Advancing SSVEP-based brain-computer interfaces: a novel approach using cross-subject multi-modal fusion technique

Kalenahally R. Swetha, Ravikumar G. Krishnegowda, Shashikala S. Venkataramu
Department of Computer Science and Engineering, BGSIT, Adichunchanagiri University, Mandya, India

Article Info

Article history:

Received Apr 30, 2024
Revised Nov 15, 2024
Accepted Nov 30, 2024

Keywords:

Brain-computer interface
Cross-subject multi-modal fusion technique
Electroencephalogram
Information transfer rates
Steady-state visually evoked potentials

ABSTRACT

Brain-computer interfaces (BCIs) represent an innovative paradigm for device control and communication, relying solely on the analysis of brain activity. Steady-state visually evoked potentials (SSVEPs), characterized by neurophysiological responses synchronized with periodic visual stimuli, have gained prominence in BCI research due to their high information transfer rates (ITRs) and minimal user training requirements. However, the translation of SSVEP-based BCIs into practical applications faces challenges stemming from variations in user responses and stimuli. To address these issues, this study introduces a groundbreaking methodology known as the cross-subject multi-modal fusion technique (CMFT). CMFT revolutionizes template design by creating invariant templates resilient to user and stimulus differences, thereby enhancing SSVEP detection across diverse subjects and stimuli. The implications of this research extend to various fields, including assistive technologies, human-computer interaction, and cognitive neuroscience. CMFT presents a promising solution to make SSVEP-based BCIs more practical and widely applicable. The methodology involves intricate steps, including spatial filters, data pre-processing, and template generation, ensuring precise SSVEP detection. Through CMFT, this study contributes to advancing the effectiveness and versatility of SSVEP-based BCIs, fostering improved accessibility and interaction in a range of domains.

Corresponding Author:

Kalenahally R. Swetha
Department of Computer Science and Engineering, BGSIT, Adichunchanagiri University
Mandya, India
Email: swethakr_12@rediffmail.com

1. INTRODUCTION

Brain-computer interfaces (BCIs) offer a novel method of controlling equipment simply through the study of an individual's brain activity, which is accomplished by merging hardware and software components for successful communication [1]. Electroencephalogram (EEG)-based BCIs, particularly those that use steady-state visually evoked potentials (SSVEPs), have gained popularity in BCI research due to their non-intrusive nature, portability, and ease of setup [2]. This work digs into the improvements in SSVEP-based BCIs, specifically their neurophysiological responses that are coordinated with periodic visual stimuli [3]. The SSVEP BCI allocates unique frequencies to different targets, allowing for the detection of user intent via EEG signals when focusing on a certain target [4]. SSVEP BCIs are notable for their high information transfer rates (ITRs), low user training requirements, and the lack of individual decoder calibration. However, obstacles come from variances in visual stimulus properties that influence SSVEP responses, as well as the scarcity of commercial or clinical systems [5]. Notably, the SSVEP pattern outperforms other EEG signal patterns in terms of correct classification, making it a focus of current BCI research [6]. The primary goal of this study is to investigate the practical applications of SSVEP-based BCIs, namely speller systems. These systems utilize graphical user interfaces (GUIs) to produce different EEG patterns in response to stimuli, which simplifies model calibration and reduces training time [7]. The addition of extra stimuli is intended to improve BCI speller efficiency [8]. The Bremen Speller, a pioneering high-speed SSVEP BCI speller, established the multi-target stimulus paradigm [9].

Recent research emphasizes BCI spellers, incorporating three EEG signals: sensorimotor rhythm (SMR), P300 event-related potential (ERP), and SSVEP [10]. The SSVEP speller's high ITR, easy deployment, and minimal user training time make it a prominent choice for real-world BCI applications [11]. Ongoing investigations into BCI spellers and other BCI applications, such as brain painting (BP) for the P300 BCI, showcase a commitment to user-centered design principles. BP, developed to address the communication needs of individuals, including those with ALS, illustrates the innovative potential of BCIs [12]-[14]. The utilization of an alternative communication channel in BP demonstrates a unique design approach, showcasing the versatility and potential impact of BCIs in diverse applications.

This research is driven by the increasing importance of non-invasive BCI systems and their wide-ranging potential applications, spanning fields from healthcare to gaming [15]. Within this context, Steady-state visually evoked potential (SSVEP)-based BCI systems emerge as a particularly promising avenue. However, the efficacy of these systems hinges on the quality of templates utilized for stimulus detection. In real-world scenarios, the intricacies of user responses and the variability in the number of stimuli present a complex challenge for template creation. This study aims to tackle these challenges by introducing an innovative approach to generate invariant templates, ensuring precise and efficient SSVEP detection across a diverse range of subjects and stimuli. The implications of this research are profound, holding the potential to significantly augment the capabilities of SSVEP-based BCIs. This improvement, in turn, can have a transformative impact on the lives of individuals with motor disabilities. Furthermore, the applications extend to fields such as human-computer interaction and cognitive neuroscience, indicating a broad spectrum of potential benefits across various domains.

