

Article

A Sequential Multilevel Frequency Stimulation Paradigm for SSVEP-Based Brain–Computer Interfaces

Nannaphat Siribunyaphat ^{1,2} , Keiji Iramina ³ and Yunyong Punsawad ^{1,2,*} 

¹ School of Informatics, Walailak University, Nakhon Si Thammarat 80160, Thailand; nannaphat.sir@mail.wu.ac.th

² Informatics Innovative Center of Excellence, Walailak University, Nakhon Si Thammarat 80160, Thailand

³ Graduate School of Systems Life Sciences, Kyushu University, Fukuoka 819-0395, Japan; iramina@inf.kyushu-u.ac.jp

* Correspondence: yunyong.pu@wu.ac.th; Tel.: +66-8-6909-1568

Abstract

This study evaluated a discrete staircase implementation of sequential frequency stimulation for steady-state visual evoked potential (SSVEP)-based brain–computer interfaces (BCIs). Five adjacent frequencies separated by 0.2 Hz were presented in consecutive 2 s epochs as ascending-frequency flicker patterns (AFFPs) or descending-frequency flicker patterns (DFFPs) within low-frequency (6–10 Hz) and high-frequency (41–45 Hz) ranges. Offline EEG responses from 15 participants were compared with conventional fixed-frequency stimulation using eight established signal-processing methods: fast Fourier transform (FFT), power spectral density (PSD), canonical correlation analysis (CCA), filter bank CCA (FBCCA), dynamic PSD, short-time Fourier transform (STFT), continuous wavelet transform (CWT), and discrete wavelet transform (DWT). Low-frequency stimulation achieved a higher average normalized classification accuracy than high-frequency stimulation (90.8% vs. 80.6%), while CWT yielded the highest descriptive average accuracy among the evaluated methods; however, post hoc comparisons did not establish CWT as significantly superior to the other evaluated methods. The fixed-frequency, AFFP, and DFFP conditions achieved average normalized accuracies of 89.7%, 85.6%, and 89.5%, respectively. Statistical analysis showed a significant main effect of the signal-processing method but no significant main effect of the stimulation pattern. Three consecutive commands achieved an average accuracy of $91.5 \pm 9.6\%$, whereas the accuracy decreased as the command sequence became longer. The results show that AFFP and DFFP staircase sequences can be detected offline, but they do not prove better classification than fixed-frequency stimulation. The small, uniform sample limits how widely these findings can be applied. Their main value may lie in assisting flexible sequential command design, which needs further testing with larger, more diverse groups and within an online closed-loop BCI system.

Keywords: brain–computer interface; steady-state visual evoked potential; sequential frequency modulation; consecutive command detection; time–frequency analysis



Academic Editor: Jie Yang

Received: 4 September 2026

Revised: 24 September 2026

Accepted: 25 September 2026

Published: 27 September 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Brain–computer interfaces (BCIs) are advanced technologies that facilitate direct communication between the brain and computers. These systems are being developed in conjunction with rehabilitation and assistive technologies for individuals with physical disabilities caused by diseases, accidents, or congenital conditions that affect daily activities [1–3]. A typical BCI system consists of three main components: brain signal acquisition,

feature extraction and classification, and translation or command generation. Two primary approaches are used for brain signal acquisition. Noninvasive techniques are widely adopted because they collect brain signals through electrodes placed outside the body, either in contact with or without touching the scalp, thereby eliminating the need for surgical procedures to implant electrodes [4,5]. However, these signals are generally low in amplitude and susceptible to noise, requiring signal processing before they can be used within the system. Electroencephalography (EEG) is the most widely used noninvasive method because of its ability to effectively capture brain activity. In addition, EEG-based BCI devices have been developed in portable formats, making them more practical and convenient for daily use [6,7].

EEG signals change either due to spontaneous brain activity associated with normal human behavior or in response to external stimuli, referred to as event-related potentials (ERPs). These signal variations can be used to generate commands for BCI systems [8,9]. One commonly used method is event-related desynchronization/synchronization, which analyzes EEG signal variations resulting from mental imagery, such as motor or verbal imagination [10,11]. Another approach is the visual evoked potential (VEP), which measures electrical potential changes in the occipital region, the brain area responsible for visual processing. VEP stimuli are categorized into two types: transient VEPs, such as the P300 response, and steady-state visual evoked potentials (SSVEPs) [12,13].

SSVEPs are elicited by visual stimuli flickering at specific frequencies. When a person focuses on a visual stimulus within the 3.5–75 Hz frequency range, the brain generates electrical responses at the same or harmonic frequencies of the stimulus. These stimuli can be presented using light-emitting diodes (LEDs), flickering images, animations, or similar visual displays [14–16]. SSVEP-based methods require relatively short training times and provide high accuracy and high information transfer rates (ITRs), which has led to their widespread use in BCI applications [17–20]. However, these systems also face several challenges, including visual fatigue and discomfort during prolonged use, which can reduce system performance [21–23]. Increasing the number of commands for controlling external devices also remains challenging because detection performance typically decreases as command complexity increases. Therefore, improving the long-term usability and efficiency of SSVEP-based BCI systems through reliable frequency encoding and multi-command generation remains an important challenge for practical applications.

Previous studies have focused on improving the practical usability and detection efficiency of SSVEP-based BCI systems through efficient EEG signal processing, optimized visual stimulus configurations, adaptive decoding, and reduced calibration requirements [24–31]. Wong et al. [28] introduced an online adaptive canonical correlation analysis (CCA) method that updates spatial filters from unlabeled data, thereby improving accuracy and ITR over time. Shi et al. [29] proposed a representative-based cold-start approach using cross-subject transfer learning for the initial system setup, followed by adaptive filter bank canonical correlation analysis (FBCCA) to support robust early-stage performance. Lee et al. [30] developed an adaptive-window FBCCA that dynamically adjusts the analysis-window length for each trial. Li et al. [31] introduced a multi-stimulus least-squares transformation with online adaptation to reduce calibration effort. In addition, Liu et al. [15] integrated dynamic window selection with CCA to improve detection efficiency. These studies demonstrate that stimulus configuration, decoding strategy, and analysis-window selection are important factors in maintaining reliable classification.

Sequential frequency coding and frequency-modulation SSVEP stimulation have previously been investigated using several approaches. Zhang et al. [32] introduced multiple-frequency sequential coding (MFSC), in which targets were represented by ordered frequency sequences presented across successive coding epochs. Two frequencies, 7.5 and

12 Hz, were presented during two equal-duration epochs lasting either 1.5 or 2 s, thereby generating four target-specific sequences. CCA identified the frequency presented in each epoch, and the resulting sequence determined the target. Dreyer and Herrmann [33] investigated carrier-based frequency-modulated SSVEP stimulation and reported reliable responses at the lower sideband frequency, together with reduced flicker perceptibility at higher carrier frequencies. Zhao et al. [34] developed trinary frequency-shift keying SSVEP (TFSK-SSVEP), in which three discrete frequencies represented the two binary symbols and an additional separator symbol for command encoding. Wang et al. [35] provided a 40-target SSVEP benchmark dataset obtained from 35 participants using frequencies from 8 to 15.8 Hz with an interval of 0.2 Hz and joint frequency–phase coding. Ge et al. [36] proposed dual-frequency biased coding, in which each target was represented by a permutation of two frequency-specific flickering periods. They reported improved offline and online performance compared with conventional MFSC. Yue et al. [37] introduced multiple time–frequency sequential coding (MTFSC), which combines steady-state motion visual evoked potentials (SSMVEPs) with omitted-stimulus potentials (OSPs). This approach integrates frequency information with temporal omission patterns and uses template-based CCA for target identification in an online nine-target paradigm with a 3 s stimulation period. Moreover, Ge et al. [38] proposed block-distributed joint temporal-frequency-phase modulation (B-JTFPM), in which a 48-target speller was divided into eight blocks and encoded using only eight frequencies across two sequential coding sessions. The approach combined temporal, frequency, and phase information to increase the number of targets while limiting the required frequency resources. Thus, sequential frequency ordering, frequency modulation, and 0.2-Hz frequency spacing have precedents in SSVEP-based BCIs.

Accordingly, the present study focuses on a specific staircase frequency stimulation configuration rather than introducing a new sequential-coding principle. Unlike previous approaches based on arbitrary frequency sequences, joint frequency–phase coding, or continuous frequency modulation [33–38], AFFP and DFFP sequentially traverse the same five adjacent frequencies in a monotonic ascending or descending order. This study evaluates whether these closely spaced frequency states can be detected within consecutive 2 s epochs and compares their offline performance across low- and high-frequency ranges and established signal-processing methods. A comparison with representative sequential SSVEP encoding paradigms is presented in Section 4.

In addition to algorithm development, many studies have optimized stimulus design to improve comfort and performance. In addition to sequential and multi-frequency coding, other studies have optimized stimulus design to enhance comfort and performance. Chailloux Peguero et al. [38] compared four visual stimulation paradigms using CCA, FBCCA, and MEC. On–off stimulation combined with FBCCA provided the best detection performance, whereas many participants preferred checkerboard stimulation for visual comfort. Ladouce et al. [14] reduced visual fatigue through lower-amplitude, lower-depth, and high-frequency JFPM stimulation while maintaining over 90% accuracy with a 40–50% intensity reduction; however, very high frequencies reduced the accuracy to approximately 45%. Li et al. [39] introduced a hybrid approach combining sinusoidal luminance and radial motion modulation to create intermodulation frequencies that improved the accuracy and user experience. Researchers have also explored multilevel stimulus scaling for flexible control. Zhang et al. [40] used multilevel brightness modulation to enable proportional robot speed control based on luminance-evoked SSVEP strength. In a related study, Zhang et al. [41] developed a spatial gradient controller utilizing multilevel spatial frequency gradients (7.2–9.0 Hz) to achieve continuous two-dimensional robot control, reducing the collision rate to 4% and reducing the task completion time by 27.7%.

Recent studies have expanded SSVEP-based BCI systems from traditional discrete selection tasks to continuous linear control, particularly for multi-degree-of-freedom (multi-DOF) applications that require low latency [42,43]. This shift involves transforming discrete classification results into continuously varying control signals. To ensure smooth and stable real-time control, methods such as control-vector accumulation, sliding-window processing with temporal smoothing, and likelihood-based adaptive gain control have been introduced. The resulting signals are transmitted to a shared control framework, where brain-derived commands are integrated with sensor data for movement execution and error correction [44]. System performance is typically assessed using metrics such as the success rate, error rate, task completion time, and trajectory deviation from the ideal path, whereas real-time device feedback supports closed-loop interaction. SSVEP-based paradigms have demonstrated strong responsiveness and robustness in practical applications [45].

Against this background, the present study provides a systematic offline evaluation of a specific staircase frequency stimulation configuration rather than a new general coding principle or classification algorithm. The main contributions are as follows: (1) the implementation and comparison of fixed-frequency stimulation with five-step ascending and descending staircase sequences using 0.2 Hz increments across low-frequency (6–10 Hz) and high-frequency (41–45 Hz) ranges; (2) the benchmarking of eight established signal-processing methods under the same experimental conditions, together with frequency-specific analysis of AFFP and DFFP detection; and (3) the quantification of the offline detection performance for three-, four-, and five-command sequences, including the decline in accuracy associated with longer command sequences. Therefore, this study focuses on the feasibility, comparative performance, and limitations of this specific staircase configuration as an offline basis for future sequential command design.

2. Materials and Methods

2.1. Multilevel Flicker Stimulus Paradigm

In this study, a discrete staircase frequency stimulation protocol was evaluated to characterize SSVEP responses to ordered changes among adjacent flicker frequencies. The term “frequency modulation” in this study refers to piecewise-constant changes in the flicker frequency across five consecutive 2 s epochs. It does not refer to continuous carrier-frequency modulation or sideband-based FM-SSVEP stimulation, as investigated by Dreyer and Herrmann [33]. Rectangular visual stimuli measuring 4 cm × 5 cm and flickering alternately between white and black, as shown in Figure 1a, were used. Five stimuli were systematically arranged on a 24-in liquid crystal display (LCD) screen to help participants focus and reduce interference between stimuli at different locations, as shown in Figure 1b.

As summarized in Table 1, the flicker frequencies were divided into two groups—low (6–10 Hz) and high (41–45 Hz)—each consisting of five fundamental frequencies. Within each range, multilevel flicker-frequency modulation was used to create control commands at multiple levels. The frequency-adjusted flicker pattern was modified in 0.2 Hz steps for both increasing and decreasing sequences. The physical luminance waveform generated by the LCD was not independently measured using a photodiode. Therefore, the programmed stimulation frequencies, particularly the 41–45 Hz high-frequency conditions and their 0.2 Hz increments, are treated as nominal display frequencies throughout this study.

