Research on SSVEP-EEG feature enhancement Algorithm based on fractional differentiation

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Abstract

Steady-State Visual Evoked Potentials (SSVEP) have garnered significant attention due to their promising applications in brain-computer interfaces (BCI), medical diagnostics, and several other domains. Enhancing the characteristics of SSVEP signals through intricate signal processing has emerged as a pivotal research focus for more efficient signal extraction. In this work, we introduce a novel layered enhancement algorithm for SSVEP electroencephalogram (SSVEP-EEG) signals based on fractional-order differentiation operators. This innovative approach marries brain signal analysis with image processing methodologies. By utilizing fractional-order differentiation operators in tandem with the Laplace pyramid, the signal undergoes hierarchical enhancement. This amplified signal is then reconstructed, which facilitates an in-depth extraction of image intricacies and attributes, ultimately accentuating the distinctiveness of SSVEP features. To validate the efficacy of the proposed method, we applied it to three recognized target identification algorithms: Canonical Correlation Analysis (CCA), Filter Bank Canonical Correlation Analysis (FBCCA), and Task-Related Component Analysis (TRCA) using a publicly available dataset. Experimental outcomes underscore that, in contrast to contemporary techniques, our proposed algorithm not only effectively attenuates the trend components of SSVEP signals but also substantially elevates the recognition precision of CCA, FBCCA, and TRCA.

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Abstract

Steady-State Visual Evoked Potentials (SSVEP) have garnered significant attention due to their promising applications in brain-computer interfaces (BCI), medical diagnostics, and several other domains. Enhancing the characteristics of SSVEP signals through intricate signal processing has emerged as a pivotal research focus for more efficient signal extraction. In this work, we introduce a novel layered enhancement algorithm for SSVEP electroencephalogram (SSVEP-EEG) signals based on fractional-order differentiation operators. This innovative approach marries brain signal analysis with image processing methodologies. By utilizing fractional-order differentiation operators in tandem with the Laplace pyramid, the signal undergoes hierarchical enhancement. This amplified signal is then reconstructed, which facilitates an in-depth extraction of image intricacies and attributes, ultimately accentuating the distinctiveness of SSVEP features. To validate the efficacy of the proposed method, we applied it to three recognized target identification algorithms: Canonical Correlation Analysis (CCA), Filter Bank Canonical Correlation Analysis (FBCCA), and Task-Related Component Analysis (TRCA) using a publicly available dataset. Experimental outcomes underscore that, in contrast to contemporary techniques, our proposed algorithm not only effectively attenuates the trend components of SSVEP signals but also substantially elevates the recognition precision of CCA, FBCCA, and TRCA.

| Introduction

Over the past three decades, Brain-Computer Interface (BCI) technology has garnered significant scholarly attention. This advanced framework facilitates direct interaction between the human brain's activity and computing systems, offering a novel avenue for encoding and decoding information predicated solely on neural activity [1]. Among various BCI modalities, the Steady-State Visual Evoked Potential (SSVEP) has emerged as a particularly salient methodology, largely because SSVEP-based BCI systems obviate the need for extensive user training [2] and boast high information transfer rates [3]. As such, it's increasingly recognized as a promising modality for interactive applications, often underpinning the development of sophisticated systems [4]. One of the paramount applications of SSVEP is within the realm of BCI, where the precise identification of a user's intent stands as a pivotal research direction [5, 6, 7, 8]. In SSVEP-based BCIs, an array of flashing modules, each oscillating at distinct frequencies, is used as stimuli, where each stimulus corresponds to a specific operational command [9]. When a user fixates on a particular stimulus, cortical neural activities get modulated, resulting in the generation of periodic rhythms that resonate at the same frequency as the stimulus. This activity is predominantly localized in the occipital region of the cortex [10]. By pinpointing the peak frequencies within the induced electroencephalographic signals, one can discern the specific stimulus the user is focusing on, thereby inferring the user's intent [11]. Several algorithms have been developed to enhance target recognition within this context, including Canonical Correlation Analysis (CCA) [12], Filter Bank Canonical Correlation Analysis (FBCCA) [13], Multivariate Synchronization Index (MSI) [14], Individual Template-based Canonical Correlation Analysis (IT-CCA) [15], Multiway Canonical Correlation Analysis (Mway CCA) [16], and Task-Related Component Analysis (TRCA) [17], among others.

