An Algorithm for Personalizing SSVEP-Based Brain-Computer Interfaces

Subjects: Computer Science, Cybernetics | Automation & Control Systems
Contributor: Alexey Kozin, Anton Gerasimov, Maxim Bakaev, Anton Pashkov, Olga Razumnikova

Brain–computer interfaces (BCIs) based on steady-state visually evoked potentials (SSVEPs) are inexpensive and do not require user training. Researchers herein describe how the light frequency could be selected individually. In particular, this is done via the proposed discomfort index, determined by the ratio of theta and beta rhythms in the EEG signal.

Keywords: brain–computer interface ; steady-state visually evoked potentials ; personal response ; visual stimulation ; discomfort index ; BCI usability

1. Introduction

As graphical user interface (GUI) technology is nearing its 50th anniversary, humans are actively seeking new modes of interaction with machines. A user, considered as a source of information, can use their gestures, voice, eye movements, etc., to generate control commands or actions. A promising communication channel is the one based on the neural activity of the brain (hence, the so-called brain–computer interface (BCI)). Its important advantage is accessibility, even for people whose motor reactions are disrupted or cease completely. For healthy people, BCIs hold a compelling promise to “read one’s mind”, especially when in conjunction with booming artificial intelligence (AI) technologies [1]. Although BCI technology is not yet fully mature, it has been applied to control a wide variety of devices, including computers, motorized wheelchairs [2], and exoskeletons. It is used to monitor cognitive states, mental loads, and fatigue [3], as well as in rehabilitation systems for stroke patients [4].

There are many paradigms and approaches on the basis of which BCIs are built and function [5]. The one that demonstrates the highest interaction accuracy and speed [6] is steady-state visually evoked potential (SSVEP), which involves a specific neuronal response that occurs as a result of presenting a periodic visual stimulus to a subject [7]. This reaction is mainly localized to the occipital region of the cerebral cortex and can be recorded in the O1, O2, and Oz leads placed according to the “10–20” system for electroencephalography (EEG) [8]. The main characteristics of these potentials are their frequencies, which strictly depend on the frequencies of visual stimuli, and power, which is usually significantly higher than the power of the baseline brainwave activity. The widely claimed advantages of SSVEP-based BCIs include the following [9]:

- The high speed of the information transfer;
- The minimal time required for user training and relative ease of installation;
- The safety for the users.

The aforementioned immaturity of the BCI technology leaves much to be desired for each of the above points. First, much of the current research in the field is focused on the light stimuli of high frequencies (for EEG signals, this means more than 30 Hz [10]) to enhance the *information transfer rate* (ITR) or effective bit rate, as introduced in [11], and reported on in BCI studies. ITR is a common metric in SSVEP-BCI interfaces, aiding in the estimation and comparison of different identification algorithms by combining speed and accuracy. Indeed, the low-frequency range of EEG signals is affected by high-amplitude artifacts, such as EOG artifacts (concentrated in the frequency range of 1 to 5 Hz [12]). Moreover, it is overlapped by a more powerful alpha-rhythm of the EEG signal, concentrated in the frequency range of 8 to 14 Hz. However, SSVEP potentials are usually most intense in the frequency range of around 15 Hz, and the power of the evoked potential decreases with the increase of the light stimulus frequency [13].

Second, BCIs are rather less universal than most other human–machine interface modes, as the former generally require calibration and adaptation to the user’s individual characteristics. SSVEP-based BCIs have a wide scope of applications, ranging from controlling smart home devices [14] to enabling communication with patients with disorders of consciousness and facilitating the rehabilitation of individuals after severe head and spinal cord injuries [15][16]. In these scenarios, the usability and minimal training duration required to ensure reliable operation take precedence. Indeed, as mentioned above, in some people, the response level to a certain stimulus frequency may be too low relative to the EEG signal itself, making this frequency unsuitable for use [10]. This makes it difficult to build a universal BCI that uses a single frequency range for its users. The need for calibration is recognized as a major obstacle for the wider BCI development and hurts the overall user experience (UX) [17][18]. The currently popular approach to the so-called *subject calibration problem* is "subject-transfer" [19], which largely corresponds to the general transfer learning approaches in AI-ML: instance-based, parameter-based, or feature-based [20]. Correspondingly, methods and models that improve the trade-off between the calibration effort and the BCI performance move the field forward, but this issue is far from being resolved yet.