- This research pioneers a novel approach, cross-subject multi-modal fusion technique (CMFT), aimed at elevating the efficiency of SSVEP-Based BCI detection. CMFT introduces innovative techniques for enhanced signal processing and feature fusion, contributing to improved performance in SSVEP-based BCI systems.
- A key innovation of this study lies in the introduction of invariant templates tailored for SSVEP-based BCIs. These templates exhibit robustness to variations in user responses, thereby significantly enhancing the accuracy of SSVEP detection. This robust template design addresses a critical challenge in real-world scenarios where user responses can vary widely.
- The research incorporates the development of spatial filters and templates that facilitate inter-subject knowledge transfer. This novel approach allows for the transfer of common knowledge across subjects, minimizing the need for individualized calibration. By doing so, the BCIs become more user-friendly, streamlining the user experience and potentially broadening the accessibility of such neuro technologies.

2. RELATED WORK

The addressed research delves into various paradigms within the context of P300-based BCIs and their associated challenges. The row-column paradigm (RCP) is a widely adopted approach with its own set of issues, impacting ITRs and recognition accuracy. The study explores an innovative modification, the rapid control prototyping (RCP) paradigm, introducing face flashing (FF) to address these challenges. This paradigm involves superimposing images onto matrix rows and columns, demonstrating potential enhancements in terms of accuracy and cognitive load [16]-[18]. Additionally, the research investigates the single character paradigm (SCP) against RCP, providing evidence favoring SCP for larger P300 peaks and higher accuracy, albeit with a greater time investment. The T9 speller, incorporating word prediction and a traditional paradigm, offers a unique approach to character selection. The study emphasizes the significance of paradigms in spelling tasks, showcasing the trade-offs between speed and accuracy [19].

Shifting focus to a three-dimensional (3-D) configuration in the P300 speller, the research explores its potential impact on user acceptance and user-friendliness. The 3-D interface introduces variations in flashing paradigms, allowing for the examination of trial fluctuations. This innovation holds implications for industries such as gaming and healthcare, highlighting the versatility of BCI technology [20]-[23]. The introduction of the BCI-Utility measure adds a quantitative dimension to the assessment of BCI systems, specifically emphasizing user experience. The metric encompasses error correction scenarios, recognizing the system-specific nature of BCI-Utility and its dependence on experimental design. The research further delves into coding schemes, introducing the time division multiple access (TDMA) scheme and spatial division multiple access (SDMA) technology [24]. TDMA utilizes temporal information for independent target flash sequences, showcasing advantages over frequency division multiple access (FDMA). Meanwhile, SDMA explores spatial data for target detection, emphasizing the impact on SSVEP power topography. However, SDMA-coded BCI systems pose challenges in stimulus characteristics [25], [26].

3. PROPOSED METHODOLOGY

SSVEP signal analysis, data preprocessing, and the development of invariant templates with spatial filters are all included in this procedure. A number of participants provide data, and templates are developed for efficient SSVEP detection. While templates are averaged over variations and individuals, spatial filters are taught using single-trial data. The SSVEP in a target subject is then found using these templates. The SSVEP signal is decomposed into smaller parts in order to obtain precise data. The target is selected based on which stimulus has the strongest relationship. This method aims to improve SSVEP-based applications' accuracy and efficiency, particularly in environments with lots of participants and inputs.

3.1. Data pre-processing

Step signal analysis is used to eliminate the visual lag in the initial set of data. The filtered sequence and band are used to obtain the data. To eliminate power noise, a 50 Hz filter notch is employed. After the data preparation is finished, the target is identified and the processing of the information is carried out. This is the suggested workflow in Figure 1.

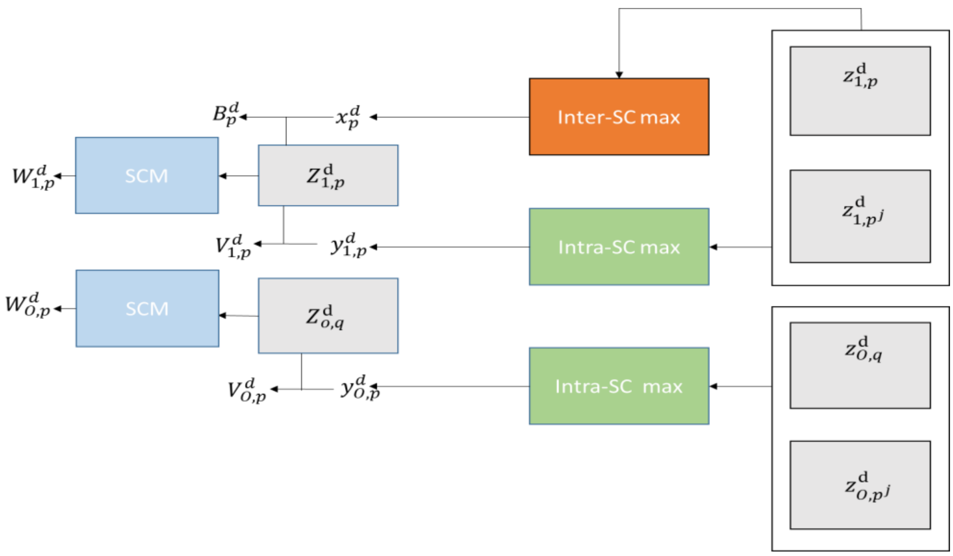

Figure 1. Proposed workflow [trans-subject multi-feature fusion for improved SSVEP-based BCI detection]

