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A Survey on Deep Learning-Driven SSVEP-Based BCIs: Trends, Challenges, and Future Directions

Mrs. Bhagya Jyothi MK[1] and Dr. Sreerangappa M[2]
Assistant Professor, Dept. of CSE[1]
Associate Professor, Dept. of ECE[2]
Sri Siddhartha Institute of Technology, SSAHE, Tumkuru, Karnataka, India
bjyoti.23@gmail.com and sreerangappa.ssit@gmail.com

Abstract: *This survey presents a comprehensive review of recent advancements in steady-state visual evoked potential (SSVEP)-based brain–computer interfaces (BCIs), a promising paradigm due to its high information transfer rate, minimal user training, and robustness in real-time applications. We analyze the core components of SSVEP-based systems, including signal acquisition, preprocessing, feature extraction, classification, and feedback mechanisms. Particular emphasis is placed on the integration of deep learning techniques, such as convolutional neural networks (CNNs), recurrent models, and hybrid architectures, which have significantly improved classification accuracy and system adaptability. The paper also explores simplified BCI setups using single-channel EEG for practical deployment, and addresses key challenges such as signal variability, low signal-to-noise ratio, visual fatigue, and the need for domain adaptation. Furthermore, emerging strategies like neural data alignment and transfer learning are examined for enhancing cross-subject generalization. This survey aims to guide researchers by summarizing state-of-the-art developments, identifying persistent challenges, and suggesting potential directions for future research in SSVEP-based BCIs.*

Keywords: Steady-state visual evoked potential (SSVEP), Brain–computer interfaces (BCIs), Deep learning, Signal variability, Transfer learning

I. INTRODUCTION

Without employing peripheral nerves or muscles, the brain–computer interface (BCI) offers a direct communication route between the human brain and computers. BCIs let users utilize their brain states to operate equipment such spelling interfaces, wheelchairs, computer games, or other assistive devices [1]. Of all BCIs, those based on electroencephalography (EEG) are the most common. Widely used in brain-computer interface applications, EEG is a non-invasive method of obtaining brain waves from the surface of the human scalp. Its safety, ease, and high temporal resolution [2] make it particularly appealing. Among the many often used paradigms to elicit brain signals to provide the control instructions for EEG-based BCIs, P300, motor imagery, and steady-state visual evoked potential (SSVEP).

Among these, SSVEP is regarded as the most appropriate paradigm for efficient high-throughput BCI as it requires minimal training, offers great classification accuracy, and has a high information transfer rate (ITR) [3]. SSVEP is oscillatory electrical potential in the brain produced when the person visually watches a stimulus flashing at a frequency of 6 Hz or above. Stimulus-related spontaneous intrinsic brain oscillation reconfiguration will probably happen. Most apparent in the occipital area (visual cortex), these SSVEP signals have a basic frequency matching the input and its harmonics.

Typically, SSVEP-based BCIs have five primary processing stages: the data collecting stage that captures neural data; the signal preprocessing stage that cleans and preprocesses the recorded data; the feature extraction stage that pulls relevant information from the neural data; the classification stage that mostly uses machine learning techniques to produce the BCI output from the processed neural data; and the feedback stage that shows the BCI output to the user [4].

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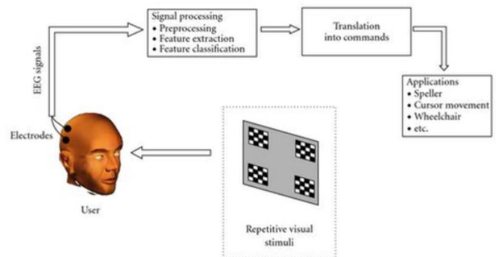

Fig 1.Functional model of an SSVEP-based BCI.

A sequence of signal processing techniques involving preprocessing (e.g., band-pass filtering), artifact detection/correction, feature extraction (e.g., spectral content at the stimulation frequencies), and feature classification allows SSVEPs to be automatically recognized. Usually, BCI performance is evaluated in terms of classification accuracy, classification speed, and the number of possible options. These can be combined into one measure called the bit rate [5]. The intensity of the SSVEP response, the signal-to-noise ratio (SNR), and the variations in the characteristics of the stimuli mostly determine classification accuracy in SSVEP-based BCIs. Classification speed is determined by how long the SSVEP is strong enough. While more targets increase the number of potential instructions, it may reduce classification accuracy and speed.

