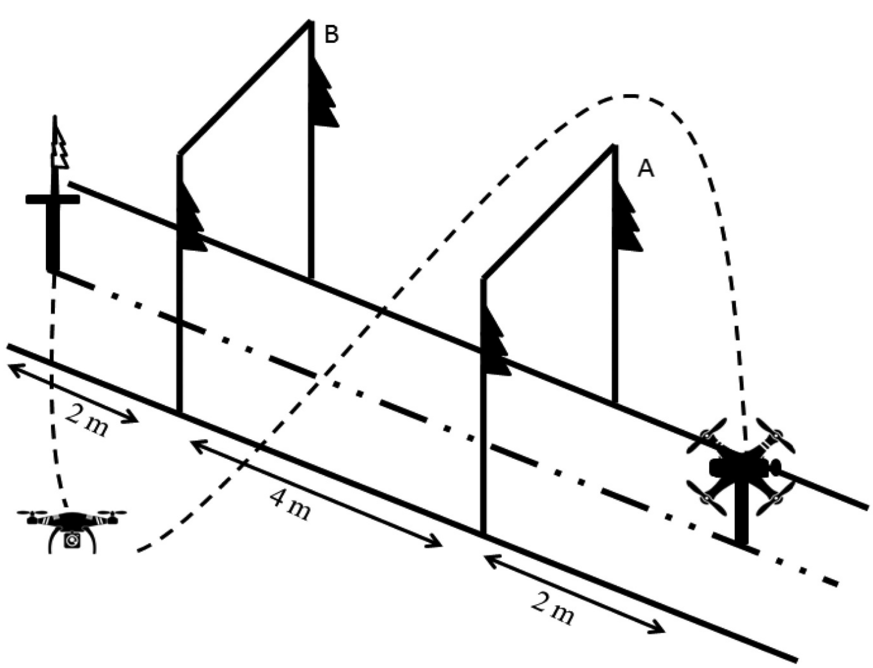

Figure 3. The view of experimental procedure layout.