3.2. Spatial filters and SSVEP template

The calibration data collected from one source is treated to the appropriate S-th stimulus and is shown as C_s=[C_s^1,C_s^2,……,C_s^(s_g)] ∈W^(s_e*s_f*s_d), and S=1,2,…,S_k. However, S_h, S_i, S_g, and S_k represent the sample point's channels, which include the blocks and the amount of stimuli. S_s^g∈W^(s_e*s_f) (g=1,2,...,S_g) represents the d-th block of data for C_s. Participants share common knowledge by using a spatial filter and SSVEP data from many blocks to construct both internally and mutually invariant templates for a trial-test assessment. Each block d divides the separated EEG data C_s in half. In (1) illustrates how trial data Z_p^d from block d is transformed into multi-trial data δ_p^d for template training.

$$\delta_s^g = [C_s^1, \dots, C_s^{g-1}, C_s^{g+1}, \dots, C_s^{S_g}] \tag{1}$$

$$\vartheta_s = \{C_{s^1}, C_{s^2}, \dots\dots\dots, C_{s^{sm}}\}, \tag{2}$$

$$\delta_{sm}^g = [C_{sm}^1, \dots, C_{sm}^{g-1}, C_{sm}^{g+1}, \dots\dots, C_{sm}^{S_g}] \tag{3}$$

The $g-th$ combination of SSVEP data consists of the target along with the neighboring stimuli data. C_s^g, δ_s^g and δ_{sj}^g $(k = 1,2,\dots,S_m)$. Whereas g is in the range from 1 to S_g for each stimulus g, there are S_g variations for the SSVEP training data. The $g-th$ variation for the SSVEP training is encountered with data, the training method involves the transferred spatial features that consist of three steps:

- The internal spatial filter and template extract frequency information from surrounding stimuli.
- Calculated mutually invariant spatial filters and templates from many sources to identify shared knowledge across subjects.
- Used internal and mutual invariant samples to train test-trial spatial filters.

The flowchart includes multiple steps as shown.

3.2.1. Internal invariant template

For every given source subject o, we can find the associated spatial filter to the s-th stimulus b_(r,t)^g ∈W^(S_e) by optimizing the subjective correlation by examining the corresponding SSVEPs for the target and neighboring stimuli δ_(〚r,t〛^)^g∈ W^(S_e*S_f*S_((g-1))) and δ_(〚r,t^m〛^)^g∈ W^(S_e*S_f*S_((g-1))) (m=1,2,…,S_m) through each subject r. In (4) defines the multi-trial data by simplifying the expressions δ_(r,t)^g and δ_(〚r,t^m〛 ^)^g from (1) and (3), respectively. δ_(r,t)^(g_m) is in W^(S_e*S_f) (p=1,2,…,S_y). S_y is the number of trials for multi-trial data, and S_y=S_g-1, as described in (5). In (6) evaluates the invariant spatial filter, y_(o,q)^d.

$$\delta_{o,q}^{d}=[\delta_{o,q}^{d1}, \delta_{o,q}^{d2},\dots\dots\dots, \delta_{o,q}^{dP_v}], \tag{4}$$

$$\delta_{o,q^j}^{d} = [\delta_{o,q^j}^{d1}, \delta_{o,q^j}^{d2}, \dots\dots\dots, \delta_{o,q^j}^{dP_v}] \tag{5}$$

$$y_{o,q}^{d} = \text{yargmax}\frac{y^V Uy}{y^V Sy} \tag{6}$$

$$U = \text{cov}(\delta_{o,q}^{d}) + \sum_{j=1}^{P_j} \text{cov}(\delta_{o,q^j}^{d}) \tag{7}$$

$$\delta_{o,q}^{d} = \frac{1}{P^V}\sum_{v=1}^{P_v} \delta_{o,q}^{dm}, \tag{8}$$

$$\delta_{o,q^j}^{d} = \frac{1}{P^V}\sum_{v=1}^{P_v} \delta_{o,q^j}^{dm}, \tag{9}$$

$$S = \sum_{v=1}^{P_v} \text{cov}(\delta_{o,q}^{dm}),+ \sum_{j=1}^{P_j} \sum_{m=1}^{P_v} \text{cov}(\delta_{o,q^j}^{dm}) \tag{10}$$

The aforementioned (10) depicts the covariances between the trial data acquired from the p-th stimulus and its nearby stimulus. In (6) solves the decomposition of S^(-1) U. The spatial filter y_(o,q)^d is assessed using the associated eigenvector. The spatial filter y_(o,q)^d and an invariant template V_(o,q)^d∈T^(P_f) for the relevant source submitted as o are derived as indicated in (11).

$$V_{o,q}^{d} = y_{o,q}^{d}\, V_{\delta_{o,q}^{d}} \tag{11}$$

A. Mutually invariant: To assess the mutually invariant template, the filter is trained with SSVEP data from O source individuals. The spatial filter X_p^d∈T^(P_e) corresponds to the p-th stimulus assessed to maximize the correlation between different individuals. In contrast to utilizing the target stimulus, inter-subject maximum correlation is assessed using the SSVEP target data for the target and surrounding stimuli.

