International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

A Refined Framework for Incorporating Facial Stimulation into Hybrid SSVEP-P300 Brain-Computer Interfaces

Ms. Monali Khune[1], Dr. Amol Y. Deshmukh[2]
[1]Research Scholar, R.T.M.N.U, Nagpur University, India.
[2]Principal, N.I.T, R.T.M.N.U, Nagpur University, India

Abstract — Background: Brain–computer interface (BCI) systems frequently utilize P300 and steady-state visual evoked potential (SSVEP) paradigms. Because neither approach yields universal success across users, recent research has explored hybrid BCI designs that merge multiple techniques to expand user compatibility. Although hybrid P300/SSVEP systems are a relatively recent innovation with limited performance optimization studies to date, they represent a promising avenue for improving system accessibility. New method: In this research, we contrast a conventional hybrid P300/SSVEP BCI framework with an innovative approach. Specifically, shape alterations are utilized instead of color modulations to evoke the P300 wave, aiming to minimize any adverse impact on SSVEP signal strength. Result: The new hybrid paradigm presented in this paper yields much better performance than the traditional hybrid paradigm. Comparison with existing method: The novel hybrid paradigm yields an SSVEP classification improvement of close to 20% over the standard approach. Furthermore, all tested paradigms—excluding the conventional hybrid model—achieve a perfect 100% accuracy rate in P300 classification. Conclusions: The innovative hybrid P300/SSVEP brain-computer interface paradigm replaces traditional color-shifting stimuli with shape-altering visual elements, matching the classification accuracy of conventional SSVEP and P300 setups. Furthermore, the author explored how presenting multiple visual stimuli at once triggers overlapping brain responses and evaluated the resulting interference on signal detection.

Keywords— P300; SSVEP; BCI; Hybrid Paradigm

I. INTRODUCTION

A brain-computer interface (BCI) establishes a direct link between the brain and external devices, decoding neural signals to control computers and machinery. Primarily benefiting individuals with motor impairments as well as unimpaired users during impractical communication scenarios, these systems predominantly capture real-time brain waves via electroencephalography (EEG). EEG-driven interfaces typically leverage three distinct neurological phenomena for user control: the P300 visual evoked potential, steady-state visual evoked potentials (SSVEP), and event-related (de)synchronization (ERD/ERS). Specifically, the P300 manifests as a positive voltage fluctuation within the EEG reading occurring roughly 300 milliseconds following a stimulus deemed significant by the user.

To overcome challenges like user fatigue, distraction, and stimulus interference common in traditional VEP-based brain-computer interfaces, investigators have explored diverse visual paradigms. Leveraging the brain's acute sensitivity to facial structures, studies have incorporated human faces as stimuli, utilizing various configurations such as altered expressions, orientations, movements, and viewpoints. When these facial stimuli flash, they elicit two prominent negative event-related potentials, the N170 and the N400, which collectively enhance overall system precision.

The P300-based brain-computer interface (BCI) was originally introduced by Farwell and Donchin in 1988 using a computer screen displaying a 6 by 6 grid of 36 characters (numbers and letters). To use the system, users concentrated on a specific "target" item within the grid and silently counted its flashes while disregarding all other items. The display systematically flashed individual rows and columns; whenever the specific row or column holding the target flashed, the user's brain generated a P300 wave, allowing the system to pinpoint the target choice.P300 BCIs are advantageous because they demand minimal user training and have been thoroughly tested and proven effective in both healthy individuals and patients. On the downside, P300 signals are weak relative to normal EEG background noise. Overcoming this requires averaging EEG responses across multiple flashes to achieve reliable accuracy, which ultimately slows down system speed and lowers the overall information transfer rate (Wolpaw et al., 2002; Pritach, 1981; Fazel-Rezai et al., 2012).

© 2026 IJSRET

Steady-state visual evoked potentials (SSVEPs) are brain signals triggered when a person focuses on a rapidly flashing visual target (Pritach, 1981; Regan, 1989). Predominantly observed over the occipital region of the brain, this steady-state signal matches the exact frequency of the visual flicker, along with its related harmonic components (Müller-Putz et al., 2005). As the earliest brain-computer interface (BCI) documented in scientific literature (Vidal, 1973), SSVEP systems have undergone extensive investigation (Ortner et al., 2011). In a standard SSVEP BCI setup, users observe multiple flickering elements, such as on-screen boxes or individual LEDs. When a user directs their attention toward a specific target, the EEG registers heightened SSVEP activity at that target's corresponding frequency, allowing the system to accurately identify where the user is looking.