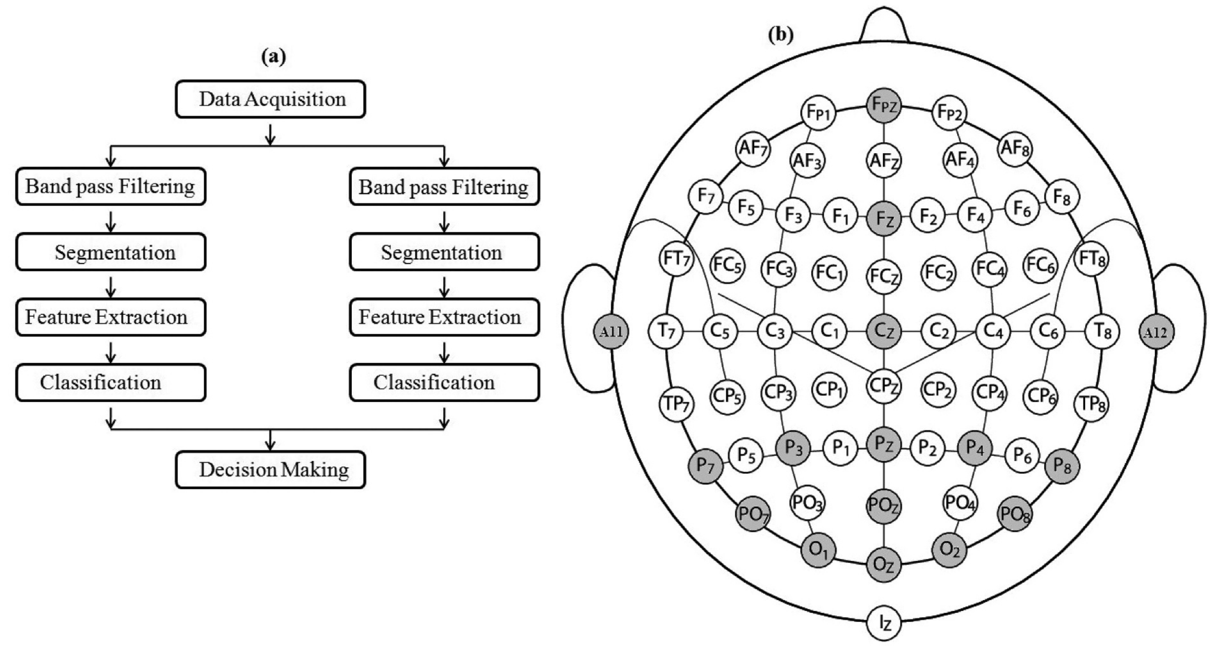

Figure 4. (a) Flow chart of EEG signal pre-processing and classification. (b) gray color shows positions of electrode montage.

It further factorized as –

$$C_{com} = U\beta U^T \tag{3}$$

Where U is a matrix of eigenvectors and β is a diagonal matrix of eigenvalues. The whitening transformation is calculated as –

$$Q_w = \sqrt{\beta^{-1}}\, U^T \tag{4}$$

The mean covariance matrices are transformed as

$$R_{class} = Q_w C_{class} {Q_w}^T \text{ and } R_{com} = Q_w C_{com} {Q_w}^T \tag{5}$$

and by simultaneous diagonalization,

$R_{class} = B\Delta_1 B^T$ and $R_{com} = B\Delta_2 B^T$ where $\Delta_1 + \Delta_2 = I$, I is identity matrix.

a projection matrix given by

$$P = \left(B^T Q_w\right)^T \tag{6}$$

CSP is given as columns of $P^{-1}$and are signified as distribution vectors of time-invariant EEG sources. Trial S is decomposed by projection matrix as –

$$X = SP \tag{7}$$

Variance calculated as

$$V = \frac{\sum\left(X_R - \overline{X_R}\right)^2}{L-1} \tag{8}$$

Where $X_R$is row of X and L is row length.

2.6. Classification

Probabilistic Multi-class Linear Discriminant Analysis classifier (Bishop, 2007) is used for classification of cortical responses among different flight control commands. Classification of SSVEP & P300 is done separately as shown in Figure 4a. Assignment of each input feature vector to a specific class is done based on pre-computed posterior probabilities (Tharwat et al., 2017). Let “m” represent a total number of data vectors, “n” number of features & “” number of classes. Then, each input feature vector may be represented as “$x \in R^n$”. Covariance matrices of each class “$C_k \in M_{n\times n}$” is calculated from Class-wise means “$\mu_k \in R^n$” as -

$$C_k = \sum\nolimits_{i=1}^{k}\left(x_i - \mu_k\right)\left(x_i - \mu_k\right)^T \tag{9}$$

Define followings as:

1) Each class pair’s average covariance matrices is given as

$$\sum\nolimits_{i,j} = \frac{C_i + C_j}{2} \text{ and } j > i \in (1, 2, \ldots\ldots\ldots, k) \tag{10}$$

2) Average mean vector of each class pair is $\mu_{i,j} = \frac{\mu_i + \mu_j}{2}$
3) Vector of weights
4) Discriminant function’s ($D_{i,j}(x)$) bias term

Classification of ’x’ input feature vector between class i & j is given by discriminant function -

$$D_{i,j}(x) = w_{i,j}^T \times x + b_{i,j} \tag{11}$$

Probability of ’x’ belonging to class ’i’ $= Q_{i,j}\left(\frac{i}{x}\right) = \sigma(D_{i,}j(x))$ where

$$\sigma\left(D_{i,j}(x)\right) = \frac{1}{1 + \exp\left(-D_{i,j}(x)\right)} \tag{12}$$

Then, we calculate the probability of assigning input feature vector ’x’ to all classes as vector P -

$$P_i(x) = \frac{\sum_{j\neq i} Q_{i,j}\left(\frac{i}{x}\right)}{\sum_k \sum_{j\neq k} Q_{i,j}\left(\frac{k}{x}\right)} \tag{13}$$

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

Where, $\bar{k}$ is highest probability class number, accordingly classifier allocates 'x' to most probable class.