In the first step the $d-th$ multi-trial data for the $p-th$ stimulus from two varied subjects o_1 and o_2 denoted as $V_{\delta_{o1,q}^{d}} \in T^{P_e*P_f*P_v}$ and $V_{\delta_{o2,q}^{d}} \in T^{P_e*P_f*P_v}$. The E_{12} and E_{21} for inter-subject cross-variance, E_{11} and E_{22} regarded as the inter-subject co-variance. Assumption of $x^V E_{11}\, x == x^V E_{22}\, x$, the term E_{21} is the transposition, whereas the optimization problem is solved as given in (12). Here $R = E_{12} + E_{21}$ and $T = E_{21} + E_{22}$, henceforth the matrices R and T are evaluated as shown in (13).

$$x_p^d = x \arg\arg\max \frac{x^V R\, x}{x^V T\, x} \tag{12}$$

$$R = \frac{1}{O(O-1)}\left[\sum_{o1} \sum_{o2\neq o1o2} \text{cov}(\delta_{o1,p}^{d}, \delta_{o2,p}^{d}) + \sum_{j=1}^{P_j} \sum_{o1} \sum_{o2\neq o1o2} \text{cov}(\delta_{o1,p}^{d}, \delta_{o2,p}^{d})\right] \tag{13}$$

$$T = \frac{1}{O}\sum_{o=1}^{O} \left[cov(\delta_{o,q}^{d}) + \sum_{j=1}^{P_j} cov(\delta_{o,q\,j}^{d})\right] \quad (14)$$

$$B_p^d = x_p^{d\ V} \delta_q^d \quad (15)$$

B. Trial spatial filter testing: the internally invariant and mutually invariant templates, a spatial filter $w_{o,q}^{d} \in T^{P_e}$ for each source subject o is trained via a single trial data $Z_{o,q}^{d}$. The spatial filter $w_{o,q}^{d}$ is obtained to simultaneously maximize to evaluate the correlation between $Z_{o,q}^{d}$ and B_p^d. The evaluation of $w_{o,q}^{d}$ is computed using a multi-objective optimization problem.

$$w_{o,q}^{d} = \text{wargmax}\vartheta w_{o,q}^{d} \text{ subjected to } \sum_{e=1}^{P_e} w^e \quad (16)$$

$$\vartheta(w_{o,q}^{d}) = \left[\alpha(w_{o,q}^{d\ V} Z_{o,q}^{d} V_{o,q}^{d})\ \alpha(w_{o,q}^{d\ V} Z_{o,q}^{d} B_p^d)\right] \quad (17)$$

$$y_{o,q} = \frac{1}{pd}\sum_{d=1}^{P_d} y_{o,q}^{d} \quad (18)$$

$$x_O = \frac{1}{pd}\sum_{d=1}^{P_d} x_p^d \quad (19)$$

$$wo,qw_{o,q} = \frac{1}{pd}\sum_{d=1}^{P\ d} x_p^d \quad (20)$$

$$V_{o,q} = \frac{1}{pd}\sum_{d=1}^{P\ d} V_{o,q}^{d} \quad (21)$$

$$B_p = \frac{1}{pd}\sum_{d=1}^{P\ d} B_o^d \quad (22)$$

3.3. SSVEP detection through transfer parameters

The transmission of spatial filters and templates as single-trial data with one target patient as A∈ T^(P_e)*P_f has been identified. SSVEP detection uses four distinct kinds of CC between spatially filtered data. The transferred templates are assessed by merging spatial filters with templates taught from source subjects, shown below in (23), (24).

$$\mu_p = [\mu_p(1)][\mu_p(2)\ ][\mu_p(3)][\mu_p(4)] \left[\alpha(x_O\ Z, B_p\ \frac{1}{O}\sum_{o=1}^{O} \alpha(y_{o,q}\ A, V_{o,q})\ \frac{1}{O}\sum_{o=1}^{O} \alpha(w_{o,q}\ A, B_p)\right] \quad (23)$$

$$\varphi_p = \sum_{\sigma=1}^{4} \text{sign}(\mu_p(\sigma))(\mu_p(\sigma))^2 \quad (24)$$

3.4. Decomposition method

The decomposition method is applied to decompose SSVEP into sub-components, which extract precise accurate information through SSVEP data. This decomposition technique is used for SSVEP performance detection which can be further enhanced. Here each subset $l(l = 1,2, \ldots\ldots P_l)$ of this technique is implemented by the zero-pulse filter. The feature τ_p^l is evaluated within each sub-band by (24). Upon integration τ_p^l through each sub-band, the end correlation feature is obtained via γ_p as given in (25). However $\mu(l) = \frac{1}{l^{1/4}} + \frac{1}{4}$ is the associated weight function, the target frequency is obtained through the h with maximum correlation as shown by (26).

$$\gamma_p = \sum_{l=1}^{P_l} \mu(l).(\tau_p^l)^2, \quad (25)$$

$$h = \text{pargmax}\gamma_p,\ p=1,2,\ldots\ldots,P_h \quad (26)$$

4. PERFORMANCE EVALUATION

The deep neural network (DNN) is assessed using the BETA (BEnchmark Database Towards BCI Application) [27] dataset. A full experimental study is performed, and the results are compared to state-of-the-art methodologies that have previously been assessed on specific datasets and shown promising results. Conv-CA, ms-eTRCA, eTRCA, TSCORRCA, m-Extended-CCA, Extended-CCA (Extended-canonical correlation analysis), and CORRCA (Two stage – correlated. This dataset comprises meticulously curated data points, meticulously selected to represent a diverse range of scenarios and conditions relevant to our study.

