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Application Bottlenecks and Solution Pathways of Steady-State Visual Evoked Potential-Based Brain-Computer Interface Systems

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Abstract

Steady-state visual evoked potential (SSVEP) has become one of the mainstream paradigms in brain-computer interface (BCI) systems due to its high information transfer rate, high recognition accuracy, and low user training requirements. It has shown potential in medical rehabilitation and intelligent control. Despite substantial technical advances in laboratory settings, SSVEP-BCI systems still face significant bottlenecks when transitioning to real-world, everyday applications, resulting in limited practical deployment. This paper examines the current application status and challenges of SSVEP-BCI systems, systematically reviews their use in medical rehabilitation, and analyzes the core difficulties from technical, hardware, and user perspectives. At the technical level, the focus is on signal denoising and asynchronous system design. At the hardware level, the analysis centers on the trade-off between device cost and performance. At the user level, the discussion addresses core needs related to comfort and portability. In response to these challenges, the paper summarizes existing solutions, including fusion with electromyography (EMG) signals for denoising, sponge electrodes made from novel materials, high-frequency stimulation, and hybrid paradigms. The paper also highlights that algorithm optimization, new material development, and hybrid paradigms will be key pathways for moving SSVEP-BCI systems from laboratories to widespread application. This review summarizes current challenges and potential solutions for the practical deployment of SSVEP-BCI systems.

Keywords

Steady-state visual evoked potential, brain-computer interface, application bottlenecks, solution pathways

1. Introduction

Brain-computer interface (BCI) technology aims to establish direct communication channels between the human brain and external devices without relying on peripheral nerves or muscles. Over the past two decades, BCI systems have made notable progress in rehabilitation medicine, artificial intelligence, mechanical control, smart homes, gaming and entertainment, and military applications. Among various BCI paradigms, steady-state visual evoked potential (SSVEP)-based systems stand out for their high information transfer rate (ITR), strong recognition accuracy, and minimal user training requirements, giving them considerable application potential [1]. SSVEP refers to the phenomenon in which flickering visual stimuli at specific frequencies elicit EEG signals of the same frequency in the brain's occipital region. By detecting these frequency-specific EEG signals, the user's visual attention target—and thus their intent—can be identified.

Yet, most current SSVEP-BCI systems remain at the laboratory research stage, with few products reaching widespread real-world use. According to Mason et al., among 79 surveyed BCI groups, only 10 (13%) had implemented assistive devices, 26 (33%) had developed demonstration systems, and the remaining 43 (54%) were limited to offline data analysis [2]. These findings suggest several barriers to practical application, such as product cost, user comfort, and device portability. Considerable advances have been made in signal extraction and feature analysis—significantly improving efficiency and accuracy—the ultimate goal of BCI systems is real-world service, so comprehensive reviews that analyze current applications and challenges are needed. This paper focuses on the application status and bottlenecks of SSVEP-BCI systems, compiles existing solutions, and provides an outlook for future development.

2. Overview of SSVEP-BCI Systems

Steady-state visual evoked potential (SSVEP) occurs when flickering external light stimuli elicit brain responses at the same frequency (or harmonics) in the occipital cortex, the region responsible for visual processing. Typical SSVEP-BCI systems use stimuli at different frequencies to represent distinct control commands. EEG signals are acquired via scalp electrodes, amplified, filtered, feature-extracted, and classified to identify the stimulus the user is focusing on. The corresponding control command is then transmitted to the actuator.

In practical applications, LED, LCD, and CRT light sources have been employed, with LEDs being the most common. LED stimuli produce prominent fundamental and harmonic components in the EEG that can be clearly distinguished from noise, thereby improving decision accuracy [3]. Stimulation frequencies are typically chosen in the low (1–12 Hz) or medium (12–30 Hz) ranges because high-frequency signals tend to be weaker. For electrodes, wet electrodes are commonly used in research for their superior signal quality and are usually placed at O1, O2, and Oz to capture occipital signals precisely. The evoked EEG signals require preprocessing to improve the signal-to-noise ratio (SNR), with filtering and blind source separation being common approaches. Filtering works well when signal and noise occupy distinct frequency bands; when overlap occurs, methods such as independent component analysis (ICA) yield better artifact removal [3]. After preprocessing, feature extraction and classification are necessary due to the inherently low SNR and high dimensionality of EEG signals. Classical algorithms include short-time Fourier transform and canonical correlation analysis. Overall, SSVEP-BCI systems have developed a relatively mature operational framework, with numerous improvements and optimizations built upon this pipeline.