2.7. ITR calculation

ITR (communication rate) of hybrid SSVEP + P300 VBCI based flight control is calculated by-

$$B = \log_2(N) + Acc * \log_2(Acc) + (1 - Acc) * \log_2\left(\frac{1 - Acc}{N - 1}\right) \tag{14}$$

$$ITR = B * \left(\frac{60}{t}\right) \tag{15}$$

Where t is time required to recognize each target, Acc is accuracy of classification, B is single target ITR, N is target items number.

2.8. Statistical analysis

ANOVA (analysis of variance) is considered for comparison of performance metrics of proposed system. The independent variables are hybrid SSVEP + P300 VBCI flight control (hybrid SSVEP+ P300), conventional SSVEP VBCI flight control (SSVEP) & conventional P300 VBCI flight control (P300). ANOVA requires data must be normally distributed, which is done by one-sample kolmogorov smirnov test & sphericity is done by mouchy's test (Nandagopal et al., 2015). Post-hoc comparison is performed using the Tucker-Kramer test.

2.9. Subjective report

Subjects were asked about their system usage experience after completion of each session. Subject's native language is preferred for questioning about system workload experience and system comfortness. To estimate system's perceived workload, assessment tool considered is NASA task load index (NASA TLX) (Colligan et al., 2015). Users have to answer about system comfortness on 1 to 5 point scale, where lower value shows disagreement and higher value represent agreement.

3. Result

3.1. Waveform analysis

In this work, we are considering three different BCI systems to control flight of quad-copter as conventional SSVEP BCI, Conventional P300 BCI and hybrid SSVEP + P300 BCI. P300 potentials are resided in time domain and SSVEP sited in frequency domain. Hence, SSVEP potential's power responses and P300 signal's amplitude are considered as parameters, to identify strength of evoked cortical potentials.

The Power Spectral Density (PSD) of SSVEP signals is calculated using Fast Fourier Transform (FFT). Average data from accumulation of all channels used for SSVEP detection is utilized for PSD calculation (Figure 5). For all types of BCI systems, PSD plot analysis reveals largest SSVEP power increased at fundamental stimulation frequency of target stimulus. While, second harmonic frequency has slight increased power. In almost all considered frequencies, hybrid SSVEP + P300 VBCI has better distinct SSVEP responses compared to conventional SSVEP BCI.

The amplitude values of P300 signals are plotted against time axes in Figure 6. Considered channels for P300 signals amplitude calculation are Oz, P7, P8, Pz & Cz. Hybrid SSVEP + P300 VBCI P300 waveforms are having minimum non-target interferences, lesser latency and maximum average amplitude strength as compared to conventional P300 BCI.

