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Optimizing SSVEP Frequency Recognition in BCI by Doubling and Averaging Trial Data for Robust Reference Signals

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***Abstract*—Steady-state visual-evoked potential (SSVEP)-based brain-computer interfaces (BCIs) provide a non-invasive method to interact using high-speed indicating systems. Correlation Component Analysis (CORRCA) is used to recognize the frequency of steady state visual evoked potential (SSVEP) for the implementation of brain computer interface (BCI). The performance of CORRCA is degraded when lower training data is used. On the other hand, BCI implementation becomes more effective when it uses lower data length which is lower calibration time. This paper presents an improved reference signal generation based frequency recognition of short-time SSVEP signals. By concatenation the training data has been increased for better fit of using CORRCA. The CORRCA is used to recognize the frequency of short-time SSVEP.The performance of the proposed method is evaluated using publicly available dataset. The accuracy of this proposed method is 92.28%. The experimental results show that this technique enhance performance of SSVEP Frequency Recognition.**

***Index Terms*—Electroencephalogram (EEG), brain–computer interface (BCI), steady-state visualevoked potentials (SSVEPs), CORRCA**

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) have emerged as a transformative technology, providing a unique communication platform that bypasses traditional output channels reliant on peripheral nerves and muscles. By interpreting neural activities into precise control commands, BCIs enable direct interaction between the brain and external systems [1]. Among various paradigms, steady-state visually evoked potentials (SSVEPs) have gained significant attention due to their robustness and ease of implementation. During an SSVEP-based BCI task, users focus on a flickering visual stimulus, eliciting neural signals in the occipital lobe at the same frequency as the stimulus and its harmonics. The key challenge in SSVEP-based BCIs is quickly and accurately detecting the target stimulus frequency from EEG signals to optimize precision and information transfer rate.(ITR) [2].

Frequency recognition algorithms for SSVEP-based BCIs include training-free methods like CCA [3], which rely on simplified reference signals but face accuracy limits [4]. Advanced methods such as MsetCCA [5], MCM [6], and FBMSI [7] improve performance using training data features. Correlated Component Analysis (CORRCA) offers improved efficiency over CCA by reducing computational complexity with a single projection vector [8]. To enhance training-based approaches, doubling and averaging training data techniques have been proposed to expand the volume of training data. In this study, training data have been increased to generate reference signals and integrated with CORRCA to evaluate its impact on SSVEP frequency recognition. Experimental validation on a publicly available SSVEP dataset demonstrates the potential of this approach to significantly improve recognition performance, paving the way for more efficient and accurate SSVEP-based BCI systems.

II. LITERATURE REVIEW

Steady-state visual evoked potential (SSVEP) BCIs have gained significant attention because of their high information transfer rate (ITR) and capability to handle multiple targets, leveraging the characteristic presence of both the stimulus frequency and its harmonics [9]. Recent studies have aimed to reduce calibration time and enhance the robustness of SSVEP-based systems. Methods such as the small-data least-squares transformation (sd-LST) have shown promise in decreasing calibration time; however, their scalability to larger datasets and more stimulation frequencies requires further investigation [10]. Additionally, while prior transfer learning approaches for SSVEP-based BCIs have achieved notable performance improvements, they often require extensive data and intricate tuning, which limits their real-time applicability. The iFuzzyTL model addresses these challenges by integrating fuzzy logic with neural networks to facilitate domain adaptation [11]. However, its complexity may still present challenges in model tuning and data requirements. In contrast, our work presents an improved reference signal generation-based frequency recognition method for short-time SSVEP signals. By concatenating the training data, our approach effectively increases the available data for training, thereby facilitating a better fit when applying correlation component analysis (CORRCA) for frequency recognition. Evaluated on a publicly available dataset, our method achieved better accuracy. This performance demonstrates that our approach not only simplifies the calibration process by reducing the required data length but also outperforms existing methods in terms of efficiency and classification accuracy.