Among BCI paradigms, SSVEP attracts attention for its high ITR and recognition accuracy, along with the advantage of requiring little user training. These characteristics make SSVEP-BCI systems highly promising for practical use, and they have matured considerably in laboratory environments. It cannot be denied that many issues must still be addressed before real-world deployment.

3. Applications of SSVEP-BCI Systems

3.1 Application Status

SSVEP-BCI systems have achieved notable progress in medical rehabilitation, which illustrates their underlying logic.

In medical diagnosis, these systems can extract disease-discriminative features from SSVEP EEG signals and compare them with healthy controls to assess pathology. For example, one study collected 166 SSVEP features, identified the six most disease-relevant ones, and used them for machine learning-based diagnosis of mild cognitive impairment, providing a basis for early Alzheimer's prevention [4]. Another study found statistically significant differences in SSVEP peak and mean values between patients with schizophrenia and bipolar disorder, enabling differentiation of these clinically similar conditions [5]. Thanks to SSVEP's high SNR, only 2–4 electrodes are typically needed to achieve high accuracy (often >90%) and rapid identification—important advantages in cost and efficiency for clinical use. In principle, SSVEP exploits disease-related functional differences in visual processing areas. Thus, any pathology affecting visual regions holds potential for SSVEP-based detection. These systems currently serve as assistive diagnostic tools rather than standalone diagnostics, but they play a significant role in early prevention.

In medical rehabilitation, applications include high-ITR spellers achieving 330.4 ± 45.4 bits/min [6], sufficient for daily communication by patients with neurological impairments, and intelligent wheelchairs controlled solely by brain signals for direction and speed [7]. These assistive devices leverage SSVEP advantages to provide good human-machine interaction. Compared with motor imagery (MI)-based control, they require less intensive user training. Frequency-phase joint coding has also greatly increased the number of available targets, enabling richer choices, more complex functions, and higher information transfer efficiency.

Compared with open-loop systems, closed-loop BCI systems add feedback from device to brain and play a key role in sensory restoration and adjunctive therapy. For instance, Ning Guo et al. developed a soft robotic glove that assists hand movements while providing real-time visual feedback on a screen to reinforce damaged motor circuits [8]. Although applications are diverse, the core principle remains the use of different stimuli to represent commands and decoding user intent from visual cortex signals.

It is worth noting that most applications remain concentrated in healthcare. In other fields, such as daily entertainment, SSVEP-based games exist but often fail to meet actual user needs. This limitation stems from SSVEP's fundamental reliance on target selection; complex games typically require more precise, continuous control that multi-target SSVEP systems cannot fully provide. This explains why most such games are limited to basic directional control rather than fine-grained actions.

3.2 Application Challenges and Solutions

3.2.1 Technical Level

From a technical perspective, denoising during preprocessing receives relatively little attention. Laboratory environments are quiet and stable, and subjects are usually asked to focus fully on tasks. In everyday scenarios, however, such ideal conditions rarely exist. Acquired signals may contain external background noise and artifacts from eye and muscle movements. Another critical issue is achieving effective denoising and feature extraction with as few electrodes as possible, since more electrodes reduce portability and increase cost. Encouragingly, Aiping Liu et al. demonstrated that incorporating additional EMG channels can improve denoising performance. They found that blind source separation alone performs poorly with few channels and may even distort key EEG signals [9], offering valuable insights for developing wearable, mobile EEG devices.

Another key consideration is asynchronous versus synchronous systems. Many current systems rely on predefined time windows and task structures, forcing users to issue commands only within specified periods—an obvious limitation in complex daily environments. Designing asynchronous systems requires balancing sensitivity and specificity to avoid both false positives (from low thresholds) and missed responses (from high thresholds), while keeping channel counts low. Algorithms such as filter-bank canonical correlation analysis (FBCCA) for classification, power spectral density analysis (PSDA), and support vector machines (SVM) for state detection have been proposed, but none perfectly reconcile sensitivity and specificity. Beyond algorithm improvements, hybrid control approaches offer promising alternatives. One study used the FEAD method to detect blink counts for system on/off control, effectively preventing false activations during idle states [10], which represents an innovative and practical complement to pure algorithmic optimization.