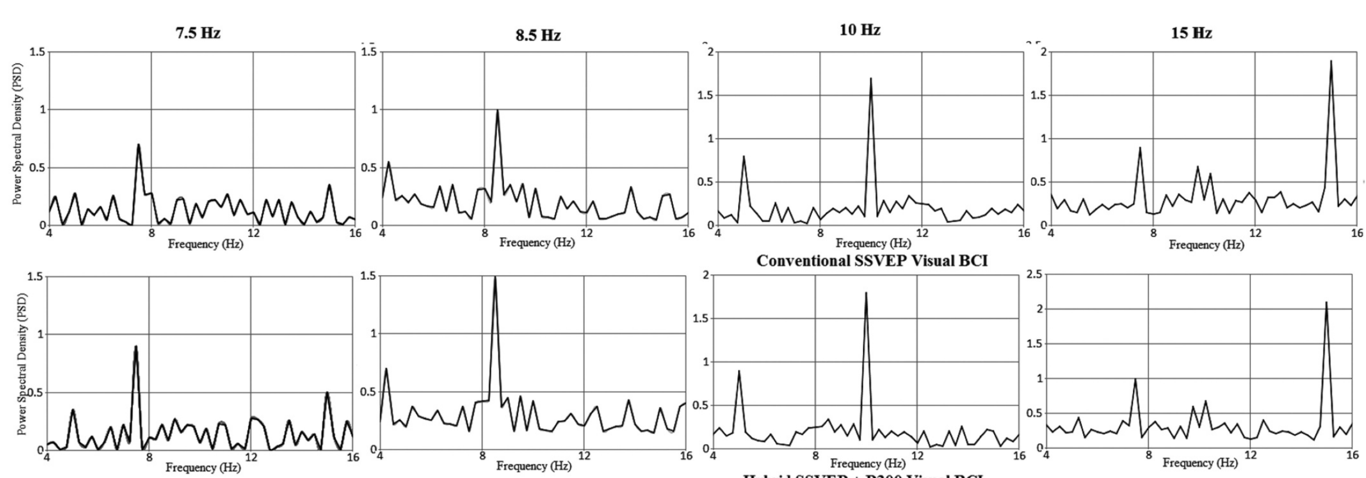

Figure 5. Average power spectral density (PSD) of each button stimulation frequency between ranges of 4–16 Hz.

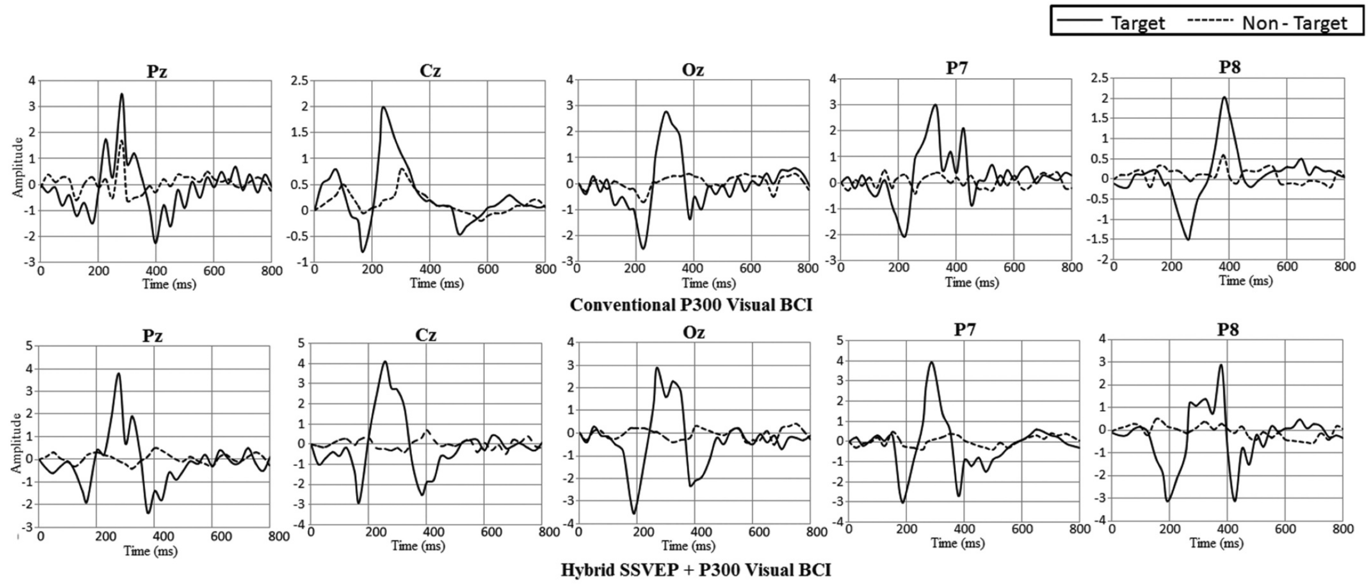

Figure 6. Average ERP waveform captured at electrodes positions P8, P7, Cz, Oz, & Pz.