4.1. Dataset details

The dataset was used to evaluate the BCI SSVEP speller. Thirty-five healthy volunteers took part in six sessions of the Benchmark dataset, which had a 5x8 character matrix flashing forty characters at rates ranging from 8 to 15.8 Hz. Data on EEG were collected from 64 channels. The BETA dataset included 70 subjects divided into four blocks who used a character display that resembled a keyboard; they experienced an average visual delay of 130 ms.

4.1.1. Beta dataset

The Beta dataset constitutes a pivotal component in our research, serving as a cornerstone for evaluating the effectiveness and performance of the proposed methodologies. This dataset comprises meticulously curated data points, meticulously selected to represent a diverse range of scenarios and conditions relevant to our study. Its comprehensive nature allows for thorough testing and validation, ensuring robustness and reliability in our findings. Through the utilization of the Beta dataset, we aim to provide a rigorous and standardized framework for assessing the capabilities and limitations of our proposed approaches, thereby contributing to the advancement of knowledge and understanding in the field of BCIs. Figure 2 displays the layout of the character matrix used for stimulus presentation in BETA dataset experiments.

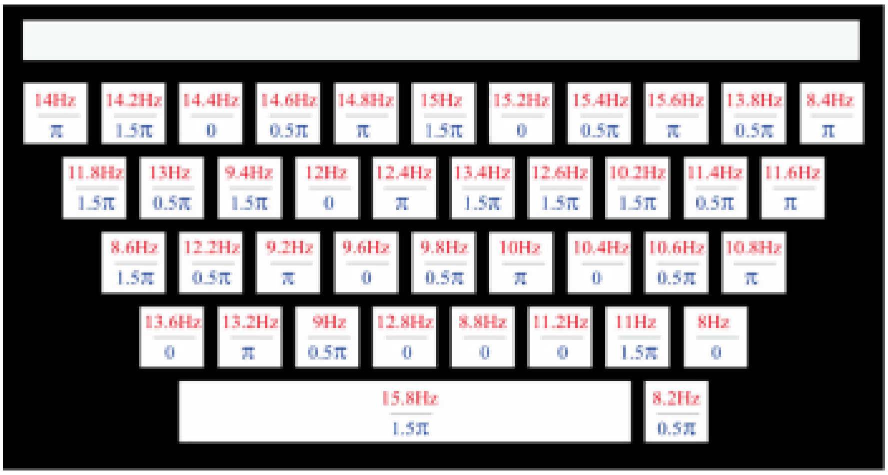

Figure 2. Layout of the character matrix used for stimulus presentation in BETA dataset experiments

4.2. Results for Beta dataset

Figure 3 shows the graph depicting performance across 9 channels illustrates the superiority of the PS algorithm over existing approaches like CORRCA and Extended-CCA. The PS algorithm consistently exhibits higher signal strengths across all channels, ranging from 46.23 at channel 0.2 to 88 at channel 1. Conversely, methods such as CORRCA and Extended-CCA consistently yield lower signal strength values. Notably, compared to the existing system (ES) [28], which shows a signal strength value of 83.45 for channel 1, the PS algorithm demonstrates even stronger and more reliable signal strengths, with a value of 88. This emphasizes the robustness and effectiveness of the PS algorithm in providing enhanced signal strengths across a spectrum of channels.

In Figure 4, a graph spanning 64 channels illustrates the consistent outperformance of the PS algorithm compared to existing approaches. Through a comprehensive evaluation of various methods alongside PS, it becomes evident that PS consistently delivers higher accuracy values across all channels. When juxtaposed with approaches above mentioned and PS consistently exhibits superior accuracy for each channel. For instance, considering the signal strength at channel 0.2, PS achieves a notably higher value of 49.5, surpassing the ES [28] value of 46.54. This underscores the remarkable performance and reliability of the PS algorithm in providing elevated accuracy values across the entire spectrum of channels.

Notably, the PS consistently surpasses the performance of existing methods, achieving the highest ITR values across all channels. For instance, at channel 0.2, PS demonstrates an ITR of 140.5, whereas the existing method achieves 137.5. The most substantial performance disparity between PS and other methods is observed at channel 0.3, where PS achieves an ITR of 182.5 compared to 180.5 attained by the existing method (ES [28]). This highlights the superior performance of PS across the entire spectrum of evaluated channels. Figure 5 visually represents the ITR graph across the nine channels, illustrating the enhanced performance of PS in comparison to other methods, based on the BETA dataset.