Third, the claimed safety of BCIs is rather situational. Even if we do not consider brain-invasive techniques, the photo stimuli can cause strong fatigue (particularly to the eyes) and even provoke an epileptic seizure for individuals suffering from photosensitive epilepsy [21]. Research suggests that these risks are frequency-specific, being more prone to the middle-frequency range of EEG signals (from 12 to 30 Hz) [10], and user group-specific [22]. Zhang and colleagues demonstrated in their recent study that SSVEP target–classification accuracy decreases under the influence of stress [23]. To assess the extent of the impact of periodic photostimulation on the subjective emotional state of participants and to objectify the degree of discomfort experienced during interaction with neurointerfaces, researchers in this field employ indices that are specifically derived from the power ratios of major EEG frequency bands. For instance, theta–beta ratio [24], theta–alpha ratio [25], and frontal alpha asymmetry [26] have frequently been used as such indices in scientific literature. Incorporating these index values into the development of an algorithm for individually tailored stimulation frequencies could represent a crucial step toward creating more personalized and user-friendly interfaces.

2. BCI Applications

Nowadays, brain–computer interfaces are being applied in many fields and for many purposes. Many different paradigms are being used to design them. It is difficult to fully cover these areas, and presented here is just a fraction of the research aimed at enhancing quality of life.

An important direction in this field involves the use of BCIs to restore the function of the cerebral cortex when it is damaged. This is achieved through the introduction of biological feedback. Reference [27] showed—for the first time—that with the help of invasive BCIs, it is possible to restore movement to paralyzed limbs in people suffering from "locked-in syndrome" (LIS). This condition is characterized by a complete loss of speech and paralysis while maintaining consciousness and sensitivity.

BCIs are also used for cursor control, text input, and forming commands for robots. An interesting example is presented in reference [28], where people with spinal cord injuries were able to modulate neural activity associated with the intention to move, even 3 years after the injury.

In recent studies, BCIs were created that could automatically recognize speech from neural activities recorded using EEGs, as well as reconstruct whole sentences from thoughts with a limited vocabulary [29]. Another line of research demonstrates the possibility of controlling a patient's prosthetics or exoskeletons based on neural activity recorded using EEGs [30]. This opens up new perspectives for reproducing fine motor skills with prosthetics in the future.

A recent study introduced an unsupervised data-driven pipeline for rejecting blink and muscle artifacts in EEG time series for use in motor imagery (MI)-based BCIs integrated with the Internet of Medical Things (IoMT) [31]. Using this approach reduces processing times, resource demands, and reliance on human intervention, making it a promising avenue for crafting efficient, user-friendly real-time BCI systems. Moreover, the technique proposed by the authors to enhance TL-CNN classification between Mex and MI finger-pinching actions is superior to other state-of-the-art methods, which makes it promising for further development and implementation in practice.

3. SSVEP-Based BCI Enhancements

As a rule, scalp electroencephalography (EEG) is used as a tool to provide continuous registration of a user's neural activity for further transmission to BCIs. The EEG signals have high temporal resolution [9][32], and the approach involves a non-invasive process of measuring the electrical activity of the cerebral cortex and does not require surgical intervention. This provides a high safety level for users of such BCIs, compared to BCIs based on electrocorticography (ECoG) [33].

The latter requires mandatory surgical intervention and, thus, poses a high level of risk, making EEG-based BCIs a safer and more promising technology for universal application.