Apart from the bit rate, one should also take into account the safety and comfort of SSVEP-based BCIs. Repetitive visual stimuli modulated at particular frequencies can trigger epileptic seizures [6] and flashes that are too intense may compromise the user's eyesight. Moreover, some stimulation frequencies might cause weariness.

Furthermore, an SSVEP-based system calls for no training time or maybe no training procedure. SSVEP has so drawn increasing notice and been used in several BCI system research during the last few years. Most of these research mostly concentrated on the use of a multi-channel headset to create BCI systems with great accuracy. But a multi-channel system might be an ineffective tool in actual applications due to its complex configuration. Maintaining the wearing comfort over time, this work offers a straightforward and practical BCI based on a single channel SSVEP signal that might improve the usability as well as lower the system complexity. To create a bipolar montage to capture the EEG signal from the O1–Oz pair and enhance the SNR, two dry electrodes were employed [7].

Compared to conventional SSVEP-based categorization techniques, deep learning offers several benefits. Deep learning is more likely to pick up subtle patterns that are not visible by humans but are useful for the categorization of EEG signals as it combines feature extraction and classification into one process. Using a neural network made up of several stacked layers of neurons, deep learning trains each layer on a different set of characteristics based on the output of prior levels. More complicated characteristics arise as the data travels throughout the network. The network may use raw SSVEP signals as the input, eliminating the need for hand-crafted feature extraction as well as conventional signal preprocessing processes [8]. This quality is especially important as it prevents implicit EEG signals or features from being lost during feature extraction or preprocessing [9].

A repeating or flickering visual stimulus causes SSVEP, an EEG response, which shares the same basic frequency as the flickering stimulus and its harmonics. SSVEP-based BCIs could provide a high transfer rate (ITR) and offer an available large variety of control instructions with less user training when compared to MI and P300 [10]. The SSVEP-based BCI system has so developed quickly in the last ten years.

Conversely, data alignment methods provide time-series SSVEP signals as output by means of sample adaptation from the source and target domains. Of particular note in this context is least-square transformation (LST), which converts SSVEP waveforms from source individuals into extra calibration data for target individuals smoothly combined with following SSVEP detection techniques. Emerging research, meantime, indicates SSVEP signals have non-linear properties [11], but LST has little ability to handle non-linear transformations and noise tolerance. Furthermore, the stimulus-dependent training method of LST limits the data availability during model fitting, hence possibly producing duplicate or erroneous transformation models. We propose SSVEP-DAN, a neural networkbased approach, to solve the present domain adaption issues in SSVEP identification. By use of stimulus-independent training, SSVEP-DAN offers

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non-linear mapping for converting source SSVEP signals into target domain data, hence facilitating strong transformations. Compatible with any training-based SSVEP detection technique, the modified SSVEP signals provide additional calibration data for the target subject [12].

Motivation and contribution

Particularly for those with movement limitations, the fast development of brain-computer interface (BCI) technology has created new opportunities for non-invasive communication and control systems. Among many BCI paradigms, steady-state visual evoked potential (SSVEP)-based systems stand out because to their high information transmission rate, low user training needs, and strong performance in real-time situations. Though, even with these benefits, the actual use of SSVEP-based BCIs runs into issues like visual weariness, inter-subject variability, and the complexity of multi-channel EEG configurations. Recent developments in deep learning, transfer learning, and domain adaptation have also greatly affected the creation of more effective SSVEP classification systems. This survey is to methodically assess and evaluate the most recent technologies, models, and frameworks used in SSVEP-based BCI research, motivated by the increasing interest in simplifying system design while preserving performance and the rise of strong data-driven methods. We aim to offer a thorough reference that not only records state-of-the-art advancements but also points out voids and future paths in this dynamic sector.

Survey of Deep Learning-Based Approaches for SSVEP Classification: The paper provides an in-depth survey of various deep learning models developed for SSVEP-based BCIs, such as 1D-CNN, multi-task CNNs, LSTMs, CNN-LSTM hybrids, and Siamese architectures. These models are analyzed with respect to their design, accuracy, and suitability for short time window classification and real-time decoding, offering a consolidated understanding of how deep learning has enhanced SSVEP detection and recognition performance.