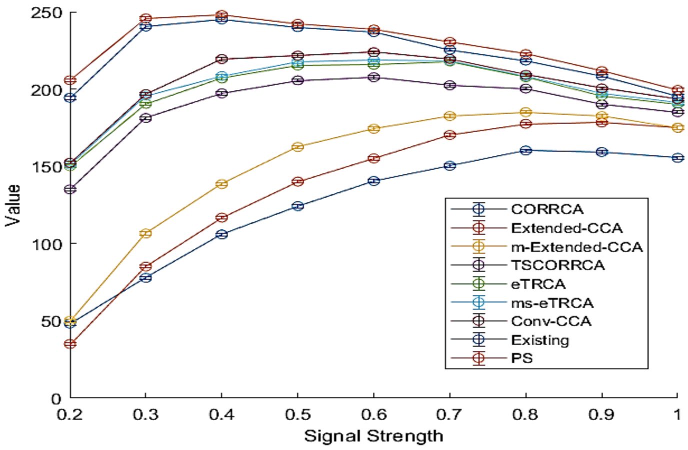

Figure 3. Comparison graph of accuracy across 9 channels for the BETA dataset

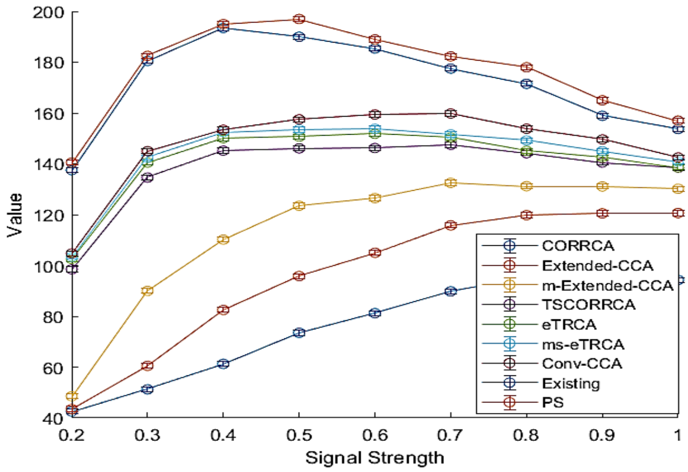

Figure 4. Comparison graph of accuracy across 64 channels for BETA dataset

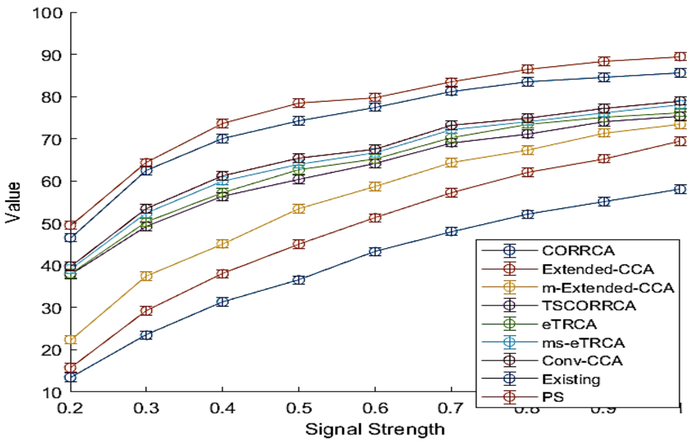

Figure 5. ITR graph data for 9 channels for BETA dataset comparisons

Figure 6 shows an evaluation of intrinsic transfer rate (ITR) over 64 channels, comparing the performance of several approaches the existing method, along with PS. Interestingly, PS consistently outperforms other approaches in all channels. For example, at channels 0.2, PS has an ITR of 142, beating ES [28]'s 138.9, proving its strong performance. This tendency is similar across all of the channels, with PS obtaining the greatest ITR levels. At channel 0.4, PS obtains an exceptional ITR value of 200.5, surpassing ES's value of 195.7. These findings illustrate PS's excellent ITR performance over the entire 64-channel spectrum.

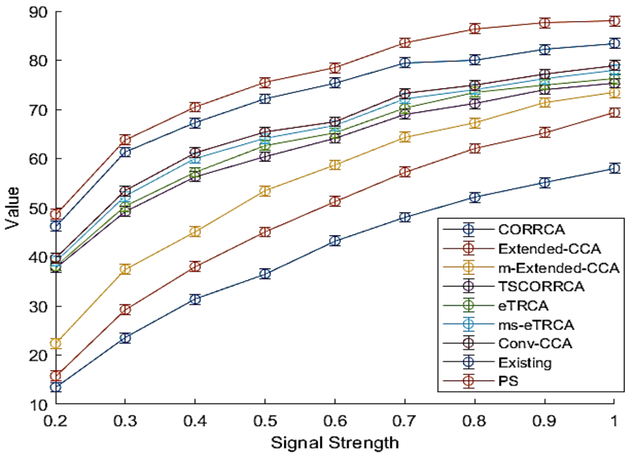

Figure 6. ITR graph of 64 channels for BETA dataset comparison

5. CONCLUSION

In conclusion, the proposed methodology represents a pioneering and thoroughgoing approach to enhance the effectiveness and precision of SSVEP-based BCIs. The introduction of invariant templates and the deployment of spatial filters address the intricate challenges associated with user-specific variations and the calibration demands inherent in SSVEP BCIs. By facilitating internal and mutual knowledge transfer across subjects, the research significantly diminishes the necessity for individual calibration, streamlining the user training process. Moreover, the decomposition method enhances the analysis of SSVEP signals, extracting precise information to elevate detection performance. These contributions hold the potential to propel SSVEP-based BCIs to new heights, rendering them more user-friendly, with elevated ITRs, and versatile across diverse domains, ranging from assistive technologies to cognitive neuroscience. The outcomes of this research mark a promising stride towards the pragmatic and efficient integration of SSVEP-based BCIs, promising improved communication and control for individuals with varying needs and capabilities.