Nevertheless, the inherent low signal-to-noise ratio of SSVEP signals poses a formidable challenge, constraining its research, analysis, and application. To enhance the extraction efficiency of SSVEP signals, it becomes imperative to augment their characteristics. Yan et al.[18] introduced an Image Filtering Denoising (IFD) method for SSVEP, initially filtering multi-channel EEG signals to retrieve noise, which is then subtracted from the original signal to procure the denoised version. This approach essentially delineates blurred details from an image and then excludes them to obtain finer details. However, this method tends to inadvertently discard some essential information in the process.

To overcome this impediment, we propose an Enhanced Feature Augmentation Algorithm based on Fractional-Order Derivative Operator, termed Enhanced Riemann-Liouville based on Laplacian Pyramid (ERLLP), to amplify SSVEP Electroencephalogram (SSVEP-EEG) signals. The strategy first employs a sharpening filter utilizing spatial differencing to extract image intricacies, followed by an application of the fractional-order derivative operator for optimal detail and contour refinement. Contrasting the integer-order differential operators, like Prewitt, Sobel, and Laplace, used in [5], fractional-order derivatives, as an extension, not only offer image sharpening but, due to their weak derivative properties, can also bolster the high-frequency components while preserving the low-frequency portions in a nonlinear fashion. This makes fractional-order derivatives more potent in analyzing and enhancing image characteristics. Hence, we integrated the fractional-order derivative operator and further refined the traditional Riemann-Liouville fractional derivative operator, leading to the inception of the Enhanced-RL operator. Subsequently, employing the Laplacian pyramid facilitates layered signal processing, followed by signal reconstruction to further delineate details and features. Ultimately, using a public dataset, the study corroborates the augmented efficacy of our ERLLP algorithm in enhancing the recognition capabilities of user intent identification algorithms like CCA, FBCCA, and TRCA. Experimental outcomes underscore that, in contrast to the IFD and the methodologies detailed in [5], our proposed ERLLP algorithm markedly escalates the accuracy of SSVEP signal recognition.

| Theoretical Framework

| Enhanced-RL Operator

Given the foundational work on the Riemann-Liouville (RL) differential, Ni et al. [19] advanced the field by introducing a specific image enhancement operator. Recognizing the computational challenges associated with higher-order complexities, they strategically executed differentiation operations, bifurcating them along both the positive and negative directions on theandaxes. Additionally, differentiation was executed across the four cardinal diagonal vectors. To facilitate this refined operation, a 3×3 template was judiciously deployed. Subsequently, the products of these eight distinctive fractional differential templates, derived from varied orientations, were amalgamated. The culmination of this intricate process resulted in a 5×5 convolution template, a depiction of which is presented in Figure 1:

a_2	0	a_2	0	a_2
0	a_1	a_1	a_1	0
a_2	a_1	$8a_0$	a_1	a_2
0	a_1	a_1	a_1	0
a_2	0	a_2	0	a_2

Figure 1 Riemann-Liouville Fractional Differential Operator

Certainly:

Given the practical implementations of the Riemann-Liouville (RL) fractional differentiation, its operational order tends to be confined predominantly between 0.1 to 0.2, as highlighted by Ni et al. [19]. Beyond this defined range, images tend to compromise their inherent details. This manifests as an uptick in noise levels, rendering the algorithm overly susceptible to noise perturbations. This noise susceptibility, coupled with the stringent constraints on the fractional differentiation order, often results in the sharpening effects falling short of desired outcomes in a multitude of scenarios.

Recognizing this intrinsic limitation, and with the overarching goal of amplifying visual fidelity whilst concurrently tempering the operator's noise impact, it becomes imperative to recalibrate the operator to be less noise-sensitive. Delving into the nuances of differentiation operators, it is discernible that the coefficient associated with the template's central pixel is represented as $8_.$ This coefficient invariably wields the most profound influence on the image enhancement process. As one moves further from this pivotal central pixel, its corresponding influence on the image undergoes a gradual attenuation.

In pursuit of diminishing the blurring effect and further curtailing the noise footprint, this study introduces a nuanced modification. We recalibrate the template coefficients of the RL fractional differential operator, anchoring our approach on a weighted scheme. The precise methodology for this modification unfolds as:

The modified differential operator with adjusted coefficients is illustrated in Figure 2 below:

b_2	0	b_2	0	b_2
0	b_1	b_1	b_1	0
b_2	b_1	$8b_0$	b_1	b_2

b_2	0	b_2	0	b_2
0	b_1	b_1	b_1	0
b_2	0	b_2	0	b_2

FIGURE 2 Enhanced Riemann-Liouville Fractional Differential Operator

2.2 | Laplacian Pyramid

The image pyramid is a canonical multi-scale representation fundamentally established via a recursive method. This formation ultimately leads to a pyramid of images with progressively decreasing resolutions. Constructing the Laplacian Pyramid is contingent upon the foundation of the Gaussian Pyramid, with the following steps:

1. Gaussian Pyramid Construction: At the heart of this step is the down-sampling of the image, which effectively reduces its size. Firstly, the image from the preceding layer undergoes convolution with a Gaussian kernel. Subsequent to this convolution, down-sampling is performed with a scale factor of 2.