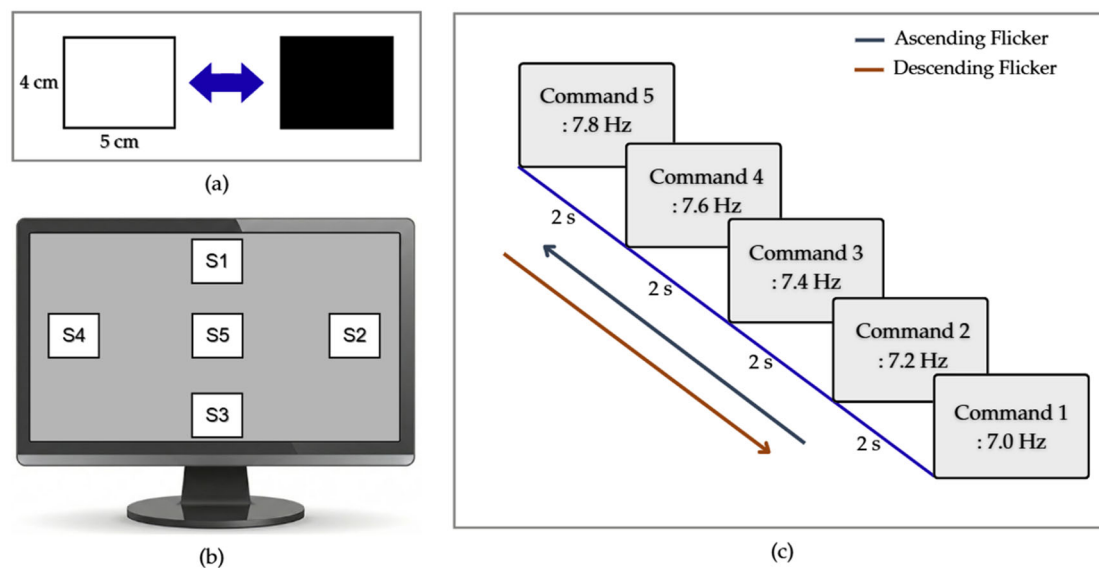


Figure 1. Proposed sequential frequency-modulated visual flicker stimuli. (a) Proposed SSVEP stimulus consisting of a rectangular target flashing alternately in white and black. (b) Spatial layout of five stimulus positions corresponding to fundamental flicker frequencies on an LCD monitor. S1–S5 denote the top, right, bottom, left, and center stimulus positions, respectively, with corresponding fundamental frequencies of 6, 7, 8, 9, and 10 Hz in the low-frequency range or 41, 42, 43, 44, and 45 Hz in the high-frequency range. (c) Example of a frequency-modulation sequence starting at 7.0 or 7.8 Hz, with the flicker frequency adjusted in 0.2 Hz steps for both ascending and descending flicker patterns (AFFPs and DFFPs). The arrows indicate the direction of frequency progression: ascending from 7.0 to 7.8 Hz and descending from 7.8 to 7.0 Hz, with each frequency presented for 2 s.

Table 1. Command–subfrequency mapping for the AFFP and DFFP stimulation patterns.

Command	AFFP	DFFP
1	f_i	$f_i + 0.8$
2	$f_i + 0.2$	$f_i + 0.6$
3	$f_i + 0.4$	$f_i + 0.4$
4	$f_i + 0.6$	$f_i + 0.2$
5	$f_i + 0.8$	f_i

Note: denotes the fundamental frequency, where $f_i \in \{6, 7, 8, 9, 10\}$ Hz for the low-frequency range and $f_i \in \{41, 42, 43, 44, 45\}$ Hz for the high-frequency range. AFFP, ascending-frequency flicker pattern; DFFP, descending-frequency flicker pattern.

Three frequency-modulation conditions were established: (1) conventional fixed-frequency flicker, (2) ascending-frequency flicker pattern (AFFP), and (3) descending-frequency flicker pattern (DFFP). For the AFFP and DFFP, the frequency was adjusted in 0.2 Hz steps every 2 s. These values were prespecified as exploratory design parameters for examining the offline detectability of closely spaced frequency states within a 10 s trial. No preliminary experiment was conducted to optimize either the frequency increment or the epoch duration, and the present experiment did not estimate the time required for the SSVEP response to stabilize after each frequency transition. Accordingly, the 2 s interval should be regarded as an analysis epoch rather than a theoretically or empirically optimized control interval. However, detecting 0.2 Hz changes within short EEG segments is challenging because conventional frequency-domain methods have limited resolution and cannot adequately capture the temporal direction of AFFP and DFFP sequences. Therefore, correlation-based and time–frequency analysis methods were applied for classification. For example, in the ascending condition, the frequency increased from 6.0 to 6.8 Hz, whereas in the descending condition, it decreased from 6.8 to 6.0 Hz (Figure 1c). The command–

frequency mapping for Commands 1–5 is summarized in Table 1. Three label levels were distinguished in the subsequent analyses. The fundamental frequency label identified one to five visual targets within each frequency range. The subfrequency label identified one of the five frequencies separated by 0.2 Hz within the selected fundamental frequency group. The command label represented the ordinal position within the AFFP or DFFP sequence. For AFFP, Command c corresponded to $f_i + 0.2(c - 1)$, whereas for DFFP, it corresponded to $f_i + 0.2(5 - c)$, where $c \in \{1, 2, 3, 4, 5\}$. Therefore, the 100 condition–command combinations, obtained from five fundamental frequencies, five command positions, two sequence directions, and two frequency ranges, were experimental instances rather than 100 classification classes. In the present offline experiment, Commands 1–5 were abstract ordinal class labels corresponding to the five subfrequency positions within each AFFP or DFFP sequence. They were not assigned to movement directions, speed levels, movement amplitudes, control gains, or other implemented device-control variables.

The staircase design was intended to determine whether each 2 s frequency step could elicit a time-localized, frequency-specific response suitable for ordinal command mapping, rather than to improve classification accuracy. The one-sided range from f_i to $f_i + 0.8$ Hz was selected so that AFFP and DFFP used the same five frequencies in opposite orders while retaining f_i as the lower anchor. Because frequencies below f_i were not evaluated, the present study cannot determine whether a symmetric frequency range would provide better detection performance.

In this study, the term “subfrequency” denotes one of the five nominal flicker frequencies separated by 0.2 Hz within a selected fundamental frequency group; it does not refer to a physiological subharmonic. For each high-frequency group, the subfrequencies ranged from f_i to $f_i + 0.8$ Hz. Conventional harmonic components were defined only as integer multiples of the presented frequency. Therefore, spectral components in the 6–10 Hz range were not treated as harmonics of the 41–45 Hz stimuli or as evidence of high-frequency SSVEP frequency locking.

2.2. EEG Acquisition

This study included 15 volunteers (5 males and 10 females) aged 19–21 years. All participants had normal or corrected-to-normal vision and reported no ocular conditions that could affect responses to visual stimuli. They also reported no history of neurological disorders or migraines. All volunteers received a detailed explanation of the experimental procedures and provided written informed consent before participation. This study complied with human research regulations and was reviewed and approved by the Human Research Ethics Committee of Walailak University (Project No. WU-EC-IN-1-402-67; Approval No. WUEC-24-413-01; approval date: 19 December 2024). All methods adhered to the Declaration of Helsinki, CIOMS guidelines, and WHO standards to safeguard participant rights, safety, and dignity. All participant data were kept confidential, and no names or identifiable information was disclosed at any stage of the study.

EEG signals were recorded from O1 and O2 using an Electro-Cap (Electro-Cap International, Inc., Eaton, OH, USA) with recessed pure tin electrodes mounted in elastic fabric and arranged according to the international 10–20 system. The cap size was selected according to each participant’s head size to provide an appropriate fit. The cap is designed for gel-based EEG recording. Data were acquired using a BIOPAC MP160 data-acquisition system equipped with a BioNomadix two-channel wireless EEG amplifier (BIOPAC Systems, Inc., Goleta, CA, USA). The BioNomadix system consisted of a matched wireless transmitter and receiver for two-channel EEG recording. O1 and O2 were selected to capture bilateral occipital responses and were referenced to A1 and A2, respectively, while Fz served as the ground electrode. Oz and additional parietal–occipital channels were not

recorded; therefore, the present study does not determine whether a broader electrode montage would improve classification performance. Electrode impedance values were not systematically recorded. The EEG signals were transmitted wirelessly to the BioNomadix receiver connected to the MP160 system and recorded using AcqKnowledge software (version 5.0; BIOPAC Systems Inc., Goleta, CA, USA) at a sampling rate of 2000 Hz. Signals were band-limited to 0.1–100 Hz during acquisition, and a 50 Hz notch filter was applied to attenuate power-line interference. No automated artifact-rejection or epoch-exclusion procedure was applied; all the recorded stimulation epochs were retained. The original sampling rate of 2000 Hz was retained throughout the analysis, and no downsampling or additional re-referencing was performed. Retaining the native sampling rate avoided an additional resampling step and preserved the original sample representation across all the signal-processing methods. This rate exceeded that required to represent the analyzed 0.1–100 Hz bandwidth and increased the data volume and computational demands. It did not improve the intrinsic frequency resolution of a fixed 2 s observation interval. The present study does not establish a classification advantage of retaining 2000 Hz over appropriately downsampled data.

2.3. Experiment

The experiments were conducted in a controlled environment with uniform lighting to minimize external effects on visual perception. The participants were seated comfortably facing an LCD monitor displaying the stimuli at a distance of approximately 60 cm, ensuring a consistent and optimal viewing angle for all participants. The experimental setup is shown in Figure 2.

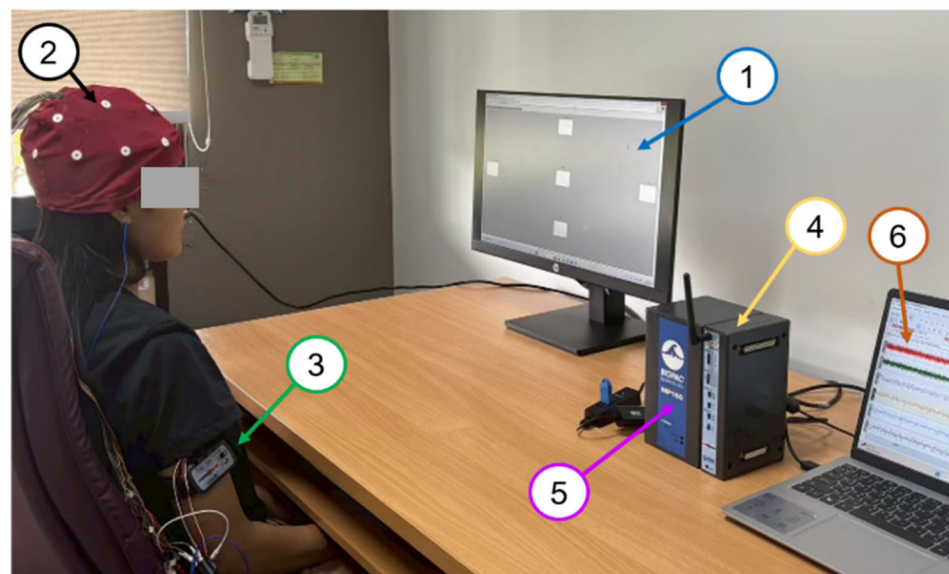


Figure 2. Experimental setup. (1) Desktop screen for visual stimuli; (2) EEG electrode cap; (3) BioNomadix wireless EEG transmitter; (4) BioNomadix wireless EEG receiver; (5) BIOPAC MP160 data-acquisition system; and (6) AcqKnowledge software for EEG recording.

Three stimulation conditions were evaluated separately within each frequency range. Each trial consisted of a 10 s baseline period, a 10 s visual stimulation period, and a 1 min rest interval. During the baseline period, the participants viewed a blank wall under the same ambient-lighting conditions used during stimulation. This baseline was selected to minimize periodic visual input and provide a non-flickering reference for baseline normalization. However, the blank-wall condition was not luminance-matched or visually equivalent to the active LCD stimulation condition.

In the fixed-frequency condition, five trials were conducted for each of the five fundamental frequencies, resulting in 25 trials per frequency range. In the AFFP condition, the 10 s stimulation period consisted of five consecutive 2 s epochs in which the frequency increased in 0.2 Hz steps. Five trials were conducted for each fundamental frequency, resulting in 25 AFFP trials per frequency range. In the DFFP condition, the same five subfrequencies were presented in the reverse order, and five trials were conducted for each fundamental frequency, resulting in 25 DFFP trials per frequency range. Therefore, each participant completed 75 stimulation trials per frequency range and 150 trials across the low- and high-frequency ranges. The numbers of repetitions were equal across the fixed-frequency, AFFP, and DFFP conditions. The 10 s stimulation duration resulted directly from concatenating five 2 s frequency epochs to form one complete staircase. It was selected for the offline characterization of all five frequency states and was not intended to represent an optimized trial duration for rapid online BCI operation.

For analysis, each 10 s stimulation period was divided into five non-overlapping 2 s epochs. In the fixed-frequency condition, all five epochs retained the same fundamental frequency label, and no subfrequency or command labels were assigned because the stimulation frequency remained constant throughout the trial. In the AFFP and DFFP conditions, the fundamental frequency label also remained constant throughout the trial, whereas the subfrequency and command labels changed every 2 s according to the order-specific mapping in Table 1. Accordingly, the fixed-frequency, AFFP, and DFFP conditions were compared at the fundamental frequency level, whereas command-level analysis was performed only for the AFFP and DFFP conditions.

After completing the low-frequency session, participants completed a 10 min eye-rest period before proceeding to the high-frequency session. The complete experimental protocol, including the fixed-frequency, AFFP, and DFFP conditions, was then repeated for the high-frequency range (41–45 Hz). The frequency-range order was therefore not randomized or counterbalanced. Within each frequency-range session, the three stimulation patterns were presented in the fixed order of fixed-frequency, AFFP, and DFFP, and this order was also not randomized or counterbalanced. The same experimental structure was used for both frequency ranges.

Trial Segmentation and Data Organization

The EEG signals were retained at the original sampling rate of 2000 Hz, and no downsampling was applied. Each 10 s stimulation period was segmented into five non-overlapping 2 s epochs; therefore, each epoch contained 4000 temporal samples per channel. Thus, the counts reported in Section 2.3 refer to complete experimental trials, whereas the counts reported below refer to analysis epochs, with five epochs obtained from each trial. Each EEG epoch was represented as a $[4000 \times 2]$ array, where the first dimension represents the temporal samples and the second dimension represents channels O1 and O2. Based on the trial structure, the fixed-frequency, AFFP, and DFFP conditions each produced 125 epochs per frequency range. Therefore, 375 epochs were obtained per frequency range, resulting in 750 epochs for each participant across the low- and high-frequency ranges. The resulting data tensor was organized as $[4000 \times 2 \times 375]$ for each frequency range or $[4000 \times 2 \times 750]$ when both frequency ranges were combined. The third dimension represents the analyzed EEG epochs rather than the number of classification classes. All epochs were accompanied by labels identifying the participant, frequency range, stimulation pattern, fundamental frequency, and trial repetition. Subfrequency and command labels were additionally assigned only to the AFFP and DFFP epochs; no command-level label was assigned to the fixed-frequency epochs.