Emphasis on Simplified BCI Systems Using Single-Channel EEG: The survey highlights the growing trend toward using single-channel EEG systems for SSVEP signal acquisition, showcasing works that successfully balance classification accuracy with system simplicity. This contribution addresses the real-world applicability of BCIs by reviewing strategies that reduce hardware complexity and setup time while maintaining signal quality through bipolar electrode configurations.

Review of Domain Adaptation and Cross-Subject Calibration Techniques: The paper discusses the critical challenge of cross-subject variability in SSVEP signals and presents existing solutions such as least-square transformation (LST) and neural network-based alignment methods like SSVEP-DAN. By compiling recent research in domain adaptation, the survey offers insights into how these methods enable stimulus-independent training and reduce calibration requirements in practical SSVEP-based BCI systems.

Challenges involved

Visual Fatigue and Safety Risks: SSVEP-based BCIs require repetitive visual stimulation at specific flickering frequencies. While effective in evoking strong neural responses, prolonged exposure can cause visual fatigue and, in some cases, trigger epileptic seizures in photosensitive individuals. Additionally, excessive brightness or poorly calibrated stimuli can strain vision and reduce user comfort.

Low Signal-to-Noise Ratio (SNR): One of the primary technical challenges in SSVEP-based systems is the inherently low SNR of EEG signals. Environmental noise, muscle artifacts, and electrode placement issues can significantly distort the quality of recorded signals, thereby affecting classification accuracy and system responsiveness.

Calibration and Cross-Subject Variability: Inter-subject and intra-subject variability make it difficult to generalize SSVEP-based models across users. Traditional calibration methods like least-square transformation (LST) struggle with non-linear signal variations, limiting their robustness and adaptability to new subjects without recalibration.

Complexity in Multi-Channel Setups: Although multi-channel EEG systems provide better spatial resolution and signal quality, they are cumbersome for real-world use due to complex setups, high cost, and reduced portability. This creates a barrier to widespread adoption, especially for consumer-grade or assistive applications.

Real-Time Processing Constraints: High-performance SSVEP systems must achieve low-latency signal processing and classification. However, real-time detection requires efficient algorithms that balance computational cost with accuracy—an ongoing challenge, especially when using deep learning models with high complexity.

Limited Data for Deep Learning: Deep learning models require large labeled datasets for effective training. In the BCI domain, acquiring such datasets is resource-intensive, time-consuming, and subject to ethical concerns. This limits the ability of researchers to develop and validate high-capacity models for SSVEP classification.

Stimulus Design and Frequency Limitations: The design of visual stimuli—such as flickering frequency, brightness, and number of targets—directly affects the performance of SSVEP-based BCIs. Increasing the number of stimulus frequencies increases command options but may reduce classification speed and accuracy due to overlapping harmonics and user confusion.

II. RELATED WORK

In a BCI speller system, Nguyen et al. created a 1D-CNN model for bipolar single-channel SSVEP frequency identification. It consists of three fully linked layers and two convolutional layers. The suggested model obtained 97.4% average accuracy in an online trial using an SSVEP speller with five flickering stimuli using a 2-s time window [13] .[14] offered a multi-task CNN applicable to visual response mapping and SSVEP categorization. There are four convolution blocks and one multi-task learning block in the network. With results of 92% classification accuracy in UI classification situations, the suggested multi-task CNN was tested on the Benchmark SSVEP dataset. To decode SSVEP signals for piloting quadcopters, [15] suggested a long short-term memory (LSTM) model. With a 0.5 s time frame on a 5-class SSVEP dataset in UD classification context, the suggested model achieved 93% accuracy, which much above other examined techniques. Pan et al. recently suggested a quick CNN-LSTM model called SSVEPNet using spectral normalisation and label smoothing techniques. Based on CNN, [16] suggested a comparison network to understand the link between SSVEP signals and the templates at every stimulus frequency. On a 4-class dataset in UD training environment, our model outperformed other conventional techniques such CCA and TRCA by using the frequency domain signal as the input. Li et al. put up a model called non-linear convolutional correlation analysis (Conv-CA). [17] suggested a Siamese correlation analysis model (SiamCA), which is made up of a top decision network and parallel two feature extractors with coupled parameters. The SiamCA employed EEG raw data and SSVEP template as the network input, as the SSVEP signal and its related reference signal could share comparable temporal patterns. When assessed on the 4-class SSVEP dataset and the Benchmark SSVEP dataset, the SiamCA outperformed the Conv-CA in UD classification situation. Notably, the SiamCA could maintain high accuracy of around 60% even with an exceptionally small time frame (0.2 s).