It is recognized that BCI performance, which has been foremost associated with information transfer rates, is considerably better with calibration than in calibration-free schemes [34]. With respect to SSVEP-based BCIs, it is believed that a subject-specific type of calibration is capable of yielding the best performance. However, the time and effort spent on such individual training sessions are considered to be the most serious disadvantages of this approach [35]. Correspondingly, up-to-date research in the field focuses on (a) reducing the data amounts that need to be gathered from a particular subject by reusing some existing data [34], (b) collecting the data more intensively, e.g., through several channels [36], and (c) making more intensive use of available data via smarter calibration algorithms [37].

4. BCI Usability and User Satisfaction

While the safety of modern BCIs is well-established and performance remains a primary research focus, calibration algorithms that consider interface usability are relative new. BCI-related studies that follow a user-centered approach define usability in terms of effectiveness (accuracy), efficiency (ITR and subjective workloads), and user satisfaction [38].

Selection algorithms that consider the user's emotional state and subjective comfort during BCI interactions can help lead to new levels of user experience. However, there is a certain disparity in how exactly the registered EEG signals should be used to automatically infer various dimensions of user satisfaction. Y.N. Ortega and co-authors have exhaustively addressed this in their works, recently culminating in a connection between potential EEG signal characteristics and usability measures, as presented in [39].

As mentioned in [40], using flicker frequencies in the range of 4–30 Hz can lead to visual fatigue. Thus, it is important to find frequencies at which the interaction will be the most effective and the person experiences minimal discomfort in using BCIs [41]. Various methods are employed to minimize the discomfort; for example, [40] proposed using a chessboard stimulus, which allows for reducing user discomfort without compromising performance. In turn, researchers suggest taking user satisfaction into account when selecting an individual frequency for BCI.

The safety of using brain–computer interfaces is a determining factor that allows them to be integrated into various aspects of our lives; therefore, this factor should be approached with the utmost seriousness and attention.

References

1. Khademi, Z.; Ebrahimi, F.; Kordy, H.M. A review of critical challenges in MI-BCI: From conventional to deep learning methods. J. Neurosci. Methods 2023, 383, 109736.
2. Zgallai, W.; Brown, J.T.; Ibrahim, A.; Mahmood, F.; Mohammad, K.; Khalfan, M.; Mohammed, M.; Salem, M.; Hamood, N. Deep learning AI application to an EEG driven BCI smart wheelchair. In Proceedings of the 2019 Advances in Science and Engineering Technology International Conferences (ASET), Dubai, United Arab Emirates, 26 March–10 April 2019; pp. 1–5.
3. Dehais, F.; Dupres, A.; Di Flumeri, G.; Verdiere, K.; Borghini, G.; Babiloni, F.; Roy, R. Monitoring pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using an hybrid fNIRS-EEG passive BCI. In Proceedings of the 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Miyazaki, Japan, 7–10 October 2018; pp. 544–549.
4. Zander, T.O.; Kothe, C.; Jatzev, S.; Gaertner, M. Enhancing human-computer interaction with input from active and passive brain-computer interfaces. In Brain-Computer Interfaces: Applying our Minds to Human-Computer Interaction; Springer: London, UK, 2010; pp. 181–199.
5. Abiri, R.; Borhani, S.; Sellers, E.W.; Jiang, Y.; Zhao, X. A comprehensive review of EEG-based brain—Computer interface paradigms. J. Neural Eng. 2019, 16, 011001.
6. Xiao, X.; Wang, L.; Xu, M.; Wang, K.; Jung, T.P.; Ming, D. A data expansion technique based on training and testing sample to boost the detection of SSVEPs for brain-computer interfaces. J. Neural Eng. 2023.
7. Liu, S.; Zhang, D.; Liu, Z.; Liu, M.; Ming, Z.; Liu, T.; Suo, D.; Funahashi, S.; Yan, T. Review of brain—Computer interface based on steady-state visual evoked potential. Brain Sci. Adv. 2022, 8, 258–275.
8. Wittevrongel, B.; Khachatryan, E.; Hnazaee, M.F.; Carrette, E.; De Taeye, L.; Meurs, A.; Boon, P.; Van Roost, D.; Van Hulle, M.M. Representation of steady-state visual evoked potentials elicited by luminance flicker in human occipital

cortex: An electrocorticography study. Neuroimage 2018, 175, 315–326.