3.2. Accuracy

Table 1 represents accuracy for each subject for every considered flight control paradigm (i.e. SSVEP, P300, Hybrid SSVEP+P300 & keyboard). ANOVA compares accuracy of experiments performed and significant difference is observed between accuracy of hybrid SSVEP + P300 VBCI flight control system & other flight control systems ($F(3,100) = 14.6, p < .01$). In pair wise comparison, hybrid SSVEP + P300 VBCI-based flight control shows significant improved accuracy than conventional SSVEP-based flight control system ($F(1,50) = 8.83, p < .01$) & conventional P300-based flight control system ($F(1,50) = 7.65, p < .01$). Also, there is no significant difference between conventional SSVEP & P300 flight control accuracy ($F(1,50) = 0.15, p = .69$). Whereas, keyboard-based flight control system has significant improved accuracy than conventional SSVEP BCI based flight control system ($F(1,50) = 32.4, p < .01$), conventional P300 BCI based flight control system ($F(1,50) = 33.8, p < .01$) & hybrid SSVEP + P300 VBCI-based flight control system ($F(1,50) = 20.5, p < .01$).

Table 1. Accuracy (Acc), ITR (system communication rate), task completion time (system speed) of every participant for every considered type of flight control systems.

	SSVEP			P300			Hybrid SSVEP +P300			Keyboard		
Sub	Acc (%)	Time (min)	ITR (bit/min)	Acc (%)	Time (min)	ITR (bit/min)	Acc (%)	Time (min)	ITR (bit/min)	Acc (%)	Time (min)	ITR (bit/min)
S1	70.0	4.72	9.6	77.5	4.48	13.1	83.4	4.12	16.3	98.7	2.36	28.2
S2	86.3	3.92	18.1	87.5	3.82	18.8	86.3	3.94	18.1	97.5	2.41	26.9
S3	77.5	4.53	13.1	78.8	4.31	13.7	82.5	4.16	15.8	93.8	3.08	23.5
S4	87.5	3.84	18.8	88.8	3.61	19.7	90.0	3.56	20.5	93.8	3.02	23.5
S5	52.5	6.41	3.7	58.7	6.31	5.5	76.3	4.65	12.5	85.0	3.91	17.3
S6	83.4	4.17	16.3	86.3	3.89	18.0	87.5	3.88	18.9	96.3	2.69	25.7
S7	85.0	3.98	17.3	87.5	3.75	18.8	86.3	3.78	18.1	93.8	3.05	23.5
S8	95.0	2.91	24.5	95.0	2.98	24.5	97.5	2.39	26.9	100	2.41	30
S9	67.5	5.42	8.6	68.8	5.31	9.1	78.8	4.27	13.7	88.8	3.60	19.7
S10	76.3	4.68	12.5	73.8	4.87	11.3	83.4	4.10	16.3	95.0	2.81	24.5
S11	83.4	4.09	16.3	80	4.28	14.4	85.0	4.01	17.3	93.8	2.99	23.4
S12	77.5	4.37	13.1	78.8	4.29	13.7	85	3.98	17.3	95.0	2.85	24.5
S13	61.3	6.14	6.4	65.0	5.93	7.6	83.4	4.15	16.3	87.5	3.79	18.8
S14	60.0	6.23	5.9	61.3	6.20	6.4	85	3.95	17.3	95	2.89	24.5
S15	70.0	4.67	9.6	76.3	4.67	12.5	95	2.89	24.5	100	2.39	30
S16	86.3	3.87	18.1	87.5	3.91	18.9	86.3	3.72	18.1	93.8	2.95	23.5
S17	93.8	3.05	23.4	90	3.42	20.6	93.8	3.11	23.5	97.5	2.39	26.9
S18	52.5	6.35	3.7	58.7	6.29	5.5	90.0	3.45	20.6	86.3	3.89	18.1
S19	87.5	3.78	18.9	88.7	3.68	19.7	93.8	3.06	23.4	100	2.36	30
S20	96.3	2.74	25.7	93.7	3.09	23.4	96.3	2.66	25.6	100	2.38	30
S21	93.8	2.98	23.5	95.0	3.08	24.5	96.3	2.71	25.6	100	2.38	30
S22	67.5	5.39	8.6	68.8	5.27	9.1	77.5	4.45	13.1	86.3	3.88	18.1
S23	83.4	4.01	16.3	82.5	4.22	15.8	86.3	3.69	18.0	98.8	2.36	28.3
S24	95.0	2.97	24.5	93.8	2.97	23.4	98.8	2.35	28.3	100	2.40	30
S25	97.5	2.41	26.9	98.8	2.31	28.2	98.8	2.33	28.3	100	2.39	30
S26	76.3	4.61	12.5	77.5	4.39	13.1	85.0	3.92	17.3	98.8	2.34	28.3
Avg.	79.3	4.31	15.2	80.7	4.28	15.7	88.0	3.58	19.6	95.2	2.84	25.2
Std. Dev.	13.3	1.14	6.9	11.7	1.08	6.3	6.5	0.6	4.6	4.8	0.5	4.2