Alternative paradigms, such as reversing checkerboard patterns, often generate stronger SSVEP signals than standard flickering lights at equivalent frequencies and are frequently utilized in research (Lalor et al., 2005; Trejo et al., 2006; Martinez et al., 2007; Allison et al., 2008). Overall, SSVEP-based BCIs stand out as some of the fastest systems available with minimal user training requirements, though they can cause visual fatigue or annoyance and carry a minor risk of triggering seizures.

To understand how the brain processes faces within a hybrid P300 and SSVEP brain-computer interface (BCI), this study incorporated facial stimuli into the visual paradigm, addressing two main questions: how visual evoked potentials (VEPs) vary between neutral, emotional, and non-face stimuli, and how BCI performance is affected when faces and non-faces elicit distinct VEP responses.

The experimental design divided the stimuli into five distinct categories:

- Sets 1–3: Neutral expressions, emotional expressions, and non-facial items, respectively, trigger both P300 and SSVEP activity.
- Set 4: The P300 signal responds to a neutral face, whereas a non-facial target drives the SSVEP response.
- Set 5: An emotional facial expression prompts the P300 component, while a non-facial object activates the SSVEP.

The researchers hypothesized that emotional facial stimuli would generate more distinct VEP responses, thereby improving overall BCI classification accuracy compared to standard non-facial stimuli.

Early brain–computer interface (BCI) research established that imagined motor tasks—such as mental fist clenching—trigger event-related desynchronization and synchronization (ERD/ERS) in sensorimotor rhythms, enabling multidimensional cursor control (Pfurtscheller & Neuper, 2001; Guger et al., 2009; Hammer et al., 2012; Lu et al., 2013). Despite these advances, sensorimotor-based systems require substantial user training and remain ineffective for a portion of the population, a phenomenon known as BCI "inefficiency," "illiteracy," or "poor proficiency" (Vidaurre & Blankertz, 2010).

Similar performance bottlenecks affect visual paradigms like P300 and steady-state visual evoked potentials (SSVEP), where individual user variance can cause complete control failure (Allison et al., 2010a; Fazel-Rezai et al., 2012). To overcome the functional limits of single-modality systems, researchers developed hybrid BCIs (Guger et al., 2009; Allison et al., 2010b). Standard hybrid architectures integrate distinct sensory cues—such as flashing elements for P300 and high-frequency flickering targets for SSVEP—to evoke concurrent signals and enhance overall decoding accuracy (Yin et al., 2013; Allison et al., 2014).

For instance, speller designs use distinct flashing rows/columns alongside flickering frequencies for individual cells. Nevertheless, conventional flash-and-flicker combinations trigger an unstable checkerboard pattern where random color changes disrupt steady flickering frequencies.

To overcome this, our study introduces an advanced hybrid SSVEP and P300 method that replaces color-changing flashes with shape changes, eliminating checkerboard irregularities. While previous strategies like Li et al. (2013) combined independent P300 and SSVEP outputs for decision-making, our optimized paradigm significantly enhances SSVEP performance to improve overall hybrid BCI reliability.

II. METHODOLOGY

1. Experimental setup and Participants

We recruited ten healthy, right-handed individuals (9 males, mean age 24.1 ± 2.5 years) with intact vision and cognitive function. Half of the cohort (subjects S4, S6, S7, S9, and S10) had no prior experience operating a BCI.

During experimental runs in a shielded environment, subjects remained relaxed and seated 60 cm from a 17" CRT screen (1024 × 768, 75 Hz) while minimizing body movements.