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, we extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process. No funding is raised for this research.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Kalenahally R. Swetha	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Ravikumar G. Krishnegowda	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		
Shashikala S. Venkataramu	✓	✓	✓	✓			✓		✓	✓		✓		

C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

Author declares no conflict of interest.

DATA AVAILABILITY

Dataset is utilized in this research mentioned in reference [23].

REFERENCES

[1] R. Zhang, G. Dong, M. Li, Z. Tang, X. Chen, and H. Cui, “A calibration-free hybrid BCI speller system based on high-frequency SSVEP and sEMG,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3492–3500, 2023, doi: 10.1109/TNSRE.2023.3308779.

[2] L. Cao *et al.*, “A novel real-time multi-phase BCI speller based on sliding control paradigm of SSVEP,” *IEEE Access*, vol. 7, pp. 133974–133981, 2019, doi: 10.1109/ACCESS.2019.2941642.

[3] K. Won, M. Kwon, S. Jang, M. Ahn, and S. C. Jun, “P300 speller performance predictor based on RSVP multi-feature,” *Frontiers in Human Neuroscience*, vol. 13, Jul. 2019, doi: 10.3389/fnhum.2019.00261.

[4] Z. Gu, Z. Chen, J. Zhang, X. Zhang, and Z. L. Yu, “An online interactive paradigm for P300 brain-computer interface speller,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 2, pp. 152–161, Feb. 2019, doi: 10.1109/TNSRE.2019.2892967.

[5] S. Duraisamy and R. M. Reddy, “Stimulus paradigm for an asynchronous concurrent SSVEP and EOG based BCI speller system,” *IEEE Access*, vol. 9, pp. 127484–127495, 2021, doi: 10.1109/ACCESS.2021.3112257.

[6] J. J. Podmore, T. P. Breckon, N. K. N. Aznan, and J. D. Connolly, “On the relative contribution of deep convolutional neural networks for SSVEP-based bio-signal decoding in BCI speller applications,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 611–618, Apr. 2019, doi: 10.1109/TNSRE.2019.2904791.

[7] T. H. Nguyen and W. Y. Chung, “A single-channel SSVEP-based BCI speller using deep learning,” *IEEE Access*, vol. 7, pp. 1752–1763, 2019, doi: 10.1109/ACCESS.2018.2886759.

[8] S. N. Aghili and A. Erfanian, “A P300-based speller design using a MINMAX riemannian geometry scheme and convolutional neural network,” *IEEE Access*, vol. 11, pp. 98633–98652, 2023, doi: 10.1109/ACCESS.2023.3313260.

[9] G. Ma, J. Kang, D. E. Thompson, and J. E. Huggins, “BCI-utility metric for asynchronous P300 brain-computer interface systems,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3968–3977, 2023, doi: 10.1109/TNSRE.2023.3322125.

[10] S. Kundu and S. Ari, “MsCNN: a deep learning framework for P300-based brain-computer interface speller,” *IEEE Transactions on Medical Robotics and Bionics*, vol. 2, no. 1, pp. 86–93, Feb. 2020, doi: 10.1109/TMRB.2019.2959559.

[11] P. Pujar, A. Kumar, and V. Kumar, “Plant leaf detection through machine learning based image classification approach,” *IAES International Journal of Artificial Intelligence*, vol. 13, no. 1, pp. 1139–1148, Mar. 2024, doi: 10.11591/ijai.v13.i1.pp1139-1148.

[12] S. H. Sreedhara, V. Kumar, and S. Salma, “Efficient big data clustering using adhoc fuzzy c means and auto-encoder CNN,” in *Lecture Notes in Networks and Systems*, vol. 563, Springer Nature Singapore, 2023, pp. 353–368.

[13] Z. Wang, C. Chen, J. Li, F. Wan, Y. Sun, and H. Wang, “ST-CapsNet: linking spatial and temporal attention with capsule network for P300 detection improvement,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 991–1000, 2023, doi: 10.1109/TNSRE.2023.3237319.

[14] M. Nakanishi, Y. Te Wang, C. S. Wei, K. J. Chiang, and T. P. Jung, “Facilitating calibration in high-speed BCI spellers via leveraging cross-device shared latent responses,” *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 4, pp. 1105–1113, Apr. 2020, doi: 10.1109/TBME.2019.2929745.

[15] R. Ma, T. Yu, X. Zhong, Z. L. Yu, Y. Li, and Z. Gu, “Capsule network for ERP detection in brain-computer interface,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 718–730, 2021, doi: 10.1109/TNSRE.2021.3070327.