[18] have suggested a bidirectional SiamCA (bi-SiamCA) model and tested it against a 12-class public dataset and the 40-class benchmark dataset. For intra-subject classification, [19] suggested a data augmentation technique, a dynamic template network (DTN), and a fixed template network (FTN). Based on the filter bank technology, [20] suggested the extended CCA. This technology has since turned into a vital tool to improve several conventional approaches. Filter bank technology was also included in DL model design in recent years. For example, [21] suggested a multi-harmonic linkage convolutional neural network (MHLCNN) model. [22] built a deep convolutional neural network (DCNN) for data categorization in a noisy setting. Data in the BETA dataset was used to initially pre-train the DCNN model; individual data from the target subject was then maintained and tested. Using the AudioSet dataset (known as VGGish), [23] first pre-trained a version of the visual geometry group (VGG) network and then changed the final three fully connected layers to two new ones, retraining using the SSVEP dataset in a leave-one-subject-out fashion.

Using CNNs with 2D kernels as classifiers, [24] converted the EEG data into pictures; these CNNs had been pre-trained using the ImageNet dataset. Using a single neural network to produce synthetic EEG data from several SSVEP categories, [25] suggested subject-invariant SSVEP GAN (SIS-GAN). Recent research [26] has looked into decoding emotional states using high-frequency SSVEPs—those above the crucial flicker frequency. This new path shows that SSVEP signals may carry emotional information, hence increasing its use outside of conventional command-based BCIs. Particularly in non-invasive affective computing applications, the decoding of emotional valence using EEG responses to high-frequency stimuli has produced encouraging outcomes. Designing an SSVEP-based wheelchair control system [27] using a harmonics-based classification approach is another major development. The system quickly and precisely decodes user intents with a time delay of around one second by combining LED and LCD visual cues. This shows the feasibility of SSVEP-driven BCIs for real-time assistive technology, especially for people with major motor limitations.

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Emphasizing the influence of electrode location on signal quality [28], a portable SSVEP-BCI system for rehabilitation purposes has also been suggested. Studies showed that certain electrode settings might greatly improve categorization accuracy. This emphasizes the need of system ergonomics and electrode tuning in creating pleasant and viable BCIs for sustained use. SSVEP paradigm [29] acknowledged limitation is visual weariness. Researchers created a quantification approach based on underdamped second-order stochastic resonance to solve this. The suggested approach provides a useful tool for fatigue-aware BCI design as it correlates well with subjective tiredness evaluations and outperforms conventional canonical correlation analysis in evaluating visual strain. Classifying performance [30] has been improved by hybrid BCIs combining SSVEP with electrooculography (EOG)-based eye movements. Such systems improve the resilience and accuracy of command recognition by using the complementing strengths of both signal modalities. This dual-modality strategy further expands the spectrum of possible applications, including gaming and communication interfaces.

SSVEP signal processing has been using deep learning more and more. A thorough study of [31] deep learning models revealed that, frequently enhancing general system accuracy, these techniques simplify feature extraction and categorization. The diversity in model designs and assessment methods indicates that although deep learning shows potential, uniformity is required for cross-study comparisons. To enhance SSVEP signal detection [32], a frequency-adaptive canonical correlation analysis (FACCA) technique was presented. Using particle swarm optimization, this method dynamically chooses ideal reference signal frequencies. Particularly in noisy settings or with individual frequency changes, the FACCA technique showed better accuracy than conventional CCA. Training SSVEP-based systems [33] continues to be hampered by data scarcity. Researchers have started to use generative adversarial networks (GANs) to create synthetic fake SSVEP data in order to offset this. Incorporated into training datasets, these synthetic samples lower reliance on massive amounts of actual data without compromising performance, hence enhancing model scalability and accessibility. Proposed for SSVEP [34] signal classification was IncepFormerNet, a hybrid model that combines Inception and Transformer architectures. Unlike conventional convolutional models, the model efficiently captures both short-term and long-term relationships in EEG data. Its capacity to generalize across people and sessions emphasizes its possible use in the actual world. The SSVEP-DAN model [35] was created to handle inter-session and inter-subject variation. By matching feature distributions across several datasets, this data alignment system lowers domain differences. Especially in situations with little calibration data, the model greatly increases classification accuracy, which makes it appropriate for plug-and-play BCI devices.