2.4. Evaluated Signal-Processing Methods

To evaluate the effectiveness of brain signal analysis methods in response to multilevel flicker stimuli with frequencies changing in discrete steps every 2 s, eight established signal-processing and classification methods were grouped into two analytical categories: spectral analysis and correlation analysis. Spectral analysis comprised fast Fourier transform (FFT), Welch-based power spectral density (PSD), dynamic PSD, short-time Fourier transform (STFT), continuous wavelet transforms (CWT), and discrete wavelet transform (DWT), whereas correlation analysis comprised canonical correlation analysis (CCA) and filter bank canonical correlation analysis (FBCCA) [19,46,47]. The spectral-analysis methods were used to characterize the frequency-domain power and temporal variations in the spectral components, while the correlation-analysis methods evaluated frequency-specific relationships between the multichannel EEG signals and artificial reference signals. These complementary methods enabled a systematic comparison of the fundamental and harmonic SSVEP responses elicited by the conventional, AFFP, and DFFP stimuli.

2.4.1. Spectral Analysis

Spectral analysis was performed using six complementary methods: FFT, PSD, dynamic PSD, STFT, CWT, and DWT. FFT and Welch-based PSD were employed as conventional frequency-domain methods for estimating the spectral power, whereas dynamic PSD, STFT, CWT, and DWT were used to characterize temporal changes in the spectral components across the sequential frequency-modulation intervals. The formulation and application of each method are described in the following subsections.

Fast Fourier Transform (FFT)

The fast Fourier transform (FFT) was employed as a conventional frequency-domain method for identifying the spectral components of the EEG signals [19]. For an EEG segment $x[n]$ containing L samples, the FFT-based spectral power at the k -th frequency bin was calculated as follows:

$$P_{FFT}(f_k) = \frac{1}{L} \left| \sum_{n=0}^{L-1} x[n] \exp\left(-j \frac{2\pi kn}{N_{FFT}}\right) \right|^2, \quad f_k = \frac{kF_s}{N_{FFT}}, \quad (1)$$

where $P_{FFT}(f_k)$ denotes the spectral power at frequency f_k , F_s is the sampling frequency, N_{FFT} is the FFT length, and $j = \sqrt{-1}$. When $N_{FFT} > L$, zero-padding was applied before FFT computation. The spectral power at the candidate fundamental frequencies and their harmonic components was subsequently normalized relative to baseline activity. For the AFFP and DFFP conditions, the FFT was applied separately to each sequential frequency-modulation interval.

Power Spectral Density (PSD)

Power spectral density (PSD) was estimated using Welch's method to reduce the variance of the spectral estimate [46]. Each analysis window was divided into K overlapping segments, each containing L_w samples. The r -th segment was multiplied by a window function $w[n]$, and the resulting modified periodograms were averaged as follows:

$$\hat{P}_{Welch}(f_k) = \frac{1}{KF_s U} \sum_{r=1}^K \left| \sum_{n=0}^{L_w-1} x_r[n] w[n] \exp\left(-j \frac{2\pi kn}{N_{FFT}}\right) \right|^2, \quad (2)$$

where

$$U = \sum_{n=0}^{L_w-1} w^2[n] \quad (3)$$

Here, $x_r[n]$ denotes the EEG samples in the r -th segment, K is the total number of overlapping segments, L_w is the segment length, and U is the window-power normalization factor. Averaging the modified periodograms reduces the estimation variance, whereas the window function reduces spectral leakage. The resulting PSD values at the fundamental and harmonic frequencies were used for baseline normalization and subsequent SSVEP response analysis.

Dynamic Power Spectral Density (Dynamic PSD)

Dynamic power spectral density (dynamic PSD) was employed to characterize temporal changes in the spectral power of the EEG signals [46,48]. It was implemented as a time-indexed extension of the Welch PSD described in Equations (2) and (3). The EEG signal was divided into (Q) consecutive analysis windows, and the Welch PSD was calculated separately for each window. The dynamic PSD was defined as

$$P_{DPSD}(f, t_q) = \hat{P}_{Welch}^{(q)}(f), \quad q = 1, 2, \dots, Q \quad (4)$$

where $P_{DPSD}(f, t_q)$ denotes the dynamic PSD at frequency f for the q -th analysis window; $\hat{P}_{Welch}^{(q)}(f)$ represents the Welch PSD estimated from the EEG samples within that window; t_q is the temporal position of the q -th window; q is the analysis-window index; and Q is the total number of analysis windows. The superscript (q) indicates the corresponding analysis window and does not represent an exponent.

Short-Time Fourier Transform (STFT)

STFT was employed to analyze the temporal evolution of spectral components in nonstationary EEG signals [49]. The signal was segmented into short time windows, and a Fourier transform was applied to each segment to obtain localized frequency information. This approach enables the tracking of neural responses across dynamically varying stimulation frequencies. The calculation is defined as follows:

$$X_{stft} = \sum_{n=-\infty}^{\infty} x(n)w(n-t)e^{-j2\pi fn} \quad (5)$$

where $X_{stft}(t, f)$ represents the time–frequency spectrum at time t and frequency f , $x(n)$ denotes the original EEG signal, $w(n-t)$ is the window function centered at time t , and $e^{-j2\pi fn}$ is the complex exponential used to extract the frequency component. The summation over n represents the Fourier transform of each windowed segment, resulting in a time-varying spectral representation of the signal.

For implementation, STFT was computed separately for O1 and O2 using a Hann window of 1.5 s (3000 samples at 2000 Hz), with 90% overlap (2700 samples) and a hop size of 0.15 s (300 samples). A 16,384-point FFT was used, yielding a frequency-bin spacing of approximately 0.1221 Hz. Each frame was mean-centered, and a one-sided transform with power-spectral-density scaling was calculated. Signal-boundary extension and end padding to complete additional frames were disabled. The FFT-bin spacing reflects the zero-padded frequency grid; the resolving capability remains constrained by the 1.5 s window and its spectral characteristics.

Continuous Wavelet Transform (CWT)

The continuous wavelet transform (CWT) [50–52] was used to analyze the time–frequency characteristics of the recorded signals. Unlike the Fourier transform, which relies on sinusoidal basis functions, the CWT employs wavelet functions that are scaled and shifted, enabling simultaneous localization in both the time and frequency domains.

This property allows the effective detection of transient features and rapidly changing signal components, making it suitable for capturing abrupt responses, particularly at higher frequencies. The CWT is defined as follows:

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (6)$$

where $W(a, b)$ represents the wavelet coefficient at scale a and translation b , characterizing the signal in the time–scale domain. The term $x(t)$ denotes the input signal, and $\psi^* \left(\frac{t-b}{a} \right)$ is the complex conjugate of the scaled and shifted mother wavelet. The scale parameter a controls the frequency resolution, while the translation parameter b determines the temporal localization. The factor $\frac{1}{\sqrt{a}}$ preserves the signal energy across scales, and the integral quantifies the correlation between the signal and the wavelet function.

CWT was implemented using a complex Morlet wavelet with a dimensionless central-frequency parameter of $\omega_0 = 6$. For each evaluated frequency f , the discrete scale in samples was calculated as $s_f = \frac{\omega_0 F_s}{2\pi f}$, where $F_s = 2000$ Hz. Each wavelet kernel was normalized to unit energy and truncated at approximately ± 4 Gaussian temporal standard deviations. The target frequencies comprised the predefined candidates within 6.0–10.8 Hz and 41.0–45.8 Hz, together with their selected harmonic components below 100 Hz. Reflection padding was applied during convolution, and 0.15 s was excluded from each end before score aggregation. Scales were evaluated at the required frequencies rather than on a uniformly spaced scale grid. The nominal power-response bandwidth of the underlying Morlet wavelet is frequency-dependent, with an approximate full width at half maximum of $\frac{2\sqrt{\ln(2)f}}{\omega_0}$. Thus, the 0.2 Hz spacing between candidate frequencies represents the spacing of evaluation points and does not imply a CWT-resolving capability of 0.2 Hz.

Discrete Wavelet Transform (DWT)

Discrete wavelet transforms (DWTs) are used to analyze the time–frequency components of an EEG signal by separating the signal into multiple resolution components using low-pass and high-pass filters. Compared to CWTs, which are calculated from a continuous scale and position, they reduce data redundancy and computational load, making them suitable for analyzing EEG signals over short time intervals [50]. DWT can be represented by the following equation:

$$a_j[k] = \sum_n a_{j-1}[n]h[n-2k], \quad d_j[k] = \sum_n a_{j-1}[n]g[n-2k] \quad (7)$$

where $a_j[k]$ and $d_j[k]$ are the estimation and detail coefficients at the j level, respectively, and $h[n]$ and $g[n]$ are the low-pass and high-pass filters, respectively. In this study, wavelet levels covering the main excitation frequency and harmonic components were selected, and the power of the coefficients was then calculated to estimate the SSVEP response at each time interval. However, because the DWT divides the signal into bands, spectral analysis of the wavelet-reverse coefficient signal was used to help identify subfrequencies that change by 0.2 Hz increments.

2.4.2. Correlation Analysis

Correlation analysis was performed using CCA and FBCCA to detect SSVEP responses by measuring the frequency-specific relationships between the multichannel EEG signals and artificial reference signals. CCA was employed as a training-free correlation-based method, whereas FBCCA extended CCA by integrating correlation information obtained

from multiple frequency subbands. The formulation and application of each method are described in the following subsections.

Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) was employed as a training-free method for detecting SSVEP responses by measuring the correlation between multichannel EEG signals and artificial reference signals at each candidate frequency [15,19]. For an EEG matrix $M \in \mathbb{R}^{C \times L}$, the reference-signal matrix $N_f \in \mathbb{R}^{2H \times L}$ was constructed as follows:

$$N_f = \begin{bmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \\ \vdots \\ \sin(2\pi Hft) \\ \cos(2\pi Hft) \end{bmatrix}, t = \left[0, \frac{1}{F_s}, \dots, \frac{L-1}{F_s}\right], \quad (8)$$

where C , L , H , and F_s denote the number of EEG channels, samples, harmonics, and sampling frequency, respectively. The canonical correlation coefficient was calculated as follows:

$$\rho_f = \max_{w_M w_N} \frac{w_M^T M N_f^T w_N}{\sqrt{(w_M^T M M^T w_M) (w_N^T N_f N_f^T w_N)}}, \quad (9)$$

where w_M and w_N are the canonical weight vectors. The detected frequency was determined by the following:

$$\hat{f}_{CCA} = \operatorname{argmax}_{f \in F} \rho_f \quad (10)$$

where F is the set of candidate frequencies. For the AFFP and DFFP conditions, CCA was applied to each analysis window corresponding to the 0.2 Hz sequential frequency-modulation intervals.

Filter Bank Canonical Correlation Analysis (FBCCA)

Filter bank canonical correlation analysis (FBCCA) extends CCA by decomposing the EEG signals into multiple frequency subbands, allowing the fundamental and harmonic SSVEP components to be jointly considered [19,30]. The EEG matrix in the k -th subband was defined as follows:

$$M_k = B_k\{M\}, \quad k = 1, 2, \dots, K, \quad (11)$$

where $B_k\{\cdot\}$ denotes the corresponding band-pass filter and K is the number of subbands. The canonical correlation coefficient $\rho_{f,k}$ between M_k and N_f was calculated for each candidate frequency and combined as follows:

$$S_f^{FBCCA} = \sum_{k=1}^K \alpha_k \rho_{f,k}^2, \quad \alpha_k = k^{-a} + b, \quad (12)$$

where α_k is the subband weight. The conventional parameters $a = 1.25$ and $b = 0.25$ assign greater weights to the lower-order subbands. The detected frequency was obtained from the following:

$$\hat{f}_{FBCCA} = \operatorname{argmax}_{f \in F} S_f^{FBCCA}, \quad (13)$$

For the AFFP and DFFP conditions, the FBCCA score was evaluated separately within each sequential frequency-modulation interval.

2.4.3. Spectral Power Normalization and Harmonic Response Scoring

For the spectral power-based methods, including FFT, PSD, dynamic PSD, STFT, CWT, and DWT, the spectral power at each stimulation frequency was computed and normalized relative to baseline activity. The relative power variation was defined as follows:

$$\Delta P_i(f, t) = \frac{P_i(f, t_i) - P_i(f, t_b)}{P_i(f, t_b)} \quad (14)$$

where $\Delta P_i(f, t)$ denotes the relative change in spectral power at frequency f and time t corresponding to the i -th target frequency. $P_i(f, t)$ represents the spectral power at the i -th target stimulation frequency during the task condition, while $P_i(f, t_b)$ denotes the spectral power during the resting-state (baseline) period. This normalization quantifies the stimulus-induced modulation of the target frequency component relative to baseline activity and reduces intersubject variability.

To enhance the robustness of classification, the response value was computed by incorporating the spectral responses of the fundamental frequency and its harmonic components. The response score $R(v)$ for each stimulation frequency v is defined as follows:

$$R(v) = \sum_{h=1}^H w_h \Delta P(hv) \quad (15)$$

where $\Delta P(hv)$ represents the normalized spectral power variation at the h -th harmonic of the stimulation frequency v , H is the number of harmonics considered, and w_h is the weighting coefficient for the h -th harmonic component.

The implemented harmonic response score did not use a single fixed number of harmonic components. For each outer test round, H was selected from $H \in \{1, 2, 3, 4, 5\}$ using the remaining rounds, while the test round was excluded from parameter selection. Only harmonic components within the recorded 0.1–100 Hz bandwidth were retained. Consequently, the selected number of harmonics ranged from one to five for the low-frequency candidates and from one to two for the high-frequency candidates. The harmonic components were weighted according to the normalized inverse-harmonic rule:

$$w_h = \frac{h^{-1}}{\sum_{r=1}^H r^{-1}} \quad (16)$$

For $H = 2$, the weights were $w_1 = 0.667$ and $w_2 = 0.333$. For the maximum setting of $H = 5$, the weights were $w_1 = 0.438$, $w_2 = 0.219$, $w_3 = 0.146$, $w_4 = 0.109$, and $w_5 = 0.088$. For the high-frequency candidates, the conventional second-harmonic components occurred approximately within 82–91.6 Hz, depending on the corresponding subfrequency. Components in the 6–10 Hz range were not included as harmonics of the 41–45 Hz stimuli.