© 2026 IJSRET

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

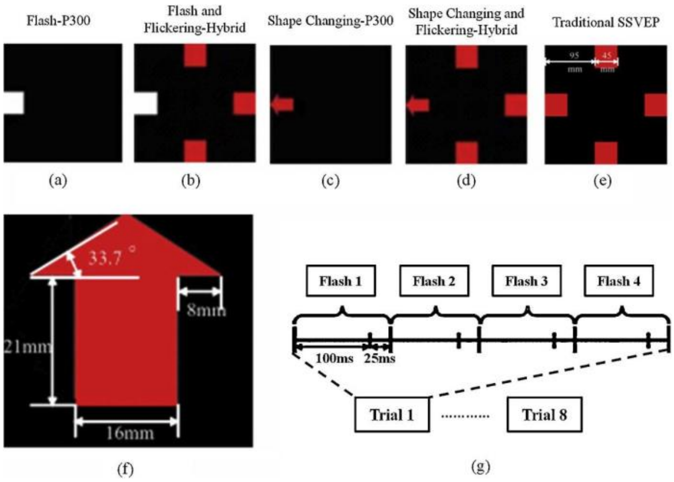

Fig. 1. Panels (a) to (e) illustrate the visual interfaces presented to participants across the five experimental conditions. Details of the directional arrow utilized in two of the paradigms are highlighted in panel (f). Panel (g) depicts the timeline for one experimental task. (Colors mentioned in the text correspond to the web edition of this article.)

2. Experimental paradigms

This study evaluated five brain-computer interface (BCI) paradigms based on P300, SSVEP, and their combinations: two novel hybrid setups (Flash and Flickering-Hybrid, and Shape-Changing and Flickering-Hybrid), two traditional P300 variants (Flash-P300 and Shape-Changing-P300), and a conventional SSVEP paradigm. Each interface presented four items against a black background (Fig. 1). Testing took place across five offline experimental sessions spanning two separate days, with paradigm order randomized for each participant. Each session comprised 20 runs targeting all four items, with each focus period lasting 4 seconds. For flash-based tasks, a single target sequence involved a 2-second cue followed by a 4-second flash phase, bringing the data recording time per run to 24 seconds S((2 + 4) \times 4)s. Including preparation and rest intervals, each session lasted approximately 30 minutes, separated by 10-minute breaks between sessions. In the Flash-P300 task (Fig. 1a), participants internally tracked target flashes following a 2-second red cue. Each sequence comprised eight trials, with all four items flashing once per trial via a 100 ms red-to-white transition and a 25 ms post-flash pause (Fig. 1g). The Shape Changing-P300 setup (Fig. 1c) duplicated this setup, using red arrows instead of white flashes. The Traditional-SSVEP paradigm (Fig. 1e) adapted this visual format but required continuous target fixations instead of counting; additionally, the items flickered at constant frequencies (10 Hz left, 9 Hz top, 8 Hz right, 6 Hz bottom). Subjects with 10 Hz stimulation frequencies were used due to software constraints in the presentation software and are referenced in previous brain-computer interface literature. Finally, the two hybrid conditions (Fig. 1b and d) integrated both mechanisms: the items flickered constantly at their assigned frequencies while simultaneously flashing white or transforming into red arrows, and participants both counted the flashes and maintained visual focus on the target.

3. EEG data collection

Brain electrical activity was recorded at a 250 Hz sampling rate using an ADS1299-powered OpenBCI system. Electrode placement followed the standard 10–20 international layout, targeting 13 scalp locations: Fz, Cz, Pz, P3, P4, P7, P8, POz, PO7, PO8, O1, Oz, and O2. The ground electrode was positioned at FPz, while A11 and A12 served as reference channels. Signal analysis was task-specific: P300 wave identification utilized eight targeted channels (Fz, Cz, Pz, P3, P4, P7, P8, and Oz), whereas steady-state visually evoked potential (SSVEP) detection focused on six occipital and parieto-occipital channels (O1, O2, Oz, PO7, PO8, and POz).

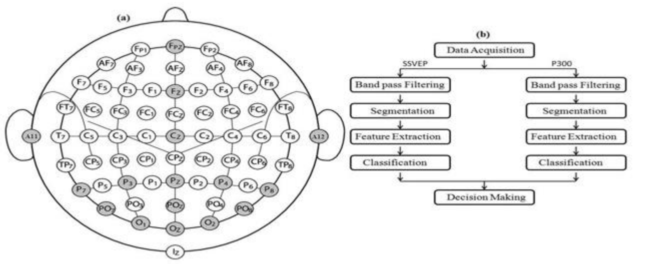

Figure 2. (a) Sensor locations shown in gray. (b) Flowchart of the EEG processing workflow.