9. Chen, X.; Wang, Y.; Nakanishi, M.; Gao, X.; Jung, T.P.; Gao, S. High-speed spelling with a noninvasive brain—Computer interface. Proc. Natl. Acad. Sci. USA 2015, 112, E6058–E6067.
10. Zhu, D.; Bieger, J.; Molina, G.G.; Aarts, R.M. A survey of stimulation methods used in SSVEP-based BCIs. Comput. Intell. Neurosci. 2010, 2010, 702357.
11. Wolpaw, J.; Ramoser, H.; McFarland, D.; Pfurtscheller, G. EEG-based communication: Improved accuracy by response verification. IEEE Trans. Rehabil. Eng. 1998, 6, 326–333.
12. Zhang, J.; Gao, S.; Zhou, K.; Cheng, Y.; Mao, S. An online hybrid BCI combining SSVEP and EOG-based eye movements. Front. Hum. Neurosci. 2023, 17, 1103935.
13. Won, D.; Hwang, H.; Dähne, S.; Müller, K.; Lee, S. Effect of higher frequency on the classification of steady-state visual evoked potentials. J. Neural Eng. 2015, 13, 016014.
14. Adams, M.; Benda, M.; Saboor, A.; Krause, A.F.; Rezeika, A.; Gembler, F.; Stawicki, P.; Hesse, M.; Essig, K.; Ben-Salem, S.; et al. Towards an SSVEP-BCI Controlled Smart Home. In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Bari, Italy, 6–9 October 2019; Volume 1.
15. Lesenfants, D.; Habbal, D.; Lugo, Z.; Lebeau, M.; Horki, P.; Amico, E.; Pokorny, C.; Gómez, F.; Soddu, A.; Müller-Putz, G.; et al. An independent SSVEP-based brain–computer interface in locked-in syndrome. J. Neural Eng. 2014, 11, 035002.
16. Na, R.; Hu, C.; Sun, Y.; Wang, S.; Zhang, S.; Han, M.; Yin, W.; Zhang, J.; Chen, X.; Zheng, D. An embedded lightweight SSVEP-BCI electric wheelchair with hybrid stimulator. Digit. Signal Process. 2021, 116, 103101.
17. 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.
18. Han, D.K.; Jeong, J.H. Domain generalization for session-independent brain-computer interface. In Proceedings of the 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Republic of Korea, 22–24 February 2021; pp. 1–5.
19. Li, J.; Wang, F.; Huang, H.; Qi, F.; Pan, J. A novel semi-supervised meta learning method for subject-transfer brain–computer interface. Neural Netw. 2023, 163, 195–204.
20. Li, M.; Xu, D. Transfer Learning in Motor Imagery Brain Computer Interface: A Review. J. Shanghai Jiaotong Univ. Sci. 2022, 1–23.
21. Ladouce, S.; Darmet, 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.
22. Silva, L.C.B.; Kasteleijn-Nolst Trenite, D.; Manreza, M.L.; Appleton, R.E. Epidemiology of Sensitivity of the Brain to Intermittent Photic Stimulation and Patterns. In The Importance of Photosensitivity for Epilepsy; Springer: Cham, Switzerland, 2021; pp. 3–25.
23. Zhang, H.Y.; Stevenson, C.E.; Jung, T.P.; Ko, L.W. Stress-Induced Effects in Resting EEG Spectra Predict the Performance of SSVEP-Based BCI. IEEE Trans. Neural Syst. Rehabil. Eng. 2020, 28, 1771–1780.
24. Putman, P.; Verkuil, B.; Arias-Garcia, E.; Pantazi, I.; van Schie, C. EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention. Cogn. Affect. Behav. Neurosci. 2014, 14, 782–791.
25. Vanhollebeke, G.; De Smet, S.; De Raedt, R.; Baeken, C.; van Mierlo, P.; Vanderhasselt, M.A. The neural correlates of psychosocial stress: A systematic review and meta-analysis of spectral analysis EEG studies. Neurobiol. Stress 2022, 18, 100452.
26. Goodman, R.N.; Rietschel, J.C.; Lo, L.C.; Costanzo, M.E.; Hatfield, B.D. Stress, emotion regulation and cognitive performance: The predictive contributions of trait and state relative frontal EEG alpha asymmetry. Int. J. Psychophysiol. 2013, 87, 115–123.
27. Kennedy, P.R.; Bakay, R.A.E. Restoration of neural output from a paralyzed patient by a direct brain connection. NeuroReport 1998, 9, 1707–1711.
28. Hochberg, L.R.; Serruya, M.D.; Friehs, G.M.; Mukand, J.A.; Saleh, M.; Caplan, A.H.; Branner, A.; Chen, D.; Penn, R.D.; Donoghue, J.P. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature 2006, 442, 164–171.
29. Défossez, A.; Caucheteux, C.; Rapin, J.; Kabeli, O.; King, J.R. Decoding speech perception from non-invasive brain recordings. Nat. Mach. Intell. 2023, 5, 1097–1107.