A participant- and frequency-specific detection threshold was calculated from frequency-matched baseline scores. Baseline windows were advanced at 0.25 s intervals, and leave-one-out baseline response scores were calculated for each candidate frequency. The detection threshold was defined as the 95th percentile of the resulting baseline-score distribution:

$$\theta_v = Q_{0.95} \left(\{R_b(v, j)\}_{j=1}^B \right) \quad (17)$$

where $R_b(v, j)$ denotes the baseline response score for candidate frequency v in baseline window j , and B is the number of baseline windows. The selected response was accepted when $R(v^*) \geq \theta_{v^*}$; otherwise, the output was assigned to the idle state.

2.4.4. Dominant Fundamental Frequency Detection

Figure 3 illustrates the two-stage SSVEP decoding framework, comprising fundamental-frequency selection, subfrequency selection, command mapping, and threshold validation. Fundamental frequency classification was performed on each 2 s EEG epoch, yielding five predictions per 10 s stimulation trial. For each epoch, the fundamental frequency group with the highest response score was selected. The fundamental frequency and command-level performance were evaluated separately; the predicted fundamental frequency group was not used to calculate the command-level accuracy.

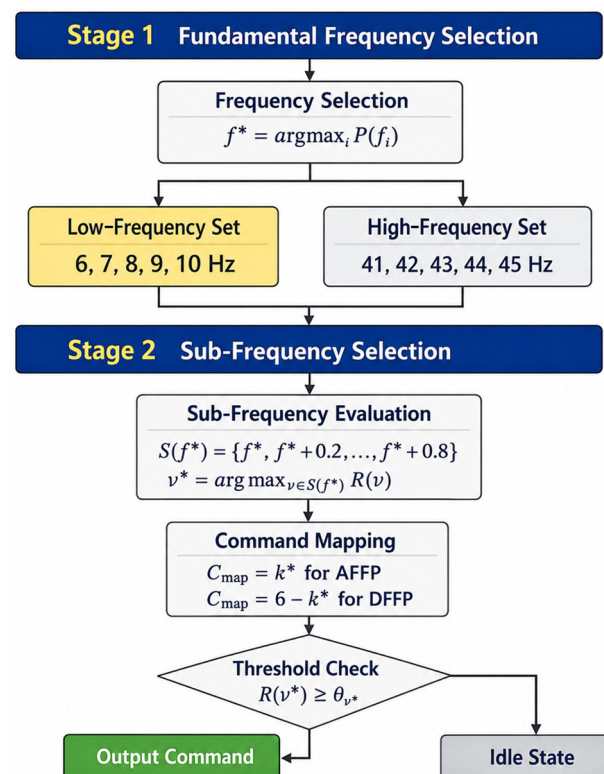


Figure 3. Two-stage SSVEP decoding framework for the proposed sequential frequency-modulated visual flicker paradigm. Fundamental frequency and command-level performance were evaluated separately, with command-level accuracy calculated within the ground-truth fundamental frequency group. The asterisk (*) denotes the selected fundamental frequency (f^*), subfrequency (v^*), or subfrequency index (k^*).

Let $F = \{f_1, f_2, \dots, f_M\}$ denote the set of candidate fundamental frequencies, where M represents the total number of fundamental frequencies considered in the stimulus set. For each fundamental frequency f_i , a set of subfrequencies is defined as follows:

$$S(f_i) = \{f_i + \delta_k | k = 1, 2, \dots, 5\} \quad (18)$$

where $\delta_k \in \{0, 0.2, 0.4, 0.6, 0.8\}$ represents the frequency modulation offsets. For each fundamental frequency f_i , five subfrequencies were generated with a modulation step of 0.2 Hz. In the AFFP, the frequencies increase sequentially from f_i to $f_i + 0.8$, whereas in the DFFP, the order of the same subfrequencies is reversed. The mapping between the fundamental frequencies, subfrequencies, and commands used in the AFFP and DFFP paradigms is summarized in Table 1.

The response score of each fundamental frequency is obtained as follows:

$$P(f_i) = \max_{v \in S(f_i)} R(v) \quad (19)$$

The dominant fundamental frequency is obtained as follows:

$$f^* = \operatorname{argmax}_{f_i \in F} (P(f_i)), \quad (20)$$

where f^* denotes the fundamental frequency that produces the strongest SSVEP response.

2.4.5. Subfrequency Detection

For command-level evaluation, the fundamental frequency group was fixed to the ground-truth group specified by the experimental label, denoted by f_{true} . Within each 2 s epoch, the subfrequency with the highest response score among the five candidates in this group was selected using

$$v^* = \operatorname{argmax}_{v \in S(S_{f_{true}})} R(v) \quad (21)$$

Let $k^* \in \{1, 2, 3, 4, 5\}$ denote the index of the selected subfrequency. The output command (C_{out}) is then determined as

$$C_{map} = \begin{cases} k^*, & AAFP, \\ 6 - k^*, & DFFP \end{cases} \quad (22)$$

where k^* denotes the index of the detected subfrequency when the five subfrequencies are arranged in ascending order. The order-specific mapping converts this subfrequency index into the corresponding command label. Therefore, the same detected subfrequency produces different command labels under AAFP and DFFP, as specified in Table 1.

2.4.6. Output Command

To prevent false detections, the decision result is validated using a predefined baseline threshold θ :

$$C_{out} = \begin{cases} C_{map}, & R(v^*) \geq \theta_{v^*} \\ idle, & R(v^*) < \theta_{v^*} \end{cases} \quad (23)$$

where θ_{v^*} denotes the participant- and frequency-specific detection threshold corresponding to the selected candidate frequency v^* . The threshold was defined as the 95th percentile of the frequency-matched leave-one-out baseline-score distribution.

The final decision is translated into the corresponding control command (Table 1) based on a predefined command-mapping scheme:

If $C_{out} = 1$,	the decision is Command 1.
If $C_{out} = 2$,	the decision is Command 2.
If $C_{out} = 3$,	the decision is Command 3.
If $C_{out} = 4$,	the decision is Command 4.
If $C_{out} = 5$,	the decision is Command 5.
Otherwise,	the decision is Idle.

2.4.7. Implementation Parameters and Frequency-Resolution Consideration

To ensure a consistent comparison, all the signal-processing methods were applied to the same EEG channels, preprocessing procedure, and trial segments. The EEG signals were retained at the original sampling rate of 2000 Hz without downsampling. Each nominal 2 s epoch therefore contained 4000 samples per channel. The method-specific processing and classification settings are summarized in Table 2.

Table 2. Parameter settings used for signal-processing and frequency-tracking evaluation.

Method	Parameter Setting
Common settings	Sampling rate: 2000 Hz; no downsampling; epoch: 2 s (4000 samples/channel); tested latency: 0–0.3 s; effective window: 1.7–2.0 s; baseline stride: 0.25 s; harmonics: 1–5 for low frequencies and 1–2 for high frequencies.
FFT	FFT-based spectral power, expressed in dB.
PSD	Power spectral density, expressed in dB.
Dynamic PSD	Baseline-calibrated dynamic spectral power, expressed in dB.
STFT	Hann window: 1.5 s (3000 samples); overlap: 90% (2700 samples); hop: 0.15 s; FFT size: 16,384 points; frequency-bin spacing: approximately 0.1221 Hz; one-sided transform with PSD scaling.
CWT	Complex Morlet wavelet, $\omega_0 = 6$; frequency-dependent scales $s_f = \frac{\omega_0 F_s}{2\pi f}$; unit-energy kernels with approximately ± 4 -standard-deviation support; candidate frequencies and selected harmonics below 100 Hz; reflection padding; edge exclusion: 0.15 s at each end.
DWT	Wavelet-packet spectral power, expressed in dB.
CCA	Squared canonical correlation used as the response score.
FBCCA	Weighted squared canonical correlation used as the response score.
Classification decision	The label with the highest response score was selected. An output below the baseline threshold was assigned as idle.
Accuracy	A prediction was correct when it matched the ground-truth label; idle outputs during stimulation were incorrect. Accuracy was calculated as $\frac{N_{correct}}{N_{total}} \times 100$.
Consecutive commands	A sequence of m commands was considered correct only when all commands were detected correctly and in order, where $m \in \{3, 4, 5\}$.

Classification was implemented by calculating frequency-specific response scores and applying a predefined decision rule to each nominal 2 s epoch. The spectral methods produced response scores for the candidate frequencies, whereas CCA and FBCCA evaluated correlations with analytically generated sinusoidal reference signals. No separate supervised classifier was fitted to labeled EEG epochs. Nevertheless, data-dependent selection of the response latency and number of harmonics required separation between parameter-selection and test data.

For analyses involving parameter selection, a within-participant leave-one-round-out procedure was used separately for each signal-processing method, frequency range, and stimulation pattern. A round comprised trials sharing the same repetition index within the corresponding condition. In each iteration, one complete round was reserved for testing, and the remaining rounds were used to select the latency and harmonic count from the settings summarized in Table 2. All five epochs from a given 10 s trial remained in the same partition. Parameter combinations were ranked by the minimum target-detection rate, followed by the mean target-detection rate and median score margin on the parameter-selection data. The selected settings were then applied to the held-out round. Detection thresholds were obtained from the corresponding resting-state baseline recordings, as described in Section 2.4.3; held-out stimulation epochs were excluded from parameter selection and threshold estimation.

For each test epoch, the candidate with the highest response score was mapped to the corresponding label using the decision rules in Sections 2.4.4–2.4.6. An output that did not satisfy the baseline threshold was assigned to the idle state. The procedure was repeated until every round had served as the test round. Predictions from the held-out rounds were pooled to calculate accuracy separately for each participant and condition, following Section 2.5, before averaging across participants. This evaluation therefore assessed participant-specific offline performance with baseline calibration.

The nominal 2 s observation interval provides an intrinsic Rayleigh frequency resolution of approximately ($1/T = 0.5$) Hz. Therefore, the 0.2 Hz difference between adjacent

AFFP and DFFP frequencies should be interpreted as the programmed spacing between predefined stimulus and command labels rather than as independent Fourier frequency resolution. The reported classification accuracy consequently represents the ability of the evaluated methods to assign the EEG responses to the correct predefined label under the experimental conditions.

2.5. Classification Tasks and Accuracy Calculation

The analyses were divided into two classification tasks. First, fundamental frequency classification was performed separately within the low- and high-frequency ranges. The low-frequency task contained five classes labeled 6, 7, 8, 9, and 10 Hz, whereas the high-frequency task contained five classes labeled 41, 42, 43, 44, and 45 Hz. Thus, each frequency range analysis was a five-class problem rather than a ten-class or 100-class problem. For the fixed-frequency condition, the true fundamental frequency label remained constant throughout the trial. For AFFP and DFFP, the fundamental frequency label also remained constant, although the presented subfrequency changed every 2 s.

Second, command-level classification was performed conditionally within each known fundamental frequency group for the AFFP and DFFP conditions. The fundamental frequency group was specified from the experimental label and was not reclassified during this analysis. Within that group, one of the five subfrequencies was detected and converted into Commands 1–5 according to the order-specific mapping in Table 1. Consequently, command-level accuracy reflects subfrequency/command discrimination within a known fundamental frequency group and does not include errors from fundamental frequency classification.

$$Accuracy(\%) = \frac{N_{correct}}{N_{total}} \times 100 \quad (24)$$

To ensure a comparable evaluation, the fixed-frequency, AFFP, and DFFP conditions were compared only in the five-class fundamental frequency classification task within each frequency range. The same five fundamental frequency labels, 2 s analysis-epoch duration, EEG channels, and signal-processing methods were used for all three conditions. The fixed-frequency condition was not included in the command-level comparison because it contained neither sequential subfrequency changes nor command positions.

A prediction was considered correct when the predicted label matched the corresponding ground-truth label. For fundamental frequency analysis, $N_{correct}$ was the number of epochs assigned to the correct fundamental frequency class. For command-level analysis, it was the number of AFFP or DFFP epochs assigned to the correct command label. An idle output during a stimulation epoch was counted as an incorrect prediction. Accuracy was calculated separately for each participant and experimental condition before averaging across the 15 participants. Because both fundamental frequency and command-level classification involved five classes, the theoretical chance level for single-epoch classification was 20%. For complete consecutive command sequences, assuming independent and uniformly random predictions, the chance level was $\left(\frac{1}{5}\right)^m \times 100$, corresponding to 0.80%, 0.16%, and 0.032% for sequences containing three, four, and five commands, respectively.

In addition to classification accuracy, an offline theoretical information transfer rate (ITR) was estimated to provide a complementary measure of classification efficiency [53]. For an N -class classification task with classification accuracy P , the information transferred per decision was calculated as follows:

$$B = \log_2 N + P \log_2 P + (1 + P) \log_2 \left(\frac{1 - P}{N - 1} \right) \quad (25)$$

where B denotes the information transferred per decision in bits, N is the number of possible classes, and P is the classification accuracy expressed as a proportion. The corresponding ITR was calculated as follows:

$$ITR = \frac{60}{T} B \quad (26)$$

where T is the decision time in seconds. In the present study, $N = 5$ and $T = 2$ s, corresponding to the five-class classification task and the duration of each analysis epoch. The resulting values therefore represent theoretical offline ITR estimates rather than measured online BCI communication rates.

For the AFFP and DFFP conditions, the command labels occurred in a predetermined temporal sequence rather than being independently selected by the participant. Therefore, the assumptions of conventional selection-based online ITR were not fully satisfied. In addition, each experimental trial required 80 s, comprising a 10 s baseline period, a 10 s stimulation period, and a 60 s rest interval. Because the 10 s stimulation period contained five labeled 2 s epochs, the experimental presentation rate was 3.75 labeled epochs/min. This value is reported as a description of the experimental protocol and should not be interpreted as conventional online BCI ITR.

3. Experimental Results

The experimental results were evaluated at three complementary levels. First, fundamental frequency classification performance was examined as a five-class problem across the signal-processing methods, frequency ranges, and stimulation patterns. Second, command-level classification performance was evaluated for the AFFP and DFFP conditions within each fundamental frequency group, with the five subfrequencies representing five command labels. Third, the ability to detect ordered sequences containing three, four, and five consecutive commands was assessed. The combinations of stimulation condition, fundamental frequency, subfrequency, and command position were used to organize the experimental data and were not treated as separate classification classes.