[16] S. Le Bars, S. Chokron, R. Balp, K. Douibi, and F. Waszak, “Theoretical perspective on an ideomotor brain-computer interface: toward a naturalistic and non-invasive brain-computer interface paradigm based on action-effect representation,” *Frontiers in Human Neuroscience*, vol. 15, Oct. 2021, doi: 10.3389/fnhum.2021.732764.

[17] M. Xu, J. Han, Y. Wang, and D. Ming, “Optimizing visual comfort and classification accuracy for a hybrid P300-SSVEP brain-computer interface,” in *International IEEE/EMBS Conference on Neural Engineering, NER*, May 2017, pp. 363–366, doi: 10.1109/NER.2017.8008365.

[18] X. Li *et al.*, “A hybrid steady-state visual evoked response-based brain-computer interface with MEG and EEG,” *Expert Systems with Applications*, vol. 223, p. 119736, Aug. 2023, doi: 10.1016/j.eswa.2023.119736.

[29] A. Kawala-Sterniuk *et al.*, “Summary of over fifty years with brain-computer interfaces—a review,” *Brain Sciences*, vol. 11, no. 1, pp. 1–41, Jan. 2021, doi: 10.3390/brainsci11010043.

[20] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, “30-targets hybrid BNCI speller based on SSVEP and EMG,” in *Proceedings - 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018*, Oct. 2019, pp. 153–158, doi: 10.1109/SMC.2018.00037.

[21] K. Chen, Y. Zhang, Z. Zhang, Y. Yang, and H. Ye, “Trans humeral prosthesis based on sEMG and SSVEP-EEG Signals,” in *IEEE International Conference on Robotics and Biomimetics, ROBIO 2019*, Dec. 2019, pp. 2665–2670, doi: 10.1109/ROBIO49542.2019.8961453.

[22] A. Chabuda, P. Durka, and J. Zygierewicz, “High frequency SSVEP-BCI with hardware stimuli control and phase-synchronized comb filter,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 2, pp. 344–352, Feb. 2018, doi: 10.1109/TNSRE.2017.2734164.

[23] X. Chen *et al.*, "Optimizing stimulus frequency ranges for building a high-rate high frequency SSVEP-BCI," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 1277–1286, 2023, doi: 10.1109/TNSRE.2023.3243786.

[24] M. Ahn, M. Lee, J. Choi, and S. C. Jun, "A review of brain-computer interface games and an opinion survey from researchers, developers and users," *Sensors (Switzerland)*, vol. 14, no. 8, pp. 14601–14633, Aug. 2014, doi: 10.3390/s140814601.

[25] Y. Zhang, S. Q. Xie, C. Shi, J. Li, and Z. Q. Zhang, "Cross-subject transfer learning for boosting recognition performance in SSVEP-based BCIs," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 1574–1583, 2023, doi: 10.1109/TNSRE.2023.3250953.

[26] Y. Wang, X. Chen, X. Gao, and S. Gao, "A benchmark dataset for SSVEP-based brain-computer interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 10, pp. 1746–1752, Oct. 2017, doi: 10.1109/TNSRE.2016.2627556.

[27] B. Liu, X. Huang, Y. Wang, X. Chen, and X. Gao, "BETA: a large benchmark database toward SSVEP-BCI application," *Frontiers in Neuroscience*, vol. 14, Jun. 2020, doi: 10.3389/fnins.2020.00627.

[28] O. B. Guney, M. Oblokulov, and H. Ozkan, "A deep neural network for SSVEP-based brain-computer interfaces," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 2, pp. 932–944, 2022.

BIOGRAPHIES OF AUTHORS

Kalenahally R. Swetha is currently working as Assistant Professor, Department of Computer Science and Engineering, BGS Institute of Technology, Adichunchanagiri University, BG Nagara, Nagamangala Tq. Mandya, Karnataka. She obtained her Master of Engineering in Computer Science from UVCE, Bangalore University, Bangalore. She is perusing PhD at Adichunchanagiri University. Qualified GATE-2009 with 3rd state Rank and 484th all over India rank. Having 10+ years teaching experience in both undergraduate and postgraduate streams. She has published 2 full length papers in IEEE conferences. She can be contacted at email: swethakr_12@rediffmail.com.

Dr. Ravikumar G. Krishnegowda received his Bachelor degree from Bangalore University during the year 1996, M. Tech from Karnataka Regional Engineering College Surthkal (NITK) during the year 2000 and Ph.D from Dr MGR University, Chennai. He is working as a Professor and Research Head in Department of Computer Science Engineering, BGSIT. His areas of interests are data warehouse and business intelligence, multimedia, databases, AI, and machine learning. He has published and presented papers in National and International conferences and journals. He can be contacted at email: ravikumargk@yahoo.com.

Dr. Shashikala S. Venkataramu received her B.E degree in Computer Science from Mysore University, Karnataka in 1990 and M. Tech in Computer Science and Engineering from Visvesvaraya Technological University in 2005, Ph.D. degree from VTU. She is a Professor and Head in the department of computer science at B.G.S Institute of Technology; B.G.Nagar, Mandya and having totally 25 years of teaching experience. She has presented many papers in National level conferences and also presented many papers in international conferences; she has published 5 papers in International Journals. Her main research interests include computer networks, big data, and data mining. She can be contacted at email: shashisv7@gmail.com.