III. DATASET DESCRIPTION AND PREPROCESSING

Publicly available SSVEP The dataset is used to assess the effectiveness of the proposed method. The Dataset was created by the Swartz Center for Computational Neuroscience [12]. The study involved 10 healthy participants, 9 males and 1 female, with an average age of 28 years of these participants, five had prior experience with SSVEP-based BCIs, while the remaining 5 were newcomers. A 12-class SSVEP dataset was recorded using a Biosemi ActiveTwo EEG system with eight occipital Ag/AgCl electrodes in a simulated online BCI task. The 12 stimuli used frequency and phase coding, ranging from 9.25 Hz to 14.75 Hz in 0.5 Hz steps. The EEG signals were sampled at 2048 Hz, and each subject was instructed to focus on one of the 12 flashing stimuli, arranged in a 4 × 3 grid representing a numeric keypad (each square 6 cm × 6 cm). The experiment involved 15 trials, subjects focused on a random stimulus for 4 seconds, covering all 12 targets. EEG signals were downsampled to 256 Hz. In offline analysis, time 0 marked stimulus onset, with each segment lasting 4 seconds.

IV. METHODOLOGY

A. Correlated Component Analysis

A method for maximizing the Pearson product moment correlation coefficient between two multi-dimensional signals is called correlated component analysis, or CORRCA [8]. For two sets of multivariate signals, CORRCA generates the same projection vectors as CCA, ensuring that the linear combination of two data points has the highest possible correlation. Additionally, in CCA, the projection vectors must be orthogonal. This restriction is loosened by the CORRCA. In contrast to CCA, CORRCA uses a single projection vector rather than two distinct projection vectors for the two sets of multivariate signals. The solution to a generalized eigenvalue problem yields the projection vectors for CORRCA, which is mathematically an optimization problem. $X \in \mathbb{R}^{N_c \times N_s}$ and $Y \in \mathbb{R}^{N_c \times N_s}$ are two multivariate signals, where N_c and N_s are the number of channels and sample points, respectively. The goal of the CORRCA optimization problem is to identify a projection vector $w \in \mathbb{R}^{N_c \times 1}$ such that the linear combination $x = w^T X$ and $x = w^T Y$ exhibits the highest correlation. The correlation coefficient (ρ) will be,

$$\rho = \arg\max_{w} \frac{x^T y}{\|x\| \, \|y\|} = \arg\max_{w} \frac{w^T R_{12} w}{\sqrt{w^T R_{11} w}\sqrt{w^T R_{22} w}} \tag{1}$$

where the covariance matrices are $R_{11} = \frac{1}{N_s} X X^T$, $R_{22} = \frac{1}{N_s} Y Y^T$, $R_{12} = \frac{1}{N_s} X Y^T$, $R_{21} = \frac{1}{N_s} Y X^T$ Now differentiating Eq. (1) with respect to w and setting to zero, we get the following eigenvalue problem (considering that $w^T R_{11} w = w^T R_{22} w$, $(R_{12} + R_{21})w = \lambda(R_{11} + R_{22})$ $(R_{11} + R_{22})^{-1}(R_{12} + R_{21})$has a major eigenvector that matches the highest coefficient of ρ. The correlation coefficient between x and y is maximized. Furthermore, the second-strongest correlation coefficient and the second-strongest eigenvalue match. Projecting the data matrices onto the eigenvector yields this coefficient. The remaining coefficients are also determined in a similar manner. Using Eq. (1), $N_c$coefficients $\rho = [\rho_1, \rho_2, ..., \rho_{N_c}]$are obtained. Only the maximal coefficient is utilized as the feature for frequency recognition out of all the coefficients. We must compute these coefficients using a separate template signal created by averaging SSVEP over several trials at frequency i in order to identify the frequency of a test signal $X \in \mathbb{R}^{N_c \times N_s}$. The frequency of the test signal is designated as the frequency of the template signal with the highest correlation coefficient,

$$f_x = \arg\max_{i} (\rho_i) \tag{2}$$

B. Doubling and Averaging Trial Data

In order to overcome small training datasets problem, we proposed a new method to generate reference signal of EEG data that helps to enhance the recognition accuracy using CORRCA for SSVEPs. Fig. 2 shows a flowchart of our increasing training data based approach to frequency recognition of SSVEPs. The data, which is four-dimensional, has dimensions of N_c x N_s x N_t x N_f, where N_c corresponds to the number of channels, N_s to the number of sample points, N_t to the number of trials, and N_f to the number of stimuli. The size of the dataset is $8 \times 1024 \times 15 \times 12$. The raw SSVEP data is pre-filtered between ranges of frequency $(6 - 120)$ Hz. Then to reduce the calibration time, short-time SSVEP signal with 1.0s is taken from the recorded signal. The steps to implement the method are mentioned below:

1) EEG signal has been taken that is one second long.
2) The data is again filtered between the frequency $(f_1 - 4)Hz$ to $120Hz$, where f_1 is the first stimulus frequency.
3) Leave one out technique has been applied and the $N_t - 1$ training signal is concatenated lenght wise with the $N_t - 1$ original training signals. That makes training data with $2(N_s)$ sample points termed a concatenated training signal.