3.1. Comparison of Signal-Processing Methods and Stimulation Patterns

This section presents the results in three parts to assess the effectiveness of the visual stimulus patterns and classification methods.

First, Figure 4 compares the classification accuracy obtained using FFT, PSD, CCA, FBCCA, dynamic PSD, STFT, CWT, and DWT across the low-frequency (6–10 Hz) and high-frequency (41–45 Hz) ranges. Overall, most methods exhibited higher median accuracy under low-frequency stimulation than under high-frequency stimulation. FFT, PSD, CCA, FBCCA, dynamic PSD, STFT, and CWT achieved relatively high performance in the low-frequency range, whereas DWT showed lower accuracy than the other methods. In the high-frequency range, STFT provided the highest median accuracy and a relatively consistent distribution. In contrast, CWT exhibited a wider distribution across subjects, indicating greater intersubject variability at high stimulation frequencies. These findings demonstrate that the performance of each classification method varied according to the stimulation-frequency range.

Second, Figure 5 compares the five-class fundamental frequency classification accuracy obtained using the eight signal-processing methods was compared among the fixed-frequency, AFFP, and DFFP stimulation patterns. Descriptive variation was observed among the three stimulation patterns across individual methods; however, no consistent directional pattern was evident. The statistical analysis showed no significant main effect of the stimulation pattern and no significant interaction between the stimulation pattern and the signal-processing method. Therefore, the observed differences do not demonstrate an overall classification advantage of AFFP or DFFP over fixed-frequency stimulation.

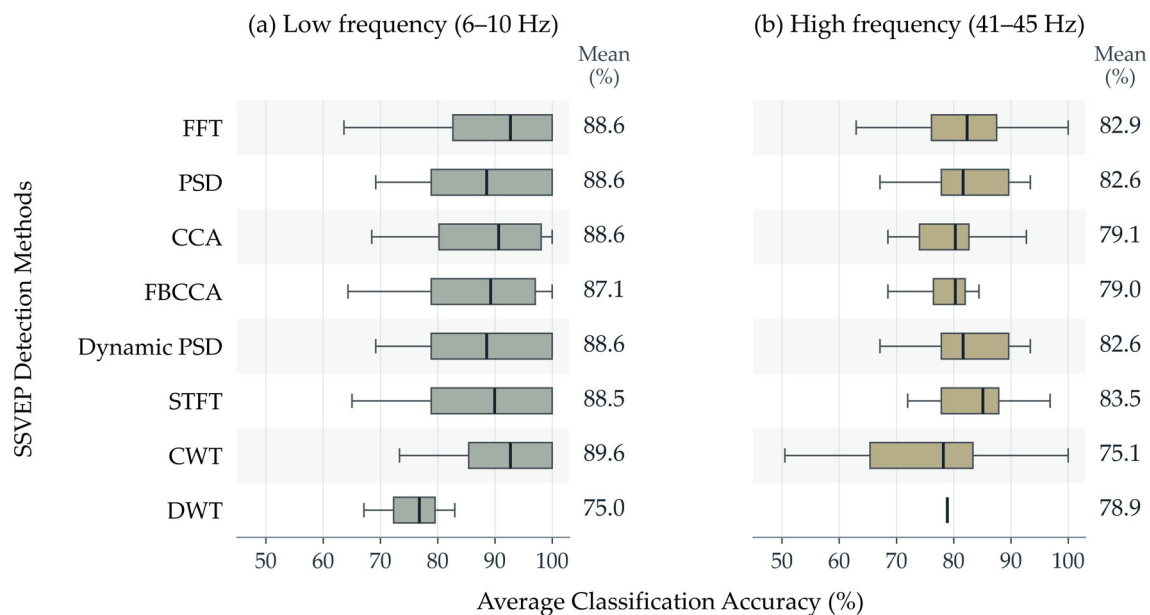


Figure 4. Five-class fundamental frequency classification accuracy across eight methods in (a) low-frequency (6–10 Hz) and (b) high-frequency (41–45 Hz) ranges. Central boxplot lines indicate medians; Mean (%) columns report means across 15 participants.

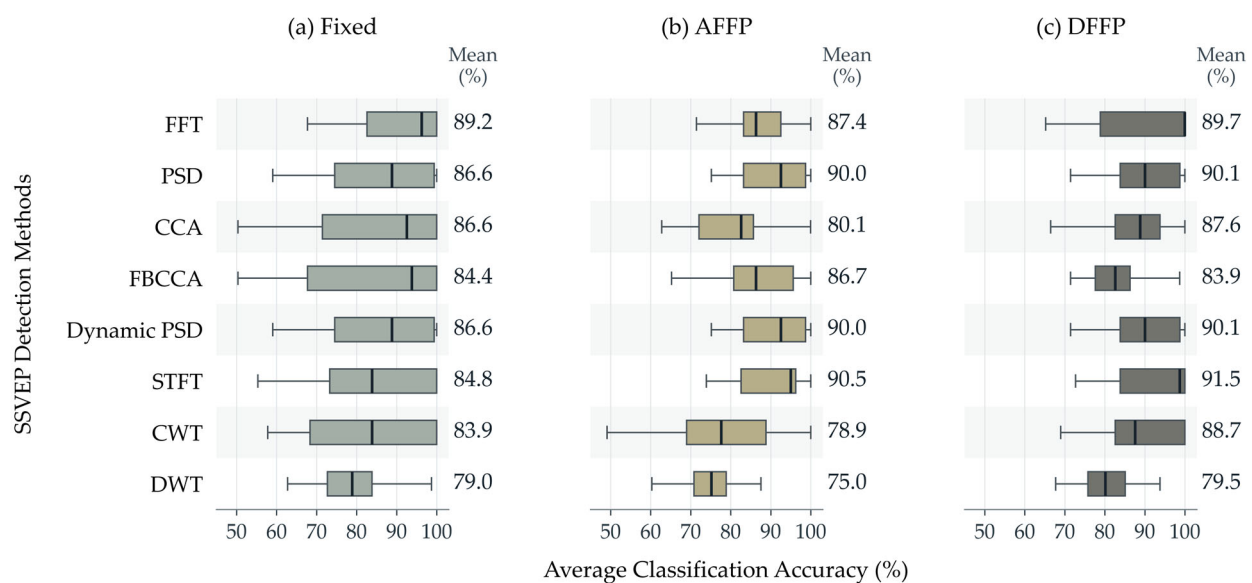


Figure 5. Five-class fundamental frequency classification accuracy across eight methods under (a) fixed-frequency, (b) AFFP, and (c) DFFP stimulation. Central boxplot lines indicate medians; Mean (%) columns report means across 15 participants.

A two-way repeated-measures ANOVA was conducted to examine the effects of the classification method and stimulation-frequency range on detection accuracy. The analysis revealed a significant main effect of the detection method, $F(7, 98) = 9.093$, $p < 0.001$, Partial $\eta^2 = 0.394$, indicating that detection accuracy differed among FFT, PSD, CCA, FBCCA, Dynamic PSD, STFT, CWT, and DWT. A significant main effect of the stimulation-frequency range was also observed, $F(1, 14) = 5.813$, $p = 0.030$, Partial $\eta^2 = 0.293$. Overall, the low-frequency range produced a higher normalized accuracy than the high-frequency range (90.8% vs. 80.6%). In addition, the interaction between the detection. The interaction between method and frequency range was significant, $F(7, 98) = 3.170$, $p = 0.005$, Partial

$\eta^2 = 0.185$, indicating that the effect of the frequency range varied according to the selected detection method.

Holm-adjusted pairwise comparisons showed that DWT produced significantly lower overall accuracy than FFT ($t(14) = 4.837$, adjusted $p = 0.007$), STFT ($t(14) = 4.576$, adjusted $p = 0.012$), PSD ($t(14) = 4.495$, adjusted $p = 0.013$), and dynamic PSD ($t(14) = 4.495$, adjusted $p = 0.013$). No other pairwise differences between methods reached statistical significance after adjustment. Follow-up comparisons between the frequency ranges showed that CCA achieved significantly higher accuracy in the low-frequency range than in the high-frequency range ($t(14) = 3.260$, adjusted $p = 0.046$). The remaining method-specific comparisons were not statistically significant after adjustment.

A two-way repeated-measures ANOVA was conducted to examine the effects of the classification method and stimulation pattern on the detection accuracy. A significant main effect of the detection method was observed, $F(7, 98) = 9.093$, $p < 0.001$, Partial $\eta^2 = 0.394$. In contrast, the main effect of the stimulation pattern was not statistically significant, $F(2, 28) = 0.731$, $p = 0.490$, Partial $\eta^2 = 0.050$. The average normalized accuracies were 89.7%, 85.6%, and 89.5% for the fixed-frequency, AFFP, and DFFP, respectively. The interaction between the detection method and stimulation pattern was also not significant, $F(14, 196) = 1.515$, $p = 0.108$, Partial $\eta^2 = 0.098$. These results illustrate a substantial impact of the signal-processing method on classification performance. However, no statistically significant differences were identified among the fixed-frequency, AFFP, and DFFP stimulation patterns under the conditions examined.

The theoretical offline ITR values corresponding to these mean classification accuracies are summarized in Table 3. Using the five-class formulation and a 2 s decision window, the estimated ITRs were 49.1 bits/min for fixed-frequency stimulation, 43.2 bits/min for AFFP, and 48.8 bits/min for DFFP. The lower ITR observed for AFFP primarily reflected its lower mean classification accuracy under the same number of classes and decision time. These values represent theoretical offline estimates and should not be interpreted as measured online communication rates. The experimental protocol itself provided a presentation rate of 3.75 labeled epochs/min because each 80 s trial contained five 2 s stimulation epochs.

Table 3. Classification accuracy and theoretical offline information transfer rate across stimulation patterns.

Stimulation Pattern	Classification Accuracy	Theoretical Offline ITR (bits/min)
Fixed-frequency	89.7	49.1
AFFP	85.6	43.2
DFFP	89.5	48.8

Note: Theoretical offline ITR was calculated using a five-class formulation and a 2 s decision window. The experimental presentation rate was 3.75 labeled epochs/min for all stimulation conditions. The reported ITR values are offline theoretical estimates and should not be interpreted as conventional online BCI communication rates.

The statistical results indicate that classification performance was primarily associated with the selected signal-processing method and stimulation-frequency range. Although CWT yielded the highest descriptive average accuracy, this result should not be interpreted as evidence that CWT was significantly superior to all other methods. In contrast, no significant overall difference was found among the fixed-frequency, AFFP, and DFFP stimulation patterns. The results therefore support the feasibility of detecting the staircase sequences but not their superiority over fixed-frequency stimulation.

In the third part, the classification performance of the AFFP and DFFP stimulus patterns was compared across the evaluated fundamental flicker frequencies using the

CWT method, as shown in Figure 6. In the low-frequency range shown in Figure 6a, the average detection accuracy ranged from 81.1% to 95.0%. DFFP achieved higher accuracy than AFFP at 6 Hz, 9 Hz, and 10 Hz, with accuracies of 86.9%, 91.7%, and 95.0%, respectively. AFFP slightly outperformed DFFP at 7 Hz and 8 Hz, achieving accuracies of 90.5% and 87.6%, respectively. The highest accuracy in the low-frequency range was obtained by DFFP at 10 Hz.

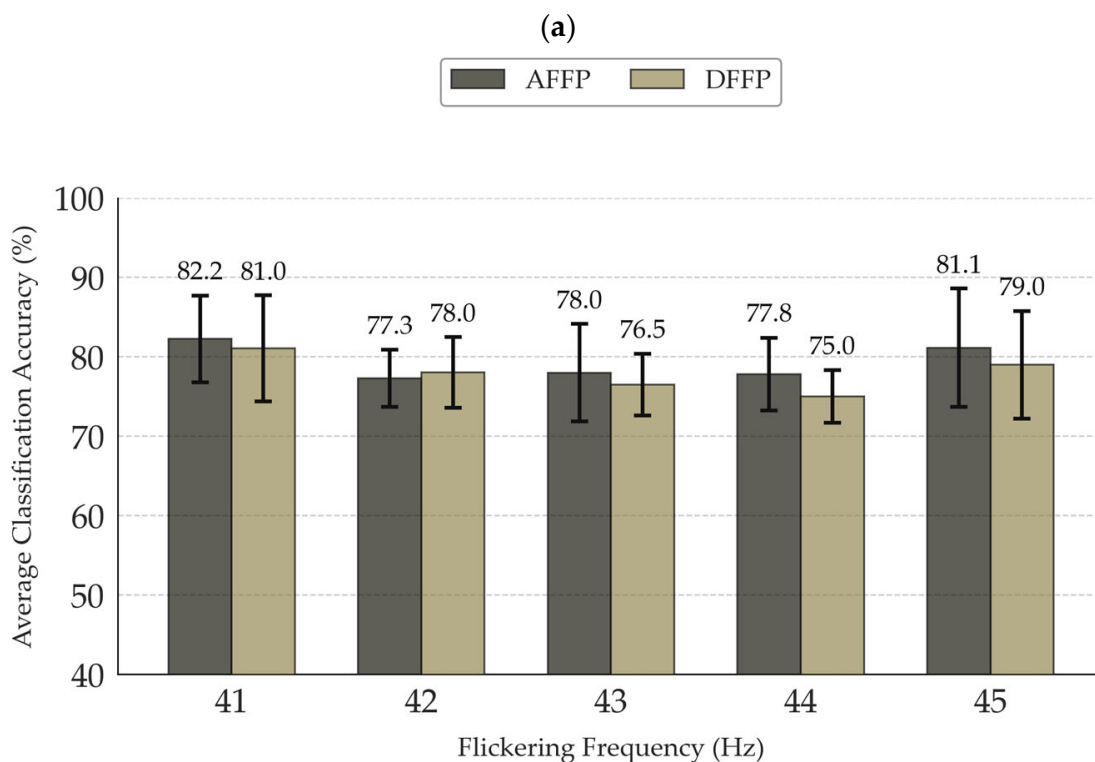
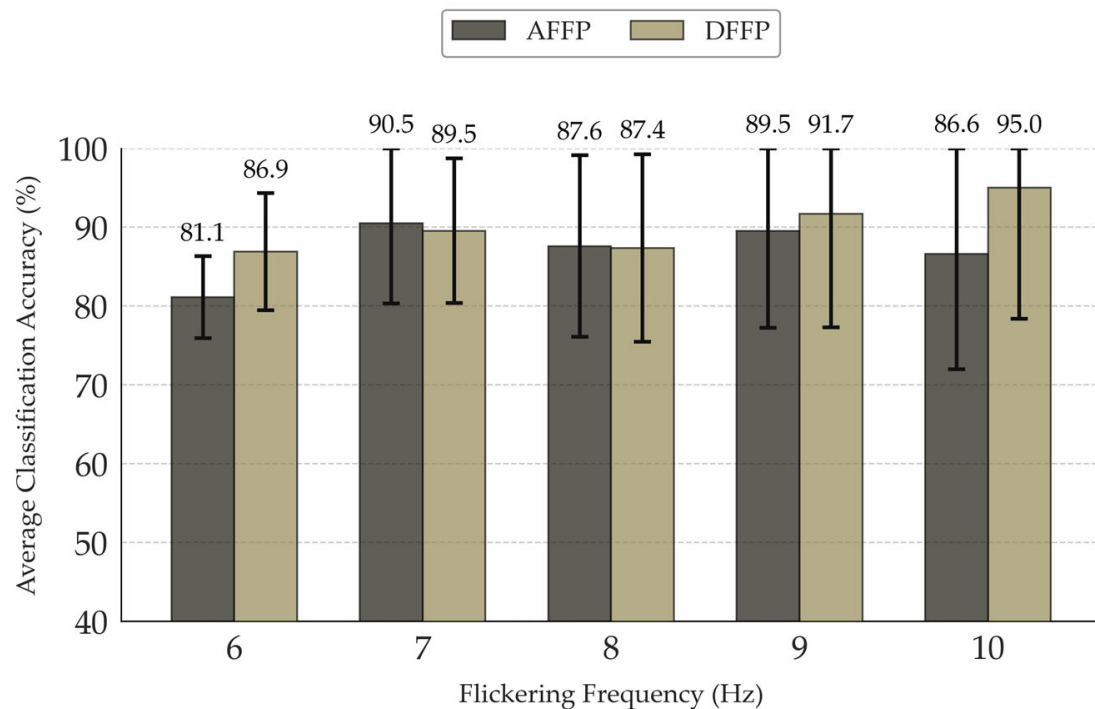