3.2.2 Hardware Level

The main hardware challenge for broader adoption is balancing cost and performance. Major costs arise from EEG acquisition and processing equipment. Traditional electrodes are divided into dry and wet types. Dry electrodes are cheaper but offer poorer signal quality, leading laboratories to favor wet electrodes. Wet electrodes provide high-quality signals but require conductive gel application before each use, lengthy preparation time, and specialized maintenance—substantially raising overall costs. Improving denoising and feature extraction algorithms to maintain accuracy with fewer dry-electrode channels is one way to reduce costs. Promising alternatives include novel-material electrodes, such as the moisture-absorbing sponge electrodes developed by Li-Wei Ko et al., which overcome many drawbacks of both dry and wet types [11]. Such materials are likely to lay the foundation for practical BCI deployment. Another major expense is the computer required for processing, especially with complex deep-learning algorithms. While feasible in research, this is prohibitively expensive for consumer devices. Several studies have explored integrated core boards for acquisition, processing, and output. The highly specialized and integrated OpenBCI platform exemplifies this approach, dramatically lowering costs through system integration. As BCI technology advances, such dedicated platforms are expected to proliferate, simplifying development while reducing costs—making them the optimal choice for SSVEP-BCI system design.

3.2.3 User Level

User needs center on three aspects: portability, comfort, and whether the system genuinely addresses real demands. Portability requires minimal electrode counts and highly integrated core boards instead of computers. The visual stimulus display—another core component—also needs optimization. On the software side, designers must create clear, concise UIs and minimize display size. On the hardware side, displays must maintain stable frequencies while remaining compact. Existing solutions include LED-based stimulators, which offer stable multi-frequency control, reduced visual strain, and easy integration into head-mounted devices. Studies have confirmed LED advantages over LCD for portability [12]. Another approach uses visual stimuli presented in head-mounted VR displays, enhancing both portability and user immersion [13]. Comfort is primarily challenged by visual fatigue. Many studies note that prolonged gaze on flickering stimuli reduces comfort and can degrade subsequent recognition accuracy. Although low- and medium-frequency stimulation is common for signal strength, high-frequency stimulation significantly alleviates visual fatigue. Xiaogang Chen et al. optimized stimulus parameters (color combinations, visual angles, etc.) to bring the ITR and accuracy of high-frequency SSVEP-BCI systems close to those of medium- and low-frequency systems [14].

SSVEP-BCI systems have broad prospects in healthcare—the primary application domain. The core user need is direct control of devices without relying on peripheral nerves or muscles. Although current systems are slower than manual operation due to detection and classification delays, they provide an effective solution for patients unable to communicate or move independently. In this sense, they fulfill the fundamental need of enabling interaction with the external world where none previously existed.

4. Future Prospects of SSVEP-BCI Systems

While single-modality SSVEP-BCI systems have seen major performance improvements, further gains remain possible. With rapid advances in artificial intelligence, signal processing, feature extraction, and classification are poised for qualitative leaps in both data utilization and accuracy, potentially breaking through translational barriers and bringing the technology into everyday life. Continued emergence of new materials may yield electrodes with higher signal quality and greater wearing comfort, fundamentally improving performance and reducing costs. Single-modality SSVEP systems have inherent functional limitations, prompting growing interest in hybrid paradigms such as P300+SSVEP, MI+SSVEP, and SSVEP+EOG. Hybrid BCIs offer several advantages: broader user applicability and mitigation of BCI illiteracy; more stable or even continuous control (e.g., combining with EOG for high-accuracy continuous commands); richer user experiences through multi-dimensional control; and improved asynchronous operation by using one modality as a reliable “switch.” In the future, single-modality SSVEP will continue to be refined, but hybrid control is likely to become the mainstream pathway toward practical application. “High coupling” may emerge as a new strategy for overcoming existing challenges.

5. Conclusion

This paper has introduced the working principles and parameter selection of SSVEP-BCI systems, systematically reviewed their application status—particularly the vigorous development in medical rehabilitation—and analyzed bottlenecks from technical, hardware, and user perspectives. Despite substantial laboratory progress, SSVEP-BCI systems still face challenges in moving toward widespread adoption, including robust denoising, reliable asynchronous control, and the cost-performance balance. The paper has summarized existing solutions such as EMG-channel-assisted denoising, core algorithm optimization, novel electrodes, and high-frequency stimulation. In addition to single-modality improvements, hybrid BCI systems offer advantages in accuracy, command set expansion, user population coverage, and asynchronous control optimization, making them a major development pathway.