3.3. Information transfer rate (ITR)

ITR or system communication rate is calculated from accuracies (explained in subsection 2.7) for each participant for every flight control system considered (Table 1). A one-way repeated measurement ANOVA comparison shows a significant difference between ITR of hybrid SSVEP + P300 VBCI flight control system & other flight control systems ($F(3,100) = 17.4, p < .01$). In pair-wise comparison, hybrid SSVEP + P300 VBCI-based flight control shows significant improved ITR than conventional SSVEP-based flight control system ($F(1,50) = 7.36, p < .01$) & conventional P300-based flight control system ($F(1,50) = 6.45$, $p = .014$). Also, there is no significant difference between conventional SSVEP & P300 flight control ITR ($F(1,50) = 0.07$, $p = .7$). Whereas, keyboard-based flight control system has significant improved ITR than conventional SSVEP BCI-based flight control system ($F(1,50) = 39.6, p < .01$), conventional P300 BCI-based flight control system ($F(1,50) = 40.3, p < .01$) & hybrid SSVEP + P300 VBCI-based flight control system ($F(1,50) = 20.7, p < .01$).

3.4. Completion time

Completion time refers to the time taken to complete a task where user has to move quad-copter along S-shaped path explained in section 2.3. ANOVA test on task completion time values (Table 1) for each subject for each flight control system shows that a significant difference between task completion time of hybrid SSVEP + P300 VBCI flight control system & other flight control systems ($F(3,100) = 15.3$, $p < .01$). In pair wise comparison, hybrid SSVEP + P300 VBCI-based flight control shows significant improved task completion time than the conventional SSVEP-based flight control system ($F(1,50) = 7.7, p < .01$) & conventional P300-based flight control system ($F(1,50) = 7.6, p < .01$). Also, there is no significant difference between conventional SSVEP & P300 flight control task completion time ($F(1,50) = 0.01$, $p = .9$). Whereas, keyboard-based flight control system has significant improved task completion time than conventional SSVEP BCI-based flight control system ($F(1,50) = 34.8$, $p < .001$), conventional P300 BCI-based flight control system ($F(1,50) = 36.09, p < .01$) & hybrid SSVEP + P300 VBCI-based flight control system ($F(1,50) = 18.7, p < .01$).

3.5. Workload index

Table 2 represents subjective self reported perceived total workload on NASA TLX assessment tool. The average total workload with standard errors for hybrid SSVEP+P300 VBCI-based flight control is 6.8 ± 4.6. This is lesser than other flight control systems as SSVEP has 7.8 ± 6.1 & P300 has 8.4 ± 5.1 average total workload, but greater than keyboard quad-copter flight control 5.3 ± 2.7.