2. Laplacian Pyramid Construction: Once the Gaussian pyramid is acquired, up-sampling of its r -th layer is car- ried out, followed by Gaussian convolution. This results in a new image whose dimensions match those of the *r-1* -th layer of the Gaussian pyramid. By subtracting the newly procured image from the *r-1* -th layer of the Gaussian pyramid, we obtain the *r-1* -th image of the Laplacian pyramid. The aforementioned steps are iteratively executed until images for all layers of the Laplacian pyramid are generated.

3. Reconstruction of the Laplacian Pyramid Images: The reconstruction mechanism mirrors the procedures fro- m step 2. Post up-sampling of the$r$ -th layer of the Gaussian pyramid and subsequent Gaussian convolution f- iltering, the resulting image, when added to the residuals stored in the Laplacian pyramid, yields a new image. Replicating the above steps facilitates the reconstruction of images from the Laplacian pyramid.

2.3 | CCA, FBCCA, and TRCA Methods

In this research endeavor, we delve into the application and consequences of the advanced ERLLP algorithm on the precision of SSVEP target identification by employing Canonical Correlation Analysis (CCA), Filter Bank Canonical Correlation Analysis (FBCCA), and Task-Related Component Analysis (TRCA) as exemplar methods. The ensuing sections elucidate the mechanisms behind these three target identification methodologies.

CCA Method: Given the acquired EEG dataset denoted asand the reference signals symbolized by,where and, the objective of Canonical Correlation Analysis (CCA) is to deduce a pair of linear transformationsandsuch that the correlation between the transformed variables and, is augmented to its zenith. The mathematical representation is:

Whererepresents the correlation coefficient, whileandare the eigenvectors corresponding to the largest eigenvalue.

For every stimulus frequency, denoted(whereand I represents the total number of stimulus frequencies), the reference signal can be constructed based on:

Whererepresents the number of harmonics, anddenotes the sampling rate. By computing the canonical correlation coefficient ofwith the reference signal under all stimulus frequencies, the stimulus frequency corresponding to the maximum correlation coefficient is identified as the target stimulus frequency.

FBCCA Method: The signalis decomposed into n sub-band signals through a filter bank, and the canonical correlation coefficientof each sub-band signalis calculated. The final discriminant coefficient is then determined by integrating the correlations of the n sub-bands as follows:

Where represents the weight corresponding to the correlation coefficient of the kth sub-band signal, and can be computed using:

In this context,is set to 1.25 andis set to 0.25, as per reference [15]. By comparing the integral coefficients of all the acquired stimulus frequencies, the stimulus frequency corresponding to the maximum correlation coefficient is selected as the target stimulus frequency

TRCA Method: This is a training-based method that requires the collection of user data through multiple experimental sessions. The collected user training data is represented as, wheredenotes the number of sampling points,indicates the number of electrode channels,represents the number of stimulus frequencies, andsignifies the number of blocks. TRCA aims to extract task-related components by spatially filtering the training data. The spatial filterfor stimulus frequencyand residing incan be expressed by the following equation:

In the above equationembodies the multi-channel EEG recordings for theblock subjected to a stimulus frequency.The concluding step involves the computation of the Pearson correlation coefficient between the spatially refined signal and the evaluation signal, which acts as the discriminating coefficient. Upon determining these coefficients for all stimulus frequencies, the target that resonates with the preeminent coefficient is recognized as the focal target. The depiction is as:

| Implementation

3.1 | Dataset

This investigation is grounded upon a benchmark SSVEP dataset introduced and curated by Wang et al. [21]. This dataset was meticulously compiled from a 40-target based BCI speller application, encapsulating the intricate nuances of Brain-Computer Interaction (BCI) paradigms. In particular, the dataset encompasses EEG recordings from a total of 35 healthy participants, spanning an eclectic mix of 8 seasoned participants with prior BCI experience and 27 novices. These recordings were obtained during dedicated target selection exercises steered by visual cues. Elaborating on the BCI speller, its virtual keyboard is intricately designed with 40 distinct visual flickers. These flickers are encoded employing the advanced Joint Frequency and Phase Modulation (JFPM) method, a testament to the rigorous scientific approach applied. The spectrum of stimulus frequencies extends from 8 Hz, reaching up to 15.8 Hz, and is demarcated at regular intervals of 0.2 Hz. Notably, there exists a phase disparity of 0.5between consecutively mapped frequencies.