4. Method for feature extraction

Preprocessing protocols for SSVEP and P300 signals were implemented as shown in Figure 2(b). P300 signals were filtered within a 0.5 to 11 Hz band, followed by the extraction of 0–800 ms post-flash data segments. Because SSVEP analysis relies on integrating multi-channel recordings to ensure accurate results [21, 22], the Common Spatial Pattern (CSP) algorithm was applied to maximize spatial contrast across channels.

5. Classification

A multi-class probabilistic Linear Discriminant Analysis (LDA) algorithm translates brain responses into distinct commands [18, 19]. The classifier evaluates each input feature vector “x” using the discriminant equation;

$$D(x) = w^T \times x + b$$

© 2026 IJSRET

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

Where, "*w*" is the weights vector. The likelihood of assigning "x" to every class is provided as: $\sigma(D(x)) = \underline{\ 1\ \ \ \ \ \ \ }$. The input is subsequently categorized into the class associated with the $1+\exp(-D(x))$ maximum likelihood value.

Where G represents the individual target Information Transmission Rate (ITR), N denotes the total number of target objects, t as the total time taken to identify all targets, and Acc is as the classification accuracy.

7. Computation of ITR
ITR is calculated by-

$$G = \log_2(Acc) * Acc + \log_2(N) + \log_2 \left\{\frac{1-Acc}{N-1}\right\} * (1 - Acc) \quad (6)$$

$$ITR = G * \langle \frac{60}{t} \rangle \quad (7)$$

8. Methodological approach
Across 12 experimental sessions, participants attempted to select each target button once per session. To evoke P300 brain signals, subjects monitored the flashing frequency of a prominent visual circle. With six trials per session (Figure 2b), the dataset comprised 288 target epochs (4 targets/trial × 6 trials/session × 12 sessions) and 864 non-target (3 non-targets × 4 × 6 × 12). For

SSVEP generation, a single round required subjects to focus on flickering small circles over a specific command button for 9.5 seconds. Participants completed 8 rounds per session across all 12 sessions. Collecting SSVEP recordings using a 4-second sliding window with a 0.5-second stride generated 1,152 data chunks in total: 1152= ((((9.5 - 4) / 0.5) + 1) × 8 × 12).

9. Statistical study
ANOVA is applied to investigate the suggested system's metrics. The criteria for ANOVA include that the data must be examined for a normal distribution and sphericity. The Tukey-Kramer tests are utilized for the purpose of carrying out post-hoc analysis.

10. Subjective report
Following each test, participants rated their comfort using the proposed BCI by answering various experiential questions. These inquiries addressed comfort levels, ease of use, subjective thoughts and feelings, and overall satisfaction, with respondents permitted to answer in their native language. Responses were recorded on a 1 to 5 scale (1 indicating strong disagreement and 5 indicating full agreement), and Table 3 presents the resulting average scores for each question.

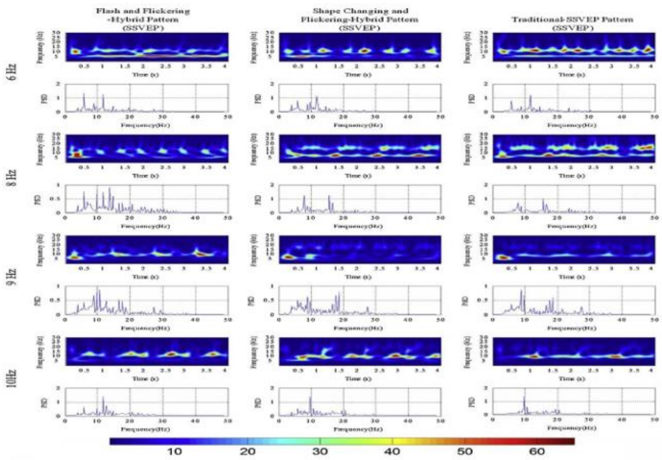

Figure 3 details the offline analysis of the three SSVEP paradigms using data averaged from channels Oz, O1, and O2. Arranged by paradigm in columns, the rows partition the results by four stimulus frequencies. Each frequency setting features a pair of subplots: a top-row spectrogram plotting frequency (Hz) over time (s), and a bottom-row graph illustrating power spectral density (PSD) relative to frequency (Hz).