By systematically organizing the application challenges of SSVEP-BCI systems, this review provides practical guidance for translational research and supports the conversion of SSVEP-BCI technology from theoretical studies to market-oriented products. Advances in artificial intelligence, materials science, and algorithm design may further improve the practical applicability of SSVEP-BCI systems to achieve widespread adoption in medical rehabilitation, human-machine interaction, smart homes, and entertainment, enabling broader applications in rehabilitation and human-machine interaction.

References

[1] Jiang, G., & Zhao, C. L. (2022). A review of EEG-based brain-computer interface development. *Computer Measurement & Control*, 30(7), 8.

[2] Mason, S. G., Bashashati, A., Fatourechi, M., Flowers, P. E., & Birch, G. E. (2007). A comprehensive survey of brain interface technology designs. *Annals of Biomedical Engineering*, 35(1), 137–169. https://doi.org/10.1007/s10439-006-9170-0.

[3] Zhu, D., Bieger, J., Garcia Molina, G., & Aarts, R. M. (2010). A survey of stimulation methods used in SSVEP-based BCIs. *Computational Intelligence and Neuroscience*, 2010, Article 702357. https://doi.org/10.1155/2010/702357.

[4] Kim, D., Park, J., Choi, H., Ryu, H., Loeser, M., & Seo, K. (2024). Early detection of patients with mild cognitive impairment through EEG-SSVEP-based machine learning model. IEEE Access, 12, 172101–172114. https://doi.org/10.1109/ACCESS.2024.3490123.

[5] Alimardani, F., Cho, J. H., Boostani, R., & Hwang, H. J. (2018). Classification of bipolar disorder and schizophrenia using steady-state visual evoked potential based features. IEEE Access, 6, 40379–40388. https://doi.org/10.1109/ACCESS.2018.2854556.

[6] Tang, J., Xu, M., Han, J., Liu, M., Dai, T., Chen, S., & Ming, D. (2020). Optimizing SSVEP-based BCI system towards practical high-speed spelling. *Sensors*, 20(15), 4186. https://doi.org/10.3390/s20154186.

[7] Na, R., Bi, L., & Feng, C. (2022). Reprint of: An embedded lightweight SSVEP-BCI electric wheelchair with hybrid stimulator. *Digital Signal Processing*, 125, 103573. https://doi.org/10.1016/j.dsp.2022.103573.

[8] Guo, N., Meng, Q., Xu, R., Gao, C., Yan, Z., Liu, S., ... & Yu, H. (2022). SSVEP-based brain computer interface controlled soft robotic glove for post-stroke hand function rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, 1737–1744. https://doi.org/10.1109/TNSRE.2022.3183533.

[9] Liu, A., Liu, Q., Zhang, X., Chen, X., & Chen, X. (2021). Muscle artifact removal toward mobile SSVEP-based BCI: A comparative study. *IEEE Transactions on Instrumentation and Measurement*, 70, 1–12. https://doi.org/10.1109/TIM.2021.3060541.

[10] Erkan, E., & Akbaba, M. (2018). A study on performance increasing in SSVEP based BCI application. *Engineering Science and Technology, an International Journal*, 21(3), 421–427. https://doi.org/10.1016/j.jestch.2018.04.002.

[11] Ko, L. W., Chang, Y., Wu, P. L., Tzou, H. A., Chen, S. F., Tang, S. C., Yeh, C. L., & Chen, Y. J. (2019). Development of a smart helmet for strategical BCI applications. *Sensors*, 19(18), 3848. https://doi.org/10.3390/s19183848.

[12] Design of portable LED visual stimulus and SSVEP analysis for visual fatigue reduction and improved accuracy (2017). [Thesis/Report, Kent Academic Repository].

[13] Koo, B., Lee, H. G., Nam, Y., & Choi, S. (2015). Immersive BCI with SSVEP in VR head-mounted display. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 703–706). IEEE. https://doi.org/10.1109/EMBC.2015.7318459.

[14] Chen, X., Wang, Y., Tang, X., Zhang, S., Han, J., Xu, M., & Ming, D. (2023). Optimizing stimulus frequency ranges for building a high-rate high frequency SSVEP-BCI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 31, 1277–1286. https://doi.org/10.1109/TNSRE.2023.3244670.

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Conflicts of Interest

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