For every participant in the study, the dataset archives a total of 240 trials (40 targets juxtaposed across 6 blocks). These trials are organized in a stochastic sequence, ensuring that the 40 flickers, guided by visual cues, appear in a randomized order. Each distinct trial has been structured to span a duration of 5 seconds. This dataset has been recognized as a pivotal reference point for scholars and researchers, aiding in the comparative analysis of diverse methods aimed at stimulus encoding and target identification within the realm of SSVEP-based BCI. This invaluable resource has been made accessible to the global research community and can be procured from http://bci.med.tsinghua.edu.cn/download.html. Encoded in MATLAB's MAT file format, the dataset is disaggregated into 35 distinct files, corresponding to individual participants. Cumulatively, this data amasses a size of approximately 3.3GB. Each of these files, meticulously labeled from S01.mat to S35.mat, encapsulates the EEG readings as double-precision floating-point representations. When decoded in MATLAB, each file unravels into a four-dimensional matrix termed "data" with demarcations across "electrode index," "time point," "target index," and "block index." Specifically, every trial encompasses 1500 data reference points from a 64-channel setup. An astute analysis reveals that the data length, which accumulates to 6 seconds (equivalent to $6 \times 250 = 1500$ time points), integrates a 0.5-second interval preceding stimulus initiation, 5 seconds post-initiation, and an additional 0.5 seconds post-stimulus cessation. For the sake of meticulous SSVEP signal scrutiny, the channels selected for this investigation are O1, O2, Oz, PO3, PO4, POZ, PO5, and PO6.

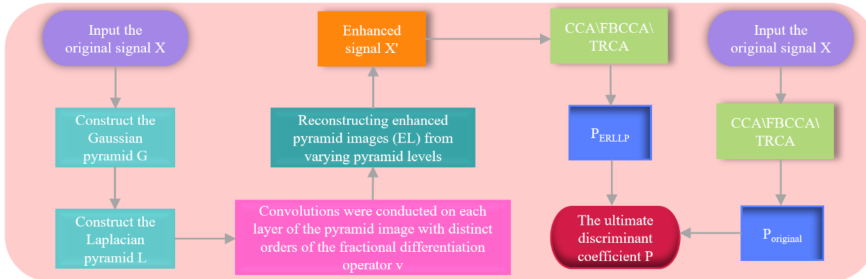

FIGURE 3 Algorithm Implementation Flowchart.

3.2 | SSVEP Feature Enhancement Method based on ERLLP

In this comprehensive study, we leverage the multi-channel signal, designated as, which encompasses selected SSVEP signal analysis channels namely O1, O2, Oz, PO3, PO4, POZ, PO5, and PO6. When conceptualized as the input image and subsequently processed through the intricacies of the Laplace pyramid in conjunction with the Enhanced-RL operator, as delineated in Figure 2, the resultant is a meticulously sharpened and filtered signal, termed . Notably, when the cutting-edge ERLLP algorithm is integrated into spectral analysis, especially in realms as nuanced as medical diagnostics and neuroscience research, this refined signalis positioned as the focal point of analysis, serving as a pivotal analyzed signal.

Drawing a comparison to prevailing methodologies outlined in literature [5], where the Prewitt, Sobel, and Laplace operators are predominantly employed, our research pivots towards utilizing the Enhanced-RL operator. This approach not only serves as an innovative filtering template, tailored for gaze target recognition in the SSVEP BCI paradigm, but also seamlessly facilitates hierarchical filtering. Intriguingly, pyramid images cultivated at diverse hierarchical levels exhibit variances in resolution and intricate detail information. The granularity of this detail information becomes increasingly conspicuous as one navigates towards the base of the pyramid. Given this gradation, higher pyramid tiers inherently dictate the selection of an augmented fractional order of differentiation. As the research progresses, there's a synthesis of this advanced sharpened filtering technique with renowned methods such as CCA, FBCCA, and TRCA. This amalgamation births the novel methodologies christened as ERLLP_CCA, ERLLP_FBCCA, and ERLLP_TRCA, visually elucidated in Figure 3.