3.6. Subjective analysis

Participants ratings about system usage comfortness has been recorded and significant difference is observed between all four flight control systems ($F(3,100) = 16.09$, $P < .01$). Users found keyboard flight control system most comfortable as compared to BCI-based flight control. Out of all BCI flight control system hybrid SSVEP + P300 VBCI has high comfort ratings. Comparative graph between system average comfortness and ITR is shown in Figure 7. The diagonal line shown in graph determines two points, one is starting point that represents minimum ITR with minimum comfort and other is end point represent maximum ITR with maximum comfort level. Plot shows the type of quad-copter flight control system which is closer to diagonal end point, is more efficient than other systems.

4. Discussion

The primary objective of this study is to evaluate the suitability and practicability of noninvasive hybrid SSVEP + P300 VBCI for quad-copter flight control. The secondary goal was to compare performance & comfortness metrics of hybrid SSVEP + P300 VBCI with conventional SSVEP BCI and P300 BCI based flight control. Another goal was to indentify whether hybrid SSVEP +P300 VBCI-based quad-copter flight control system can be a alternative substitute to replace commercially available keyboard flight control system in case of normal users (not disabled).

First, in this work we developed VBCI system where SSVEP & P300 are evoked simultaneously, these evoke potentials are used for quad-copter flight control command generation. The hybrid design used in this study constitutes visual stimuli, where color changing (yellow ↔ green) flickering stimuli evokes SSVEP and random flashing emotional human facial stimuli evoke P300. Earlier studies proved that yellow and green color elicit stronger SSVEP responses (Chu et al., 2017; Tello et al., 2015) than other color. This results in generation of better distinct PSD plot with highest power of cortical potentials. Additionally, emotional faces evoke additional N400 (related to semantic information) and N170 (related to human face) ERPs along with P300 (Duszyk et al., 2014). This results in further increase in system accuracy and communication rate. Also, our design reduces inter-

Table 2. Users self reported scores of workload (NASA TLX). NASA TLX scale: 1 (low) to 20 (high).

Dimension	SSVEP	P300	Hybrid SSVEP +P300	Keyboard
Mental Demand	9.8 ± 5.7	10.6 ± 6.7	8.9 ± 4.5	1.8 ± 4.5
Physical Demand	6.3 ± 4.6	5.9 ± 2.8	4.1 ± 3.7	3.8 ± 7.6
Temporal Demand	9.9 ± 7.9	6.1 ± 5.7	3.7 ± 8.3	4.6 ± 1.3
Performance	8.6 ± 4.7	9.4 ± 7.9	14.6 ± 1.2	19.8 ± 0.6
Effort	8.2 ± 8.5	10.9 ± 5.1	6.1 ± 2.4	1.7 ± 2.4
Frustration	4.9 ± 8.5	7.7 ± 3.4	3.4 ± 8.4	1.1 ± 0.7
Total Workload	7.8 ± 6.1	8.4 ± 5.1	6.8 ± 4.6	5.3 ± 2.7