Table 1. Survey Table

Method	Advantage	Disadvantage	Research Gap
1D-CNN for single-channel SSVEP	High accuracy (97.4%), lightweight model	Limited to 5 stimuli, fixed time window	Scalability to more commands and varied stimuli
Multi-task CNN	Simultaneous classification and visual mapping	Computational complexity	Optimization for real-time deployment
LSTM for quadcopter control	Temporal pattern learning, high accuracy (93%)	Requires fixed time window	Adaptability to asynchronous control
CNN-LSTM (SSVEPNet)	Enhanced generalization, label smoothing	Increased model complexity	Data-efficient training and real-time performance
CNN comparator with frequency domain input	Outperforms CCA/TRCA in 4-class setting	Limited to frequency domain only	Inclusion of temporal-spatial features

Siamese CA (bi-SiamCA)	High short-window accuracy (0.2s), robust model	Requires template data	Template-free training methods
FTN, DTN + data augmentation	Improved intra-subject classification	Limited generalization to new subjects	Cross-subject augmentation techniques
Extended CCA + Filter Bank	Enhanced frequency detection accuracy	Complex filter bank tuning	Adaptive filter bank optimization
Multi-Harmonic Linkage CNN (MHLCNN)	Performs well in noisy environments	Large model size	Model compression strategies
DCNN with BETA dataset (pre-trained)	Robust to noise via pretraining	Subject-dependent performance variability	Unsupervised pretraining approaches

III. RESEARCH GAP

Limited Generalization Across Subjects: Many SSVEP-based models suffer from poor performance when applied to new users due to high inter-subject variability. This highlights the need for more effective domain adaptation and transfer learning techniques to enable cross-subject generalization without requiring extensive individual calibration.

Visual Fatigue and User Comfort: Continuous exposure to flickering visual stimuli can lead to visual fatigue and discomfort, particularly at high stimulation frequencies. There is a lack of adaptive stimulus design methods that can dynamically adjust parameters based on user tolerance and real-time feedback.

Dependence on Multi-Channel EEG Systems: While multi-channel systems improve classification accuracy, they are not practical for daily use due to complexity and discomfort. More research is needed to optimize single-channel or minimal-channel SSVEP systems that balance performance with usability.

Insufficient Real-Time Capability in Deep Models: Many high-performing deep learning models are computationally intensive, making them unsuitable for real-time BCI applications. There is a gap in designing lightweight, efficient models that maintain accuracy while enabling fast processing.

Scarcity of Large, Diverse Datasets: Training robust deep models requires large-scale, labeled EEG datasets. However, publicly available SSVEP datasets are limited in size, diversity, and recording conditions. This restricts the generalizability and reproducibility of research findings.

Inadequate Noise Robustness in Real Environments: Real-world BCI applications face signal degradation due to movement artifacts and electrical noise. Existing methods often fail to generalize beyond controlled lab environments. More robust preprocessing and adaptive filtering strategies are needed for deployment in dynamic settings.

Lack of Standardized Evaluation Benchmarks: The diversity in evaluation metrics, datasets, and experimental protocols makes it difficult to compare different SSVEP approaches fairly. There is a strong need for unified benchmarks and cross-study validation frameworks to assess progress consistently.

IV. CONCLUSION

In conclusion, SSVEP-based brain–computer interfaces have demonstrated remarkable potential for creating reliable, high-speed, and user-friendly communication systems, particularly for individuals with motor impairments. This survey has highlighted the rapid progress made in recent years, especially through the integration of deep learning techniques and the shift toward more practical single-channel systems. Despite significant advancements, several challenges such as inter-subject variability, signal quality, visual fatigue, and the scarcity of large-scale labeled datasets remain unresolved. Emerging solutions like neural domain adaptation, data augmentation, and stimulus optimization offer promising pathways to address these limitations. By synthesizing current methodologies, performance trends, and technical gaps, this paper aims to serve as a foundational resource for future research, encouraging the development of more robust, accessible, and adaptive SSVEP-based BCI systems.

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