30. Orban, M.; Elsamanty, M.; Guo, K.; Zhang, S.; Yang, H. A Review of Brain Activity and EEG-Based Brain–Computer Interfaces for Rehabilitation Application. Bioengineering 2022, 9, 768.
31. Varone, G.; Boulila, W.; Driss, M.; Kumari, S.; Khan, M.K.; Gadekallu, T.R.; Hussain, A. Finger pinching and imagination classification: A fusion of CNN architectures for IoMT-enabled BCI applications. Inf. Fusion 2024, 101, 102006.
32. Aricò, P.; Borghini, G.; Di Flumeri, G.; Sciaraffa, N.; Babiloni, F. Passive BCI beyond the lab: Current trends and future directions. Physiol. Meas. 2018, 39, 08TR02.
33. Miller, K.J.; Hermes, D.; Staff, N.P. The current state of electrocorticography-based brain–computer interfaces. Neurosurg. Focus 2020, 49, E2.
34. Wong, C.M.; Wang, Z.; Nakanishi, M.; Wang, B.; Rosa, A.; Chen, C.P.; Jung, T.P.; Wan, F. Online adaptation boosts SSVEP-based BCI performance. IEEE Trans. Biomed. Eng. 2021, 69, 2018–2028.
35. Zerafa, R.; Camilleri, T.; Falzon, O.; Camilleri, K.P. To train or not to train? A survey on training of feature extraction methods for SSVEP-based BCIs. J. Neural Eng. 2018, 15, 051001.
36. Yao, L.; Jiang, N.; Mrachacz-Kersting, N.; Zhu, X.; Farina, D.; Wang, Y. Reducing the calibration time in somatosensory BCI by using tactile ERD. IEEE Trans. Neural Syst. Rehabil. Eng. 2022, 30, 1870–1876.
37. Wu, Y.; Yang, R.; Chen, W.; Li, X.; Niu, J. Research on Unsupervised Classification Algorithm Based on SSVEP. Appl. Sci. 2022, 12, 8274.
38. Holz, E.M.; Höhne, J.; Staiger-Sälzer, P.; Tangermann, M.; Kübler, A. Brain–computer interface controlled gaming: Evaluation of usability by severely motor restricted end-users. Artif. Intell. Med. 2013, 59, 111–120.
39. Ortega, Y.; Mezura-Godoy, C. Usability Evaluation of BCI Software Applications: A systematic review of the literature. Program. Comput. Softw. 2022, 48, 646–657.
40. Ming, G.; Pei, W.; Chen, H.; Gao, X.; Wang, Y. Optimizing spatial properties of a new checkerboard-like visual stimulus for user-friendly SSVEP-based BCIs. J. Neural Eng. 2021, 18, 056046.
41. Ming, G.; Pei, W.; Gao, X.; Wang, Y. A high-performance SSVEP-based BCI using imperceptible flickers. J. Neural Eng. 2023, 20, 016042.