Figure 6. Five-class command-level classification accuracy for AFFP and DFFP within each fundamental frequency group: (a) low-frequency range and (b) high-frequency range.

In the high-frequency range shown in Figure 6b, the average detection accuracy ranged from 75.0% to 82.2%, which was lower than that observed in the low-frequency range. AFFP achieved higher accuracy at 41 Hz, 43 Hz, 44 Hz, and 45 Hz, with values of 82.2%, 78.0%, 77.8%, and 81.1%, respectively. At 42 Hz, the corresponding accuracies were 77.3% for AFFP and 78.0% for DFFP. These results indicate that both AFFP and DFFP produced classifiable EEG responses under all nominal programmed frequency conditions, although their relative performance varied across fundamental frequency groups. Because the adjacent command states differed by only 0.2 Hz and the physical LCD luminance waveform was not independently verified, these results should not be interpreted as direct evidence that the displayed frequencies were physically separated at exact 0.2 Hz intervals.

3.2. Evaluation of Consecutive Command Detection

To examine the potential suitability of the proposed stimulation paradigm for future BCI applications, consecutive command detection was evaluated using offline EEG data. This analysis assessed whether sequences containing three, four, and five commands could be detected under the AFFP and DFFP conditions. It did not involve real-time BCI operation or closed-loop device control. The average offline classification accuracies were compared between the AFFP and DFFP stimulation patterns within the low- and high-frequency ranges.

The consecutive command accuracy was evaluated at the complete-sequence level. Within each AFFP or DFFP trial, the detected subfrequency labels from consecutive 2 s epochs were compared with the expected ordered sequence. Consecutive command analysis was performed within each known fundamental frequency group using the command-level outputs described above. Sequence evaluation always started from the first 2 s stimulation epoch. For $m = 3$, the first three epochs were evaluated; for $m = 4$, the first four epochs were evaluated; and for $m = 5$, all five epochs were evaluated. No sliding or alternative starting positions were used. A sequence was considered correct only when all m command labels were detected correctly and in the expected order. For example, for the 7 Hz fundamental frequency group, the expected AFFP sequences were [7.0, 7.2, 7.4] Hz for three commands, [7.0, 7.2, 7.4, 7.6] Hz for four commands, and [7.0, 7.2, 7.4, 7.6, 7.8] Hz for five commands. For DFFP, the corresponding sequences were evaluated in the reverse order. The consecutive command accuracy was calculated as follows:

$$Accuracy_m(\%) = \frac{N_{correct,m}}{N_{evaluated,m}} \times 100 \quad (27)$$

where $N_{correct,m}$ denotes the number of sequences in which all m commands were detected correctly and in the correct order, and $N_{evaluated,m}$ denotes the total number of evaluated sequences of length m . Accuracy was calculated separately for each participant, stimulation pattern, frequency range, and sequence length before being averaged across participants.

Table 4 summarizes the classification accuracy for three, four, and five consecutive commands under low- and high-frequency AFFP and DFFP stimulation. For three consecutive commands, the overall average accuracy was $91.5 \pm 9.6\%$. High-frequency DFFP achieved the highest accuracy of $95.0 \pm 27.0\%$, followed by low-frequency DFFP at $94.3 \pm 17.6\%$. The corresponding accuracies for low- and high-frequency AFFP were $86.7 \pm 16.2\%$ and $89.1 \pm 14.2\%$, respectively. When the number of consecutive commands increased to four, the overall average accuracy decreased to $80.3 \pm 6.8\%$. The accuracies were $78.3 \pm 6.9\%$ and $79.4 \pm 7.6\%$ for low-frequency AFFP and DFFP, respectively, and $79.4 \pm 9.9\%$ and $83.9 \pm 21.7\%$ for high-frequency AFFP and DFFP, respectively. For five consecutive commands, the overall average accuracy further decreased to $76.7 \pm 4.7\%$. Low-frequency AFFP and DFFP both achieved an accuracy of $75.0 \pm 0.0\%$, whereas high-

frequency AFFP and DFFP achieved $77.2 \pm 8.6\%$ and $79.4 \pm 17.2\%$, respectively. These results indicate that the classification accuracy gradually decreased as the number of consecutive commands increased. The stimulation pattern did not have a significant main effect on consecutive command accuracy; therefore, the observed pattern-specific differences were not interpreted as evidence of a performance advantage for either AFFP or DFFP.

Table 4. Average classification accuracy for different numbers of consecutive commands under low- and high-frequency visual flicker patterns.

Visual Stimulus Pattern	Average Classification Accuracy (%)		
	3 Commands	4 Commands	5 Commands
Low—AFFP	86.7 ± 16.2	78.3 ± 6.9	75.0 ± 0.0
Low—DFFP	94.3 ± 17.6	79.4 ± 7.6	75.0 ± 0.0
High—AFFP	89.1 ± 14.2	79.4 ± 9.9	77.2 ± 8.6
High—DFFP	95.0 ± 27.0	83.9 ± 21.7	79.4 ± 17.2
Average	91.5 ± 9.6	80.3 ± 6.8	76.7 ± 4.7

Statistical analysis of the participant-level complete-sequence accuracies using a two-way repeated-measures ANOVA showed a significant main effect of the number of consecutive commands, $F(2, 28) = 62.98$, $p < 0.001$, partial $\eta^2 = 0.818$. Holm-adjusted paired comparisons showed that the accuracy for three commands was significantly higher than that for four commands, $t(14) = 6.83$, adjusted $p < 0.001$, and five commands, $t(14) = 8.30$, adjusted $p < 0.001$. The accuracy for four commands was also significantly higher than that for five commands, $t(14) = 8.74$, adjusted $p < 0.001$. In contrast, the main effect of stimulation pattern was not significant, $F(1, 14) = 0.64$, $p = 0.439$, partial $\eta^2 = 0.043$, and no significant interaction was observed between stimulation pattern and command number, $F(2, 28) = 1.10$, $p = 0.347$, partial $\eta^2 = 0.073$. These results quantify the expected reduction in complete-sequence reliability as classification errors accumulate across successive command epochs, while no statistically significant difference was detected between AFFP and DFFP.

For the consecutive command analysis, participant-level complete-sequence accuracies were analyzed using a two-way repeated-measures ANOVA with stimulation pattern (AFFP and DFFP) and sequence length (three, four, and five commands) as within-subject factors. Significant effects of sequence length were further examined using paired-samples t -tests with Holm adjustment for multiple comparisons.

4. Discussion

Based on the experimental results, three main aspects were analyzed: the effects of the classification method and stimulation-frequency range; the performance of the fixed-frequency, AFFP, and DFFP stimulation patterns across the evaluated frequencies; and the effect of the number of consecutive commands on detection accuracy.

First, the results showed that classification performance was influenced more strongly by the selected signal-processing method than by the stimulation pattern. The frequency-domain and correlation-based methods, including FFT, PSD, CCA, and FBCCA, provided generally reliable detection performance. Among the evaluated methods, CWT yielded the highest descriptive average accuracy, whereas DWT generally produced lower accuracy. The lower performance of DWT may be associated with its relatively broad discrete frequency bands, which can limit the discrimination of small frequency changes within short analysis intervals. These findings indicate that the observed classification performance should be attributed primarily to the signal-processing method rather than to an inherent advantage of the AFFP or DFFP stimulation patterns.

Regarding the stimulation-frequency range, the methods generally achieved higher and more consistent performance in the low-frequency range than in the high-frequency range. This result is consistent with previous findings showing that low-frequency visual stimulation generally elicits stronger SSVEP responses in the visual cortex [54]. However, the effect of the frequency range varied among the detection methods, indicating that the selection of an appropriate signal-processing technique should consider the target stimulation frequencies and the temporal characteristics of the EEG response.

The present study characterizes the offline classification of a monotonic, five-step staircase comprising adjacent nominal frequencies and compares ascending and descending sequences across low- and high-frequency ranges. The fixed-frequency, AFFP, and DFFP stimulation patterns demonstrated comparable overall classification performance, with no statistically significant main effect of stimulation pattern; however, this finding does not establish equivalence. Frequency-specific descriptive differences between AFFP and DFFP revealed no consistent directional pattern and provided no evidence that either staircase direction was superior. These findings support the feasibility of offline classification of successive frequency states within a known fundamental-frequency group. Their potential application to multilevel command mapping requires online, closed-loop validation before any improvements in adaptive or robotic control can be established. This contribution should be considered in conjunction with established SSVEP encoding approaches, including MFSC, TFSK-SSVEP, DFBC, and MTFSC [32,34,36,37], as well as the use of 0.2-Hz frequency spacing in joint frequency–phase coding [35]. Accordingly, its contribution consists of evaluating the specific staircase configuration and its frequency-state classification performance, rather than introducing a novel sequential-coding principle or frequency-spacing strategy.

Table 5 compares the present study with representative sequential SSVEP encoding paradigms. Zhang et al. [32] reported 95.87% offline accuracy for four-target MFSC, whereas Ge et al. [36] achieved 76.6% offline and 79.3% online accuracy for 48-target DFBC. Yue et al. [37] reported 89.04% online accuracy and 36.37 bits/min for nine-target MTFSC, while Ge et al. [38] achieved 86.81% offline and 91.36% online accuracy using block-distributed joint temporal-frequency-phase modulation for 48 targets. In the present study, AFFP and DFFP achieved pattern-level accuracies of 85.6% and 89.5%, with theoretical offline ITRs of 43.2 and 48.8 bits/min, respectively. These accuracies fall within the range reported in the comparison studies but do not demonstrate equivalent performance. The main contribution of the present study is the offline evaluation of individual states within ascending and descending frequency staircases across two frequency ranges using eight established methods. Classification and ITR calculations involved five command states within a known fundamental-frequency group rather than all 25 mappings jointly. Differences in command definitions, timing, EEG montages, decoding methods, and evaluation protocols limit direct comparisons. Moreover, the theoretical offline ITRs do not demonstrate practical throughput; online closed-loop validation is needed to establish the utility of staircase stimulation for multilevel command mapping.

The observed between-subject variation in frequency-specific responses was descriptive and was not used to construct or evaluate a personalized stimulation strategy. Consequently, the present study does not demonstrate that subject-specific frequency selection improves the classification accuracy, stability, or information transfer rate relative to non-personalized stimulation. Further studies directly comparing personalized and non-personalized frequency selection are required before any benefit of personalization can be established.

Second, the effects of consecutive commands were analyzed. The results indicate that the number of consecutive commands affected the classification accuracy. The high-

est performance was achieved with three consecutive commands, whereas the accuracy gradually decreased when the number of commands increased to four and five. Because complete-sequence accuracy required every constituent command to be correctly classified, the decline in performance for longer sequences was an expected consequence of detection errors accumulating across successive decisions. Accordingly, this analysis is interpreted as an operational estimate of sequence reliability rather than as a novel effect of command number or as evidence of an advantage of DFFP over AFFP. Within the present offline dataset, three-command sequences yielded higher accuracy than four- and five-command sequences. At the present stage, the paradigm therefore appears more suitable for short offline command sequences than for longer command sequences or real-time control. Whether three commands provide an appropriate balance between command diversity and practical reliability requires further validation in an online BCI task. Figure 7 is presented solely as a hypothetical framework for future online implementation. The robotic controller, adaptive feedback mechanism, and closed-loop interaction illustrated in the figure were not implemented or validated using the present offline dataset.