4) Y_1^i,The mean of the original training signal of frequency i, $Y_1^i \in \mathbb{R}^{N_c \times N_s}$
5) Y_2^i, the mean of the concatenated training signal of frequency i, $Y_2^i \in \mathbb{R}^{N_c \times N_s}$
6) Two coefficient vectors are generated using CORRCA with two pairs $(X, Y_1^i)$and (X, Y_2^i). In both cases, a set of $N_c$coefficients $\lambda_1^1, \lambda_2^1, ..., \lambda_{N_c}^1$ and $\lambda_1^2, \lambda_2^2, ..., \lambda_{N_c}^2$ are generated.
7) $\lambda^1 = \max(\lambda_i^1)$, where $i = 1, 2, ..., N_c$
8) $\lambda^2 = \max(\lambda_i^2)$, where $i = 1, 2, ..., N_c$
9) Maximal coefficient vector $\rho_i \in \mathbb{R}^{N_f}$ for each stimulus frequency is created from that coefficient vectors $\lambda_{N_c}^{N_f}$. i.e. $\rho_i = \max(\lambda_{N_c}^{N_f})$.
10) Recognized frequency $F_{X_{test}}$ is abstracted from maximum coefficient vector ρ_i index. $i.e.$ $F_{X_{test}} = \arg\max(\rho_i)$

The block diagram of the proposed frequency recognition method is illustrated in Fig. 2

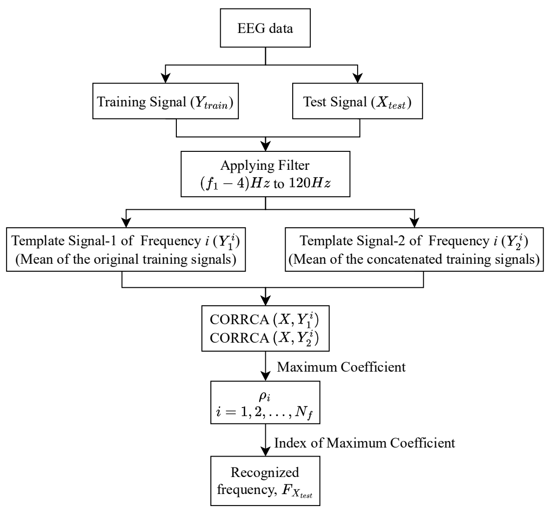

Figure 1: Proposed diagram of ssvep frequency recognition.

V. EXPERIMENTAL RESULTS AND DISCUSSION

This study evaluates the proposed method using classification accuracy and ITR. A comparison was conducted between CORRCA with and without the method, using four data lengths (0.25s, 0.50s, 0.75s, 1.00s) to assess BCI performance. Accuracy was measured through leave-one-out cross-validation and ITR was used to quantify information transmission efficiency.

The accuracy of classification and information transfer rate (ITR) averaged over all the subjects with different time windows from 0.25 s to 1.00s with a step size of 0.25s are displayed respectively in Fig 3(a) and 3(b). The mean accuracy is shown with for two different methods. The first one is the standard CCA and the second one is the proposed method based on CORRCA. As shown in Fig. 3, The proposed method enhances the performance based on CORRCA a consistent approach That outruns standard method CCA in terms of