SSVEP
By averaging signals from the Oz, O1, and O2 channels, we evaluated time-frequency data using the Morlet wavelet transform (MWT) and power spectral density (PSD) via fast Fourier transform (FFT) (Fig. 3). The outcomes reveal that all paradigms tested, including Flash, SSVEP Flickering-Hybrid, and Shape Changing Flickering-Hybrid, can potentially impair steady-state visually evoked potential (SSVEP) responses. Conversely, specific geometric alterations, such as the red indicators in the Shape Changing and Flickering-Hybrid setup, appear to leave SSVEP responses unaffected. These observations are further supported by the classification accuracies detailed in Table 1, which elucidate how SSVEP activity influences overall system performance.

We summarized the SSVEP classification accuracy and ITR metrics across three experimental formats (Flash Flickering-Hybrid, Shape-Changing Flickering-Hybrid, and Traditional SSVEP) in Table 1. Formatting conventions distinguish the lowest score per subject (italics), peak performance per category (bold), and aggregate means (bold italics). Main effects evaluated via a within-subject ANOVA indicated significant differences across paradigms in accuracy (F(2, 27) = 7.56, p = 0.0025$) as well as ITR (F(2, 27) = 8.11, p = 0.0017).

© 2026 IJSRET

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

Post-hoc comparisons revealed that the Flash Flickering-Hybrid paradigm yielded significantly lower classification accuracy (F (1,18) = 12.78, p = 0.0022) and ITR (F (1,18) = 15.7, p = 0.0009). compared to the Shape-Changing Flickering-Hybrid model. Similarly, the Flash Flickering-Hybrid setup performed significantly worse than Traditional SSVEP in both accuracy (F (1,18) = 8.45, p = 0.0094) and in ITR (F (1,18) = 0.89, p = 0.0056 < 0.016). These outcomes indicate that the conventional Flash Flickering-Hybrid format underperforms relative to both Shape-Changing and Traditional SSVEP designs. Consistent with prior observations, substantial inter-subject variability was evident; notably, participant S3 demonstrated consistently poor classification accuracy across all three paradigm configurations.

- Flash and Flickering-Hybrid (SSVEP): 67.5%
- Shape Changing and Flickering-Hybrid (SSVEP): 68.75%
- Traditional SSVEP: 65.0%

Marked inter-subject variance was recorded, aligning with former studies and highlighting the limitations of conventional SSVEP paradigms for specific users. Low classification performance was observed for subject S3 across the three SSVEP modalities (Traditional SSVEP at 65%, Flash-Hybrid at 67.5%, and Shape-Changing Hybrid at 68.75%). However, prominent P300 activity enabled high accuracy for S3 in the Shape-Changing Hybrid setup. Likewise, subject S9 exhibited limited accuracy in SSVEP-reliant conditions (67.5% in Flash-Hybrid, 73.75% in Traditional-SSVEP), yet attained a 95% accuracy rate when isolated P300 features were utilized in the Shape-Changing Hybrid paradigm.

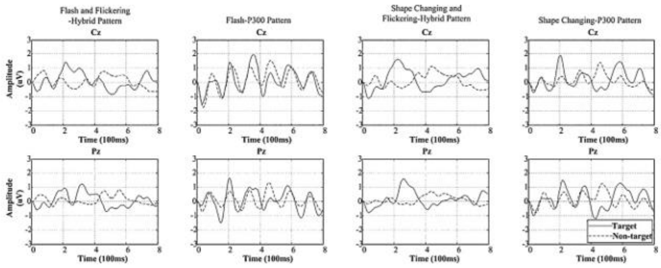

Figure 4. The average waveform of the event-related potential at Cz, P7, Oz, Pz, and P8 for each experiment.

Fig. 4 shows the grand-averaged ERPs across subjects 1–10 over channels Cz and Pz. It shows that all four P300 paradigms can evoke identifiable P300 signals. shows the performance of four P300 paradigms only using the P300 features with the BLDA classifier accuracy (Flash and Flickering-Hybrid (P300), Shape Changing and Flickering-Hybrid (P300), Flash-P300, and Shape Changing-P300) of all subjects and the average. We measured the classification accuracy and bit rate using a single trial for four paradigms. No significant difference was found between these four paradigms (classification accuracy of P300: F(3,36) = 2.13, p = 0.1132 > ¸, and ITR of P300: F(3,36) = 1.14, p = 0.3444 > ¸). This means the hybrid paradigms (Flash and Flickering-Hybrid (P300) and Shape Changing and Flickering-Hybrid (P300)) can work as well as the traditional paradigms (Flash-P300 and Shape Changing-P300).