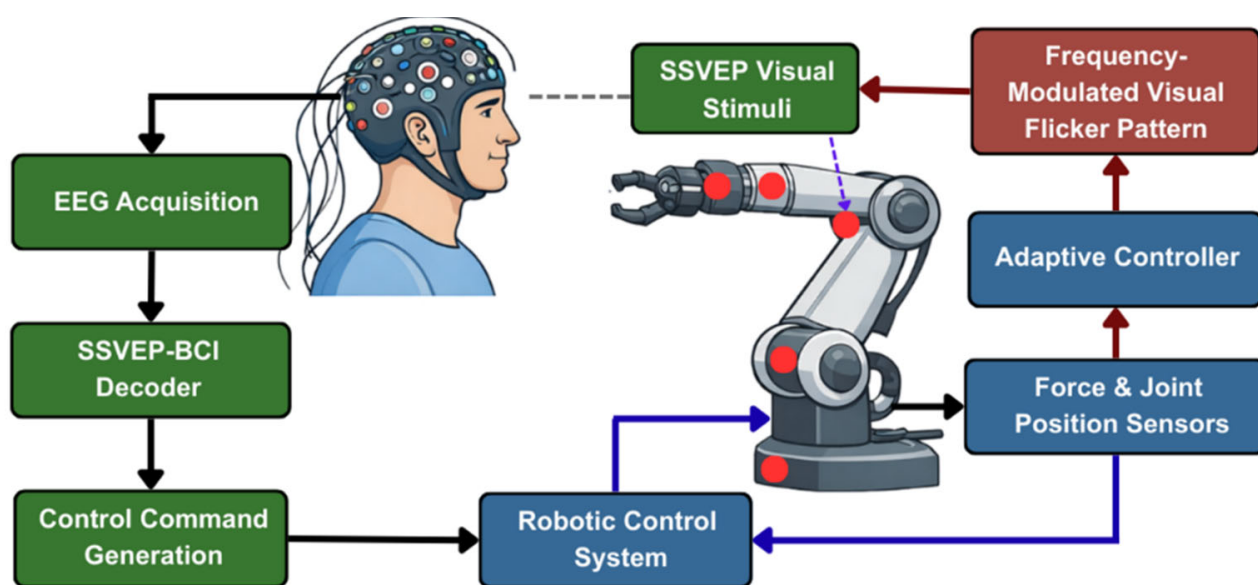


Figure 7. Hypothetical conceptual architecture for future online implementation of the sequential frequency-modulated SSVEP-BCI paradigm in robotic arm control. Red dots on the robotic arm indicate the proposed locations of SSVEP visual stimuli. The illustrated closed-loop robotic-control system was not implemented or evaluated in the present study.

Two mechanisms should be distinguished when interpreting this decline. First, complete-sequence accuracy was defined conjunctively, such that every command in the sequence had to be classified correctly. If the average probability of correctly detecting one command is p , the expected probability of correctly detecting an entire n -command sequence decreases approximately as p^n , even when single-command performance remains constant. Second, adjacent command states differed by only 0.2 Hz and were decoded from consecutive 2 s epochs, whose nominal Fourier resolution was approximately 0.5 Hz. Frequency-transition responses, incomplete stabilization within an epoch, residual activity from the preceding frequency step, and within-trial fluctuations in attention may therefore have produced correlated rather than independent errors. These factors were not measured separately in the present experiment. Because visual fatigue was not assessed, the observed decline cannot be attributed specifically to fatigue.

Table 5. Comparison of representative sequential SSVEP encoding paradigms and the present study.

Study	Stimuli	No. of Commands	Features	Methods	Accuracy (%)	ITR (bits/min)
Zhang et al. [32]	MFSC using 7.5 and 12 Hz; two successive 2 s coding epochs	4	Frequency-specific responses across successive epochs	CCA	95.87 (offline)	22.87 (simulated online)
Ge et al. [36]	DFBC using 10, 12, 14, and 16 Hz across four coding epochs	48	Temporal sequence and dual-frequency allocation	FBCCA with majority-voting self-correction	76.6 (offline); 79.3 (online)	53.7 †; 55.9 (online)
Yue et al. [37]	Motion stimuli with temporal omissions (MTFSC)	9	Frequency and temporal omission features	Template-based CCA	89.04 (online)	36.37 (online)
Ge et al. [38]	B-JTFPM using eight frequencies across two sequential coding sessions; 48 targets arranged in eight blocks	48	Temporal, frequency, and phase features	FBCCA-based recognition	86.81 (offline); 91.36 (online)	N/A
Present study	AFFP: five adjacent nominal frequencies in ascending order at 0.2-Hz intervals	5 per group (25 mappings) *	Spectral, time-frequency, and correlation features	FFT, PSD, Dynamic PSD, STFT, CWT, DWT, CCA, FBCCA	85.6 (offline)	43.2 †
Present study	DFFP: five adjacent nominal frequencies in descending order at 0.2-Hz intervals	5 per group (25 mappings) *	Spectral, time-frequency, and correlation features	FFT, PSD, Dynamic PSD, STFT, CWT, DWT, CCA, FBCCA	89.5 (offline)	48.8 †

Note: * Five command states within each of five fundamental frequency groups yield 25 frequency-command mappings per frequency range. Classification was performed within a known group, rather than jointly across 25 classes. † Theoretical offline ITR based on five command states. Present-study accuracies are averages for each stimulation pattern. Differences in timing and evaluation protocols limit direct comparisons.

These results should be considered in light of several limitations. The sample was limited to 15 healthy participants aged 19–21 years. Accordingly, the statistical findings should be considered exploratory, and their generalizability to broader age groups and clinical BCI populations is limited.

In addition, EEG acquisition was limited to two occipital channels (O1 and O2), and Oz and other parietal–occipital channels were not recorded. This limited montage may have reduced the available spatial information, and the potential benefit of a broader electrode configuration could not be evaluated in the present study. Electrode impedance values were also not systematically recorded; therefore, the recording quality could not be retrospectively characterized using impedance measurements. The controlled laboratory environment may also restrict the generalizability of the results to real-world conditions. Because the frequency-range and stimulation-pattern orders were not randomized or counterbalanced, potential order, fatigue, and carry-over effects could not be separated completely from the effects of frequency range and stimulation pattern. The detection performance also decreased as the number of sequential commands increased, indicating difficulty in maintaining reliable performance during longer command sequences. In addition, the relatively broad frequency bands produced by DWT may limit its ability to distinguish frequency changes of 0.2 Hz. Visual fatigue was not assessed in the present study; therefore, its potential relationship with stimulation frequency, stimulation pattern, and sequence length could not be evaluated. Most importantly, the present study was limited to offline EEG classification and did not include real-time BCI operation, online ITR, end-to-end latency, false-activation rate, task completion time, trajectory deviation, or robotic and assistive-device validation. Therefore, the practical control performance of the proposed staircase stimulation paradigm remains to be evaluated in an online closed-loop BCI system.

The theoretical offline ITR analysis provides a complementary description of classification efficiency under a common five-class formulation and 2 s decision window. The estimated ITRs were 49.1, 43.2, and 48.8 bits/min for the fixed-frequency, AFFP, and DFFP conditions, respectively. Because the number of classes and decision time were identical across the three conditions, these ITR differences primarily reflected the corresponding differences in classification accuracy. Accordingly, the ITR analysis does not indicate an advantage of AFFP or DFFP over fixed-frequency stimulation.

These theoretical estimates should also be distinguished from practical experimental throughput. The complete experimental protocol required 80 s per trial, including baseline, stimulation, and rest periods, and therefore yielded a presentation rate of 3.75 labeled epochs/min. Moreover, the AFFP and DFFP command states occurred in predetermined temporal sequences rather than through independent user selections. Consequently, the reported theoretical ITR values should not be interpreted as validated online BCI communication rates. Practical ITR should be evaluated in a future real-time closed-loop system incorporating user-driven command selection, decoding latency, idle decisions, false activations, and classification errors.

In addition, the blank-wall baseline was not luminance-matched to the LCD stimulation condition. Differences in visual input between the baseline and stimulation periods may therefore have contributed to the baseline-normalized response scores. Because a luminance-matched control condition was not recorded, we cannot accurately measure this potential contribution from the current dataset. These scores should thus be interpreted carefully. Future research should include a luminance-matched control to better evaluate how background luminance influences the normalized responses.

The high-frequency results should also be interpreted cautiously because the physical luminance waveform of the LCD monitor was not independently measured using a photodiode. Consequently, the programmed 41–45 Hz frequencies and their 0.2 Hz increments should be regarded as nominal display conditions. Refresh-rate quantization, frame-timing jitter, display response time, and unintended spectral components may have affected the actual luminance output. The present results therefore demonstrate offline classification

under the programmed stimulus conditions but do not independently verify the physical separation of the displayed frequencies at 0.2 Hz intervals.

Future research should compare frequency increments of 0.2, 0.5, and 1 Hz together with shorter and longer modulation intervals. These experiments should quantify the response onset and stabilization time, classification accuracy, spectral separability, and decoding latency to determine whether finer frequency increments provide sufficient gains in command resolution to offset their reduced separability. Accordingly, the present 0.2 Hz step and 2 s interval should be regarded as one exploratory configuration rather than an optimized parameter combination. These frequency levels could subsequently be mapped to robotic variables such as movement speed, position, or assistance level in an online closed-loop system [55–58].

5. Conclusions

This study evaluated a discrete five-step staircase frequency stimulation protocol for SSVEP-based BCIs. Adjacent frequencies separated by 0.2 Hz were presented in ascending and descending orders and compared with conventional fixed-frequency stimulation across low- and high-frequency ranges using eight established signal-processing methods. Classification performance was influenced primarily by the signal-processing method and stimulation-frequency range, whereas the stimulation pattern did not have a significant main effect. CWT demonstrated the highest average descriptive accuracy among the evaluated signal-processing methods; however, this descriptive finding did not establish a statistically significant overall superiority of CWT over the other methods. The fixed-frequency, AFFP, and DFFP conditions yielded comparable overall performance, and neither staircase direction was consistently superior. AFFP and DFFP nevertheless elicited detectable SSVEP responses throughout the staircase sequences, supporting their offline feasibility for flexible sequential command design. Three-command sequences produced higher accuracy than longer sequences, but their practical utility remains to be evaluated. The small, homogeneous sample of 15 healthy participants aged 19–21 years constrains how broadly these findings can be applied to other age groups and clinical populations. The current results do not show that this method is better than fixed-frequency stimulation or effective online control. Additional validation with larger and more diverse samples and testing within an online closed-loop BCI system are necessary.

Author Contributions: Conceptualization, N.S., K.I. and Y.P.; methodology, N.S., K.I. and Y.P.; software, N.S. and Y.P.; validation, K.I. and Y.P.; formal analysis, N.S. and Y.P.; investigation, N.S. and Y.P.; resources, Y.P.; data curation, N.S. and Y.P.; writing—original draft preparation, N.S., K.I. and Y.P.; writing—review and editing, N.S., K.I. and Y.P.; visualization, Y.P.; supervision, K.I. and Y.P.; project administration, N.S. and Y.P.; funding acquisition, N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was partially supported by Walailak University under the international research collaboration scheme (Contract Number: WU-CIA-04404/2025) and partly by the Research and Innovation Institute of Excellence (RIIE), Walailak University.

Institutional Review Board Statement: The study was conducted in accordance with the guidelines of the Declaration of Helsinki and approved by the Office of the Human Research Ethics Committee of Walailak University (Project No. WU-EC-IN-1-402-67; Approval No. WUEC-24-413-01; approval date: 19 December 2024).

Informed Consent Statement: Informed consent was obtained from all subjects participating in the study, and written informed consent was obtained from the participants to publish this article.

Data Availability Statement: The data presented in this study are available upon reasonable request.