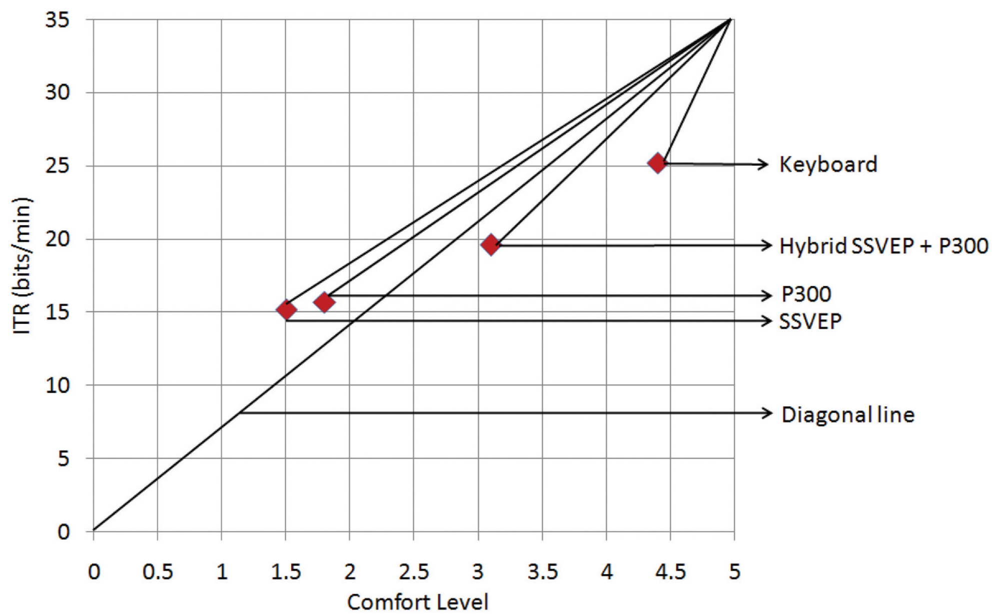

Figure 7. Comparative plotting of average ITR vs comfortable rating.

stimulus interval and neural adaptation effect. This reduces user tiredness; increase user attentiveness and system comfort that result in further improvement in system accuracy.

Secondly, performance metrics of proposed system is compared with conventional P300 BCI, SSVEP BCI and keyboard flight control. Results showed that proposed hybrid SSVEP + P300 VBCI system has higher accuracy, ITR and speed (i.e., minimum task completion time) as compared to conventional SSVEP BCI & P300 BCI. But proposed system is unsuccessful to perform better than commercially available keyboard-based flight control system. All considered system's workload ratings (NASA TLX) display slight variability along certain dimensions. Nevertheless, hybrid SSVEP + P300 VBCI has least average total workload as compared to conventional SSVEP BCI and P300 BCI.

At the beginning of study, users reveal satisfaction with commercial keyboard flight control system, but were still interested in testing the proposed BCI-based flight control. Participants also reported that ease and quickness of learning of proposed BCI system and keyboard flight control is nearby same. After all experiments, results proved commercial keyboard flight control outperforms the proposed BCI-based flight control system in all parameters. However, participants still interested in using proposed system in regular basis. Participants allegedly believed that independent use of proposed BCI based flight control on a long-term basis could potentially improve their life quality. Though, it is unclear whether participants thought proposed system could potentially replace a commercial keyboard-based quad-copter flight control system. Supplementary hybrid SSVEP + P300 VBCI-based flight control system has minimum/negligible training time, effortless usage, efficient performance over other BCI-based flight control and is feasible for real world applications. So, this may be hypothesized that for normal participants (not disabled), the proposed system may or may not alternative to commercially present keyboard flight control. But for people with sever motor disability the proposed system is prominent and best mechanism for enhancing quality of day-to-day life activities.

5. Conclusion

In this paper, we have developed four quad-copter flight control systems based on conventional SSVEP VBCI, conventional P300 VBCI, hybrid SSVEP+P300 VBCI and keyboard control. We have evaluated all systems & compared them with one another about system accuracy, ITR, task completion time, workload & system comfortness. Results proved proposed hybrid SSVEP+P300 VBCI-based flight control performed effectively in all aspects that other BCI-based quad-copter flight control systems & proved its suitability in real world applications. This study indicates that hybrid SSVEP+P300 VBCI-based flight control can be reliable alternative to commercial keyboard-based flight control system, especially among users having severe motor impairments, but further testing is required. In proposed hybrid paradigm, we have elicited SSVEP potentials by color change flicker & P300 potentials by human emotional face flashing. This presentation possesses several advantages as negligible training time, reduced neural adaptation effect & trouble-free usage.

Disclosure of potential conflict of interest

None of the authors has any conflict of interest.

Ethical approval

All procedures performed in this study involving human participants were in accordance with the ethical standards of the Nagpur university research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Research Recognition

Committee (RRC) of Nagpur University approves this research work with approval number "RTMNU/RRC/Engg./2729".

Informed consent

As per Good Clinical Practices (GCP) certification suggestions, a written consent (informed consent) was taken from all participants.

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