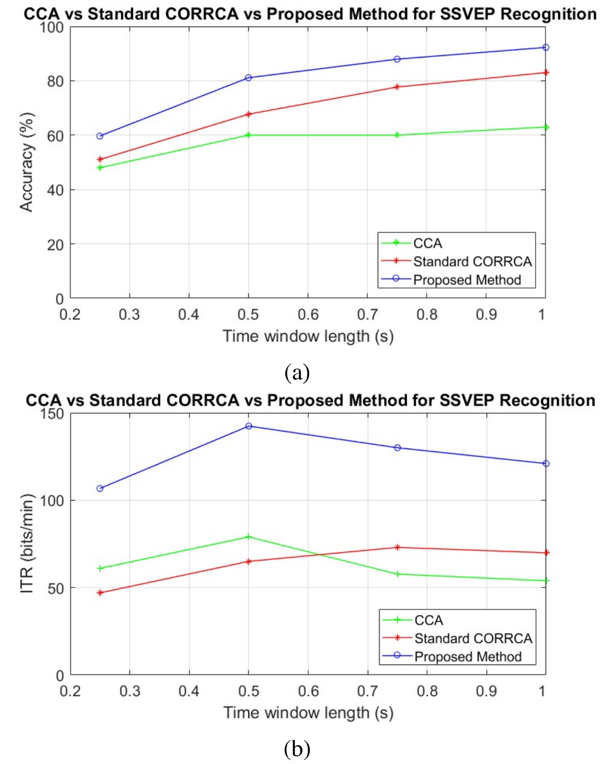

Figure 2: Frequency recognition accuracy and ITR were assessed using CCA, CORRCA, and the proposed method with time windows from 0.25s to 1.00s in 0.25s steps.

accuracy and ITR and among them, maximum precision is obtained for the time window of 1s. This is why the subject-wise detailed precision and ITR for this method are presented in Table I and Table II, respectively. Here, the maximum accuracy and ITR is obtained for the time window of 1.00s. These results show that the proposed method is possible so that the performance of the existing CORRCA techniques can be improved. In addition, we can see the classification accuracy standard deviation using the proposed method has decreased outstandingly compared to conventional methods that specify that the proposed methods improve the authenticity of the frequency detection for all frequencies stimulation. These results further exemplify that the proposed framework can produce more robust functionality than existing methods.

Canonical Correlation Analysis (CCA) is widely used for SSVEP frequency recognition but suffers from long calibration times and suboptimal performance. To address these limitations, advanced methods like Hybrid Subject Correlation Analysis (HSCA) [13] and small-data least-squares transformation (sd-LST) [10] have been developed, offering improved usability and faster calibration. The Multivariate Synchronization Index (MSI) and its modified version, inter-subject and intra-subject template-based MSI (IIST-MSI), further enhance SSVEP frequency detection by leveraging dynamic temporal feature extraction [14]. Additionally, Correlated Component Analysis (CORRCA) outperforms conventional techniques like

TABLE I: Accuracy (%) for each subject.

Subject	0.25 s	0.50 s	0.75 s	1.00 s
S1	43.33	70	76.67	86.11
S2	35	52.78	64.44	70.56
S3	58.33	82.22	93.33	95
S4	72.22	92.22	98.89	100
S5	83.33	98.33	100	100
S6	85	94.44	99.44	100
S7	71.11	78.89	80.56	81.11
S8	72.78	95.56	96.67	100
S9	48.89	87.22	93.89	99.44
S10	26.67	59.44	75.56	90.56
Avarage Accuracy (%)	59.666	81.11	87.945	92.278

TABLE II: ITR (bits min1) for each subject.

Subject	0.25 s	0.50 s	0.75 s	1.00 s
S1	50.99	119.65	79.96	100.92
S2	32.18	57.22	67.96	67.69
S3	93.08	137.68	144.04	125.02
S4	141.72	175.29	166.01	143.39
S5	188.65	204.28	172.08	143.39
S6	196.49	184.97	168.75	143.39
S7	137.46	126.67	105.68	89.29
S8	143.89	190.15	156.44	143.39
S9	65.38	155.49	146.01	140.63
S10	16.92	72.46	92.98	112.29
ITR(bits min1)	106.676	142.386	129.991	120.94

CCA by using a single projection vector, reducing computational complexity. The proposed method surpasses these approaches, achieving higher accuracy (92.28%) and competitive ITR (120.94 ± 27.35 bits/min) compared to HSCA, sd-LST, IIST-MSI and iFuzzyTL.