III. RESULT

The Information Transfer Rate (ITR) serves as a standard metric for measuring the communication throughput of Brain-Computer Interface (BCI) systems (Wolpaw et al., 2002). This calculation assumes a trial setup with N equally likely choices, where the target selection accuracy (Acc) remains constant, and any incorrect selection has an identical probability of occurring. The total ITR, expressed in bits per minute, reflects this balance between speed and precision. Separately, when evaluating visual stimulation paradigms such as steady-state visual evoked potential (SSVEP), traditional SSVEP, and related variants a 6 Hz stimulus frequency successfully triggers robust brain responses. Across all three paradigms, both the primary fundamental frequency (6 Hz) and its second harmonic (12 Hz) are clearly elicited in the neural signals.

IV. DISCUSSIONS

The study's main objective was to introduce an innovative hybrid BCI paradigm that combines P300 and SSVEP signals, specifically integrating shape-changing and flickering visual stimuli—to make brain-computer interfaces more accessible to a broader population. System efficiency was measured by comparing classification accuracy and estimated information transfer rates (ITR) across the different paradigms. When evaluating steady-state visual evoked potential (SSVEP) features, the proposed Shape Changing and Flickering Hybrid paradigm achieved a 91.63% classification accuracy. This performance significantly surpasses the 72.50% accuracy of the conventional Flash and Flickering-Hybrid setup by more than 18 percentage points (F(1,18)= 12.78, p = 0.0022). Furthermore, the new approach performs on par with the standard Traditional-SSVEP method, which logged an 87.05% accuracy rate with no statistically significant difference between the two (F(1,18) = 0.37, p = 0.5532). The lower performance observed in the conventional hybrid system stems from the temporal instability of its random flashes, which disrupts the traditional checkerboard stimulation pattern. Reinforcing earlier findings, significant performance variations

© 2026 IJSRET

emerged between participants, highlighting how certain individuals struggle with conventional SSVEP systems. For instance, participant S3 scored poorly across all three SSVEP setups (Flash and Flickering-Hybrid at 67.45%, Shape Changing and Flickering-Hybrid at 68.55%, and Traditional-SSVEP at 65%), yet performed exceptionally well in the Shape Changing and Flickering-Hybrid setup by relying on strong P300 responses. Similarly, participant S9 showed low accuracy under the Flash and Flickering-Hybrid (67.45%) and Traditional SSVEP (73.05%) conditions, but reached outstanding accuracy within the Shape Changing and Flickering-Hybrid paradigm by utilizing P300-based features.

Flash and flickering-hybrid (SSVEP)Shape changing and flickering-hybrid (SSVEP)Traditional-SSVEP(SSVEP)

Table 1. Each paradigm's ITR and accuracy

	Flash and flickering-hybrid (SSVEP)		Shape changing and flickering-hybrid (SSVEP)		Traditional-SSVEP(SSVEP)	
	Acc (%)	ITR (bits/min)	*Acc (%)*	ITR (bits/min)	*Acc (%)*	ITR (bits/min)
s1	73.75	11.30	97.50	26.88	97.50	26.88
s2	47.50	2.55	77.50	13.11	86.25	18.07
s3	67.50	8.63	68.75	9.13	65.00	7.67
s4	80.00	14.42	96.25	25.65	90.00	20.59
s5	88.75	19.71	98.75	28.25	98.75	28.25
s6	78.75	13.75	95.00	24.52	96.25	25.65
s7	72.50	10.73	96.25	25.65	82.50	15.80
s8	58.75	5.53	85.00	17.29	93.75	23.45
s9	67.50	8.63	95.00	24.52	73.75	11.30
s10	87.5	18.87	96.25	25.65	97.75	23.45
Avg	72.25 ± 12.69	11.41 ± 5.46	90.63 ± 10.16	22.07 ± 6.52	87.75 ± 11.10	20.11 ± 6.84