Acknowledgments: We used Grammarly (8.937.0) for grammar and language correction. These were used solely to improve the language and readability of the manuscript and did not contribute to the scientific content, data analysis, interpretation, or conclusions.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kawala-Sterniuk, A.; Browarska, N.; Al-Bakri, A.F.; Pelc, M.; Zygarlicki, J.; Sidikova, M.; Martinek, R.; Gorzelanczyk, E.J. Summary of over fifty years with brain–computer interfaces—A review. *Brain Sci.* **2021**, *11*, 43. [\[CrossRef\]](#)
2. Maiseli, B.; Abdalla, A.T.; Massawe, L.V.; Mbise, M.; Mkocho, K.; Nassor, N.A.; Ismail, M.; Michael, J.; Kimambo, S. Brain–computer interface: Trend, challenges, and threats. *Brain Inf.* **2023**, *10*, 20. [\[CrossRef\]](#)
3. Karikari, E.; Koshechkin, K.A. Review on brain–computer interface technologies in healthcare. *Biophys. Rev.* **2023**, *15*, 1351–1358. [\[CrossRef\]](#)
4. Yuan, H.; Li, Y.; Yang, J.; Li, H.; Yang, Q.; Guo, C.; Zhu, S.; Shu, X. State of the art of non-invasive electrode materials for brain–computer interface. *Micromachines* **2021**, *12*, 1521. [\[CrossRef\]](#)
5. Veena, N.; Anitha, N. A review of non-invasive BCI devices. *Int. J. Biomed. Eng. Technol.* **2020**, *34*, 205–233. [\[CrossRef\]](#)
6. Vărbu, K.; Muhammad, N.; Muhammad, Y. Past, present, and future of EEG-based BCI applications. *Sensors* **2022**, *22*, 3331. [\[CrossRef\]](#)
7. Dadebayev, D.; Goh, W.W.; Tan, E.X. EEG-based emotion recognition: Review of commercial EEG devices and machine learning techniques. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 4385–4401. [\[CrossRef\]](#)
8. Gu, X.; Cao, Z.; Jolfaei, A.; Xu, P.; Wu, D.; Jung, T.-P.; Lin, C.-T. EEG-based brain–computer interfaces (BCIs): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications. *IEEE/ACM Trans. Comput. Biol. Bioinform.* **2021**, *18*, 1645–1666. [\[CrossRef\]](#)
9. Leoni, J.; Strada, S.C.; Tanelli, M.; Jiang, K.; Brusa, A.; Proverbio, A.M. Automatic stimuli classification from ERP data for augmented communication via brain–computer interfaces. *Expert Syst. Appl.* **2021**, *184*, 115572. [\[CrossRef\]](#)
10. Rimbert, S.; Trocellier, D.; Lotte, F. Impact of the baseline temporal selection on the ERD/ERS analysis for motor imagery-based BCI. In Proceedings of the 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Sydney, Australia, 24–28 July 2023; pp. 1–4. [\[CrossRef\]](#)
11. Rimbert, S.; Lotte, F. ERD modulations during motor imagery relate to users’ traits and BCI performances. In Proceedings of the 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Glasgow, UK, 11–15 July 2022; pp. 203–207. [\[CrossRef\]](#)
12. Hamilton, R.; Bach, M.; Heinrich, S.P.; Hoffmann, M.B.; Odom, J.V.; McCulloch, D.L.; Thompson, D.A. VEP estimation of visual acuity: A systematic review. *Doc. Ophthalmol.* **2021**, *142*, 25–74. [\[CrossRef\]](#)
13. Gao, Z.; Dang, W.; Liu, M.; Guo, W.; Ma, K.; Chen, G. Classification of EEG signals on VEP-based BCI systems with broad learning. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *51*, 7143–7151. [\[CrossRef\]](#)
14. Ladouce, S.; Darnet, L.; Torre Tresols, J.J.; Velut, S.; Ferraro, G.; Dehais, F. Improving user experience of SSVEP BCI through low amplitude depth and high frequency stimuli design. *Sci. Rep.* **2022**, *12*, 8865. [\[CrossRef\]](#)
15. Liu, C.; Duan, M.; Duan, Z.; Liu, A.; Lu, Z.; Wang, H. An SSVEP-based BCI with LEDs visual stimuli using dynamic window CCA algorithm. *Biomed. Signal Process. Control* **2022**, *76*, 103727. [\[CrossRef\]](#)
16. Gu, M.; Pei, W.; Gao, X.; Wang, Y. Optimizing visual stimulation paradigms for user-friendly SSVEP-based BCIs. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2024**, *32*, 1090–1099. [\[CrossRef\]](#)
17. Wong, C.M.; Wang, Z.; Wang, B.; Lao, K.F.; Rosa, A.; Xu, P.; Jung, T.-P.; Chen, C.L.P.; Wan, F. Inter- and intra-subject transfer reduces calibration effort for high-speed SSVEP-based BCIs. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2020**, *28*, 2123–2135. [\[CrossRef\]](#)
18. De la Cruz, D.R.; Alfonso-Morales, W.; Caicedo-Bravo, E. Analysis of the information transfer rate-ITR in linear and non-linear feature extraction methods for SSVEP signals. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2021**, *11*, 761–768. [\[CrossRef\]](#)
19. Wu, J.; Wang, J. An analysis of traditional methods and deep learning methods in SSVEP-based BCI: A survey. *Electronics* **2024**, *13*, 2767. [\[CrossRef\]](#)
20. Li, X.; Wang, J.; Cao, X.; Huang, Y.; Huang, W.; Wan, F.; To, M.K.-T.; Xie, S.Q. Evaluation of an online SSVEP-BCI with fast system setup. *J. Neurorestoratol.* **2024**, *12*, 100122. [\[CrossRef\]](#)
21. Diez, P.; Orosco, L.; Garcés Correa, A.; Carmona, L. Assessment of visual fatigue in SSVEP-based brain–computer interface: A comprehensive study. *Med. Biol. Eng. Comput.* **2024**, *62*, 1475–1490. [\[CrossRef\]](#)
22. Azadi Moghadam, M.; Maleki, A. Fatigue factors and fatigue indices in SSVEP-based brain–computer interfaces: A systematic review and meta-analysis. *Front. Hum. Neurosci.* **2023**, *17*, 1248474. [\[CrossRef\]](#)

23. Chai, X.; Zhang, Z.; Guan, K.; Zhang, T.; Xu, J.; Niu, H. Effects of fatigue on steady-state motion visual evoked potentials: Optimised stimulus parameters for a zoom motion-based brain–computer interface. *Comput. Methods Programs Biomed.* **2020**, *196*, 105650. [\[CrossRef\]](#)
24. Zhang, S.; Ma, K.; Yin, Y.; Ren, B.; Liu, M. A personalized compression method for steady-state visual evoked potential EEG signals. *Information* **2022**, *13*, 186. [\[CrossRef\]](#)
25. Chang, C.-T.; Pai, K.-J.; Huang, C.-H.; Chou, C.-Y.; Liu, K.-W.; Lin, H.-B. Optimizing user experience in SSVEP-BCI systems. In *Progress in Brain Research*; Jao, C.-W., Wu, Y.-T., Eds.; Elsevier: Amsterdam, The Netherlands, 2024; Volume 290, pp. 105–121. [\[CrossRef\]](#)
26. Siribunyaphat, N.; Tohkhwan, N.; Punsawad, Y. Investigation of personalized visual stimuli via checkerboard patterns using flickering circles for SSVEP-based BCI system. *Sensors* **2025**, *25*, 4623. [\[CrossRef\]](#)
27. Tang, J.; Xu, M.; Han, J.; Liu, M.; Dai, T.; Chen, S.; Ming, D. Optimizing SSVEP-based BCI system towards practical high-speed spelling. *Sensors* **2020**, *20*, 4186. [\[CrossRef\]](#)
28. Wong, C.M.; Wang, Z.; Nakanishi, M.; Wang, B.; Rosa, A.; Chen, C.L.P.; Jung, T.-P.; Wan, F. Online adaptation boosts SSVEP-based BCI performance. *IEEE Trans. Biomed. Eng.* **2022**, *69*, 2018–2028. [\[CrossRef\]](#)
29. Shi, N.; Li, X.; Liu, B.; Yang, C.; Wang, Y.; Gao, X. Representative-based cold start for adaptive SSVEP-BCI. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2023**, *31*, 1521–1531. [\[CrossRef\]](#)
30. Lee, T.; Nam, S.; Hyun, D.J. Adaptive window method based on FBCCA for optimal SSVEP recognition. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2023**, *31*, 78–86. [\[CrossRef\]](#)
31. Li, D.; Wang, X.; Dou, M.; Zhao, Y.; Cui, X.; Xiang, J. Multi-stimulus least-squares transformation with online adaptation scheme to reduce calibration effort for SSVEP-based BCIs. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2024**, *32*, 1606–1615. [\[CrossRef\]](#)
32. Zhang, Y.; Xu, P.; Liu, T.; Hu, J.; Zhang, R.; Yao, D. Multiple Frequencies Sequential Coding for SSVEP-Based Brain-Computer Interface. *PLoS ONE* **2012**, *7*, e29519. [\[CrossRef\]](#)
33. Dreyer, A.M.; Herrmann, C.S. Frequency-Modulated Steady-State Visual Evoked Potentials: A New Stimulation Method for Brain-Computer Interfaces. *J. Neurosci. Methods* **2015**, *241*, 1–9. [\[CrossRef\]](#)
34. Zhao, X.; Zhao, D.; Wang, X.; Hou, X. A SSVEP Stimuli Encoding Method Using Trinary Frequency-Shift Keying Encoded SSVEP (TFSK-SSVEP). *Front. Hum. Neurosci.* **2017**, *11*, 278. [\[CrossRef\]](#)
35. Wang, Y.; Chen, X.; Gao, X.; Gao, S. A Benchmark Dataset for SSVEP-Based Brain-Computer Interfaces. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2017**, *25*, 1746–1752. [\[CrossRef\]](#)
36. Ge, S.; Jiang, Y.; Zhang, M.; Wang, R.; Iramina, K.; Lin, P.; Leng, Y.; Wang, H.; Zheng, W. SSVEP-Based Brain-Computer Interface with a Limited Number of Frequencies Based on Dual-Frequency Biased Coding. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2021**, *29*, 760–769. [\[CrossRef\]](#)
37. Yue, Z.; Wu, Q.; Ren, S.-Y.; Li, M.; Shi, B.; Pan, Y.; Wang, J. A Novel Multiple Time-Frequency Sequential Coding Strategy for Hybrid Brain-Computer Interface. *Front. Hum. Neurosci.* **2022**, *16*, 859259. [\[CrossRef\]](#)
38. Ge, S.; Yang, H.; Wang, R.; Leng, Y.; Iramina, K.; Lin, P.; Wang, H. Block distributed joint temporal-frequency-phase modulation for steady-state visual evoked potential based brain-computer interface with a limited number of frequencies. *IEEE J. Biomed. Health Inform.* **2023**, *27*, 1835–1844. [\[CrossRef\]](#)
39. Li, M.; Chen, X.; Cui, H. A high-frequency SSVEP-BCI system based on simultaneous modulation of luminance and motion using inter-modulation frequencies. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2023**, *31*, 2603–2611. [\[CrossRef\]](#)
40. Zhang, Y.; Qian, K.; Xie, S.Q.; Shi, C.; Li, J.; Zhang, Z.-Q. SSVEP-based brain–computer interface-controlled robotic platform with velocity modulation. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2023**, *31*, 3448–3458. [\[CrossRef\]](#)
41. Zhang, D.; Liu, S.; Zhang, J.; Li, G.; Suo, D.; Liu, T.; Luo, J.; Ming, Z.; Wu, J.; Yan, T. Brain-controlled 2D navigation robot based on a spatial gradient controller and predictive environmental coordinator. *IEEE J. Biomed. Health Inform.* **2022**, *26*, 6138–6149. [\[CrossRef\]](#)
42. Willett, F.R.; Young, D.R.; Murphy, B.A.; Memberg, W.D.; Blabe, C.H.; Pandarinath, C.; Stavisky, S.D.; Rezaii, P.; Saab, J.; Walter, B.L.; et al. Principled BCI decoder design and parameter selection using a feedback control model. *Sci. Rep.* **2019**, *9*, 8881. [\[CrossRef\]](#)
43. Mei, J.; Xu, M.; Wang, L.; Ke, Y.; Wang, Y.; Jung, T.-P.; Ming, D. Using SSVEP-BCI to continuously control a quadcopter with 4-DOF motions. In Proceedings of the 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Montreal, QC, Canada, 20–24 July 2020; pp. 4745–4748. [\[CrossRef\]](#)
44. Tariq, M.; Trivailo, P.M.; Simic, M. EEG-based BCI control schemes for lower-limb assistive robots. *Front. Hum. Neurosci.* **2018**, *12*, 312. [\[CrossRef\]](#)
45. Yazdi, G.E.; Nezamfar, H.; Moghadamfalahi, M.; Akcakaya, M.; Shafai, B.; Erdogmus, D. An adaptive proportional BCI-controller for linear dynamic systems. In Proceedings of the World Automation Congress (WAC), Stevenson, WA, USA, 3–6 June 2018; pp. 1–5. [\[CrossRef\]](#)
46. Sharma, R.; Meena, H.K. Emerging trends in EEG signal processing: A systematic review. *SN Comput. Sci.* **2024**, *5*, 415. [\[CrossRef\]](#)

47. Lee, D.-G.; Lee, S.-B. EEG feature extraction for neurodegenerative disease diagnosis: A review. *Digit. Health Res.* **2025**, *3*, e5. [[CrossRef](#)]
48. Chiarion, G.; Sparacino, L.; Antonacci, Y.; Faes, L.; Mesin, L. Connectivity analysis in EEG data: A tutorial review of the state of the art and emerging trends. *Bioengineering* **2023**, *10*, 372. [[CrossRef](#)]
49. Negi, T.; Sharma, S. Analysis and processing of EEG signal: A review. In Proceedings of the International Conference on Smart Data Intelligence (ICSMDI 2021), Kongunadu, India, 29–30 April 2021. [[CrossRef](#)]
50. Guo, T.; Zhang, T.; Lim, E.; López-Benítez, M.; Ma, F.; Yu, L. A review of wavelet analysis and its applications: Challenges and opportunities. *IEEE Access* **2022**, *10*, 58869–58903. [[CrossRef](#)]
51. Zhang, Z.; Li, X.; Deng, Z. A CWT-based SSVEP classification method for brain–computer interface system. In Proceedings of the International Conference on Intelligent Control and Information Processing (ICICIP), Dalian, China, 12–15 August 2010; pp. 43–48. [[CrossRef](#)]
52. Liu, C.; Huang, J.; Ma, Y.; He, Z. AMWTCNN: A wavelet transform convolutional neural network with attention mechanism for cross-subject SSVEP signal classification. In Proceedings of the Chinese Control and Decision Conference (CCDC), Xiamen, China, 16–19 May 2025; pp. 1985–1990. [[CrossRef](#)]
53. Chen, X.; Chen, Z.; Gao, S.; Gao, X. A high-ITR SSVEP-based BCI speller. *Brain Comput. Interfaces* **2014**, *1*, 181–191. [[CrossRef](#)]
54. Herrmann, C.S. Human EEG responses to 1–100 Hz flicker: Resonance phenomena in visual cortex and their potential correlation to cognitive phenomena. *Exp. Brain Res.* **2001**, *137*, 346–353. [[CrossRef](#)]
55. Mashud, G.; Hasan, S.; Alam, N. Advances in control techniques for rehabilitation exoskeleton robots: A systematic review. *Actuators* **2025**, *14*, 108. [[CrossRef](#)]
56. Sakurada, T.; Kawase, T.; Takano, K.; Komatsu, T.; Kansaku, K. A BMI-based occupational therapy assist suit: Asynchronous control by SSVEP. *Front. Neurosci.* **2013**, *7*, 172. [[CrossRef](#)]
57. Ehrlich, M.; Zaidel, Y.; Weiss, P.L.; Melamed Yekel, A.; Gefen, N.; Supic, L.; Tsur, E. Adaptive control of a wheelchair-mounted robotic arm with neuromorphically integrated velocity readings and online learning. *Front. Neurosci.* **2022**, *16*, 1007736. [[CrossRef](#)]
58. Stewart, A.; Pretty, C.; Chen, X. A portable assist-as-needed upper-extremity hybrid exoskeleton for FES-induced muscle fatigue reduction in stroke rehabilitation. *BMC Biomed. Eng.* **2019**, *1*, 30. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.