Comparison Table		
Methods	**Accuracy (%)**	**ITR (bits min1)**
HSCA [13]	88	82
Sd-LST [10]	84.25	123.71±43.19
IIST-MSI [14]	81	57
iFuzzyTL [11]	89.70	149.58
Proposed Method	92.28	120.94±27.35

VI. Conclusions

This study highlights advancements in SSVEP-based BCI systems by addressing the challenges of accurate frequency recognition and enhancing the information transfer rate (ITR). SSVEP signals, with their high signal-to-noise ratio and reduced training requirements, continue to be a promising modality for BCI applications. While conventional methods like CCA offer a foundation for frequency recognition, their limitations in calibration time and accuracy necessitate more robust solutions. Advanced algorithms such as HSCA, sd-LST, and CORRCA have made notable strides in improving calibration efficiency and recognition performance. Our proposed method integrates enhanced training data strategies with CORRCA, leading to superior accuracy (92.28%) and competitive ITR (120.94 ± 27.35 bits/min). Experimental results validate the efficacy of this approach, positioning it as a significant step forward in the development of efficient and reliable SSVEP-based BCI systems. These findings pave the way for practical applications in various domains, emphasizing the importance of continuous innovation in algorithmic design to meet the growing demands of BCI technology. While our current study validates performance using a publicly available dataset, we acknowledge the importance of scalability. In future work, we will evaluate the method on larger EEG datasets to further verify its robustness and scalability, ensuring it can handle increased data volumes without compromising speed or accuracy.

References

[1] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, T. M. Vaughan, *et al.*, "Brain-computer interface technology: a review of the first international meeting," *IEEE transactions on rehabilitation engineering*, vol. 8, no. 2, pp. 164–173, 2000.

[2] S. Mahmood, J. Shin, I. Farhana, M. R. Islam, and M. K. I. Molla, "Frequency recognition of short-time ssvep signal using corrca-based spatio-spectral feature fusion framework," *IEEE Access*, vol. 9, pp. 167744–167755, 2021.

[3] Z. Lin, C. Zhang, W. Wu, and X. Gao, "Frequency recognition based on canonical correlation analysis for ssvep-based bcis," *IEEE transactions on biomedical engineering*, vol. 53, no. 12, pp. 2610–2614, 2006.

[4] N. Jrad and M. Congedo, "Identification of spatial and temporal features of eeg," *Neurocomputing*, vol. 90, pp. 66–71, 2012.

[5] Y. Zhang, G. Zhou, J. Jin, X. Wang, and A. Cichocki, "Frequency recognition in ssvep-based bci using multiset canonical correlation analysis," *International journal of neural systems*, vol. 24, no. 04, p. 1450013, 2014.

[6] Y. Jiao, Y. Zhang, Y. Wang, B. Wang, J. Jin, and X. Wang, "A novel multilayer correlation maximization model for improving cca-based frequency recognition in ssvep brain–computer interface," *International journal of neural systems*, vol. 28, no. 04, p. 1750039, 2018.

[7] K. Qin, R. Wang, and Y. Zhang, "Filter bank-driven multivariate synchronization index for training-free ssvep bci," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 934–943, 2021.

[8] J. P. Dmochowski, P. Sajda, J. Dias, and L. C. Parra, "Correlated components of ongoing eeg point to emotionally laden attention–a possible marker of engagement?," *Frontiers in human neuroscience*, vol. 6, p. 112, 2012.

[9] J.-H. Lim, H.-J. Hwang, C.-H. Han, K.-Y. Jung, and C.-H. Im, "Classification of binary intentions for individuals with impaired oculomotor function:'eyes-closed'ssvep-based brain–computer interface (bci)," *Journal of neural engineering*, vol. 10, no. 2, p. 026021, 2013.

[10] R. Bian, H. Wu, B. Liu, and D. Wu, "Small data least-squares transformation (sd-lst) for fast calibration of ssvep-based bcis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 446–455, 2022.

[11] X. Jiang, B. Cao, L. Ou, Y.-C. Chang, T. Do, and C.-T. Lin, "ifuzzytl: Interpretable fuzzy transfer learning for ssvep bci system," *arXiv preprint arXiv:2410.12267*, 2024.

[12] M. Nakanishi, Y. Wang, Y.-T. Wang, and T.-P. Jung, "A comparison study of canonical correlation analysis based methods for detecting steady-state visual evoked potentials," *PloS one*, vol. 10, no. 10, p. e0140703, 2015.

[13] R. Miao, L. Zhang, and Q. Sun, "Hybrid template canonical correlation analysis method for enhancing ssvep recognition under data-limited condition," in *2021 10th International IEEE/EMBS Conference on Neural Engineering (NER)*, pp. 65–68, IEEE, 2021.

[14] H. Wang, Y. Sun, Y. Li, S. Chen, and W. Zhou, "Inter-and intra-subject template-based multivariate synchronization index using an adaptive threshold for ssvep-based bcis," *Frontiers in Neuroscience*, vol. 14, p. 717, 2020.