V. CONCLUSION

This research proposes an innovative hybrid brain-computer interface (BCI) framework that combines P300 and SSVEP electroencephalographic signals, evaluating its effectiveness against both conventional hybrid and single-modality systems. Testing involving ten healthy participants showed that the proposed hybrid approach achieved a notable performance boost compared to standard SSVEP-based hybrid designs. Furthermore, the Shape Changing and Flickering-Hybrid setup demonstrated exceptional outcomes, averaging 100% accuracy and an information transfer rate of 30 bits per minute across eight trials when utilizing Bayesian Linear Discriminant Analysis (BLDA). These findings suggest that the newly developed paradigms can enhance system efficiency for specific users, thereby expanding BCI application possibilities. Upcoming investigations will center on exploring the novel visual display.

CRediT authorship contribution statement

- Monali S. Khune: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.
- Amol Y. Deshmukh: Visualization, Validation, Supervision.

Funding: This research was not funded.

Acknowledgments: The author is thankful to the Vice Chancellor, R.T.M.N.U, Nagpur University, and the Director, P.G.T.D, R.T.M.N.U, Nagpur University, Nagpur.

Statements

- Conflict of Interest: None of the people writing this paper have any conflicts of interest.
- Ethical endorsement: The research got the endorsement from the RTMNU University's Research Recognition Committee (RRC) with approval number “RTMNU/PH.D CELL/RRC/2023/R1/1143”. Before we started doing anything with human participants, we made sure everything we were planning to do was okay according to the RTMNU University, Nagpur Research Committee, the 1964 Helsinki Declaration and any other ethical rules that are essentially the same.
- Consent: For this research, anyone participating gave their written approval, following what the Good Clinical Practices guidelines suggest.
- Statement on data accessibility: If someone wants to see the data we collected or analyzed, they only have to politely ask the person in charge of the study, and they can get it.

REFERENCES

1. Reitelbach, C., & Oyibo, K. (2024), “Optimal Stimulus Properties for Steady-State Visually Evoked Potential Brain–Computer Interfaces: A Scoping Review”. Multimodal Technologies and Interaction, 8(2), 6. DOI: https://doi.org/10.3390/mti8020006.
2. Bekhelifi O, Berrached NE, Bendahmane A. (2024), “Effects of the presentation order of stimulations in

sequential ERP/SSVEP Hybrid Brain-Computer Interface", Biomed Phys Eng Express, 13, 10(3). DOI: 10.1088/2057-1976/ad2f58.

3. Zhichuan Tang, Xinyang Wang, Jiayi Wu, Yaqin Ping, Xiaogang Guo, Zhixuan Cui (2022), "A BCI painting system using a hybrid control approach based on SSVEP and P300", Computers in Biology and Medicine, Volume 150, 106118, DOI: https://doi.org/10.1016/j.compbiomed.2022.106118.
4. Jin Han, Chuan Liu, Jiayue Chu, Xiaolin Xiao, Long Chen, Minpeng Xu, Dong Ming (2022), "Effects of inter-stimulus intervals on concurrent P300 and SSVEP features for hybrid brain-computer interfaces", Journal of Neuroscience Methods, Volume 372, 109535, DOI: https://doi.org/10.1016/j.jneumeth.2022.109535.
5. Bai X, Li M, Qi S, Ng ACM, Ng T and Qian W (2023), "A hybrid P300-SSVEP brain-computer interface speller with a frequency enhanced row and column paradigm", Front. Neurosci. 17:1133933. DOI: 10.3389/fnins.2023.1133933.
6. Kaufmann, T. et al. (2011), "Flashing characters with famous faces improves ERP-based brain–computer interface performance", Journal of Neural Engineering, IOP Publishing, 8.
7. Zhang J, Gao S, Zhou K, Cheng Y and Mao S (2023), "An online hybrid BCI combining SSVEP and EOG-based eye movements", Front. Hum. Neurosci, 17:1103935. DOI: 10.3389/fnhum.2023.1103935.
8. Vakli, P. et al. (2014), "The face evoked steady-state visual potentials are sensitive to the orientation, viewpoint, expression and configuration of the stimuli", Elsevier International Journal of Psychophysiology, 94, 336–350.
9. Rossion, B. et al. (2012), "A steady-state visual evoked potential approach to individual face perception: Effect of inversion, contrastreversal and temporal dynamics", Elsevier NeuroImage, 63, 1585–1600.
10. Jin, J., Allison, B. Z., Kaufmann, T., Kbler, A., Zhang, Y., et al. (2012), "The changing face of P300 BCIs: A comparison of stimulus changes in a P300 BCI involving faces, emotion, and movement", PLoS ONE, 7 (11). https://doi.org/10.1371/journal.pone.0049688.
11. Kellicut-Jones, M. R., & Sellers, E. W. (2018), "P300 brain-computer interface: Comparing faces to size matched non-face stimuli. Brain-Computer Interfaces", 5(1), 30–39. https://doi.org/10.1080/2326263X.2018.1433776.
12. Rossion, B. et al. (2011), "Robust sensitivity to facial identity in the right human occipito-temporal cortex as revealed by steady-state visual evoked potentials", Journal of Vision, 11(2), 1–21, 16.
13. Li, Y. et al. (2013), "A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control", IEEE Transactions on Biomedical Engineering, 60(11), 3156–3166.
14. Allison, B. et al. (2014), "A four-choice hybrid P300/SSVEP BCI for improved accuracy" Brain-Computer Interfaces.
15. Wang, M. et al. (2015), "A new hybrid BCI paradigm based on P300 and SSVEP", Journal of Neuroscience Methods, 244, 16–25.
16. Singla, R. et al. (2018), "Hybrid brain–computer interface paradigm—a study", Biomedical Engineering: Applications, Basis and Communications, 30(3). https://doi.org/10.4015/S1016237218500229.
17. Weissman, B., & Tanner, D. (2018), "A strong wink between verbal and emoji-based irony: How the brain processes ironic emojis during language comprehension", PLoS ONE, 13(8). https://doi.org/10.1371/ journal.pone.0201727.
18. Bishop, C. M. (2007), "Pattern recognition and machine learning" Springer.
19. Tharwat, A., et al. (2017), "Linear discriminant analysis: A detailed tutorial", AI Communications; IOS Press; 0921-7126; doi:10.3233/AIC170729.
20. Gruss, L. et al. (2012), "Face-evoked steady-state visual potentials: Effects of presentation rate and face inversion", Frontiers in Human Neuroscience, 6. Article 316.
21. Ojha, M.K., Gupta, D. (2023), "A Review on Different Preprocessing and Feature Extraction Technique for SSVEP BCI Inference System", Lecture Notes in Electrical Engineering, vol 948. DOI: https://doi.org/10.1007/978-981-19-6383-4_39.
22. Susan Philip, B., Prasad, G., & Hemanth, D. J. (2023), "A systematic review on artifact removal and classification techniques for enhanced MEG-based BCI systems", Brain-Computer Interfaces, 10(2–4), 99–113. https://doi.org/10.1080/2326263X.2023.2233368.
23. Grigoryan, R. K. et al. (2018), "Visual stimuli for P300-based brain computer interfaces: Color, shape, and mobility", published in Vestnik Moskovskogo Universiteta, Seriya 16. Biologiya, 73(2), 111–117.
24. Jin, J. et al. (2014), "An optimized ERP brain–computer interface based on facial expression changes", Journal of Neural Engineering IOP Publishing, 11.
25. Värbu, K., Muhammad, N., & Muhammad, Y. (2022), "Past, Present, and Future of EEG-Based BCI Applications", Sensors, 22(9), 3331. https://doi.org/10.3390/s22093331
26. C M Bishop., "Pattern recognition and machine learning.", Springer-Verlag, New York, 978-0-387-31073-2, 2007.
27. Vidaurre C, Kawanabe M, von Bünau P, Blankertz B, Müller KR., "Toward unsupervised adaptation of LDA for brain-computer interfaces", IEEE Trans Biomed

Engineering, 58(3), pp. 587-97, 2011, DOI: https://doi.org/10.1109/TBME.2010.2093133.

28. Llera A, Gómez V, Kappen HJ., “Adaptive multiclass classification for brain computer interfaces.” Neural Comput.,26(6), 1108-27, 2014, DOI: https://doi.org/10.1162/NECO_a_00592.

© 2026 IJSRET