To dissect the analytical approach further, initially, the discrimination coefficients of the pristine test signal , as calculated through CCA, FBCCA, and TRCA methodologies, are labeled as. Subsequent to this, the ERLLP algorithm is harnessed to refine X. Post this enhancement, the discrimination coefficients of the sharpened and meticulously filtered signal, as derived from CCA, FBCCA, and TRCA techniques, are christened as. Culminating the analysis, the ERLLP_CCA, ERLLP_FBCCA, and ERLLP_TRCA methodologies harness an integration of the coefficients fromand, presenting them as the ultimate discrimination coefficients, aptly captured in the ensuing mathematical equation:

| Experimental Results and Discussion

4.1 | Signal Processing

Figure 4 provides a visual elucidation of the transformative impact of ERLLP on SSVEP signals, offering a comparative analysis of waveforms before and after the application of ERLLP as a sharpening mechanism for the SSVEP signals.

In Panel 4-A, the depicted waveform represents the innate characteristics of the unaltered SSVEP signal. This original waveform prominently showcases significant fluctuations, where the signal intermittently deviates from its baseline, leading to an inconsistent distribution over time. This pronounced deviation, termed as the 'trend term', carries substantial weight, as it profoundly impacts the overall efficacy and interpretability of the signal.

Transitioning to Panel 4-B, a striking contrast is observed. Presented here is the waveform of the SSVEP signal post its refinement through the ERLLP algorithm. The resultant waveform demonstrates a remarkable stability, underscoring the prowess of ERLLP in adeptly mitigating the previously observed trend term inherent to the SSVEP signal. This not only enhances the clarity and consistency of the waveform but also underscores the algorithm's efficacy. Additionally, the refined waveform subtly alludes to another advantageous trait of ERLLP: its capability to attenuate extraneous noise in the SSVEP signal, further bolstering the signal's integrity and reliability for subsequent analytical endeavors.

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FIGURE 4 (a) Original Signal.

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FIGURE 4 (b) Signal Enhanced by ERLLP.

The layered enhancement effect is illustrated in Figure 5. As we traverse the pyramid, images at different levels exhibit distinct resolutions and varying degrees of detail. The lower the layer, the more pronounced the detail. Specifically, the detail becomes more pronounced as we descend the levels. The image at level L1 is replete with intricate details, whereas the image at level L4 is characterized by fewer nuances. Consequently, in this paper, differential operators of lower orders were employed for convolution operations on the lower layers of the pyramid images. For the upper layers of the pyramid, differential operators of higher orders were chosen. The fractional order differentials $V1, V2, V3, V4$, and V4V4 were selected as 0.5, 0.6, 0.7, and 0.8 respectively. The enhanced Laplacian pyramid images are denoted as EL 1, EL 2, EL 3, and EL 4 respectively. A comparison of the pyramid layer images before and after enhancement, as shown in Figure 5, indicates that the signal trend items and noise of the pyramid images at different layers can be effectively eliminated.

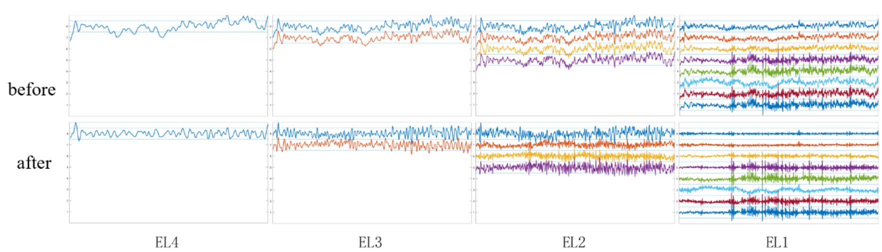

FIGURE 5 Comparison of Signals Before and After ERLLP Enhancement.

4.2 | Recognition Accuracy

Figure 6a illustrates the contrast in recognition accuracies between the SF_CCA method pioneered by Yan et al. [5] and the novel ERLLP_CCA approach introduced in this research, spanning a data analysis length from 1 to 2 seconds in 0.2-second increments. Within this framework, the CCA is applied to the foundational signal X , the SF_CCA is implemented on the refined filtered signal X' , and the ERLLP_CCA focuses on the ERLLP-amplified signal X'' . As highlighted in Figure 6a, irrespective of the stimulus durations, the ERLLP_CCA showcases a remarkable enhancement in recognition accuracy compared to the original SSVEP signal, distinctly outperforming the capabilities of SF_CCA. For stimulus durations at intervals of 1, 1.2, 1.4, 1.6, 1.8, and 2 seconds, the ERLLP_CCA methodology yields improved accuracy rates by 3.08%, 4.28%, 2.02%, 2.08%, 2.02%, and 1.08% compared to the baseline SF_CCA method, respectively.

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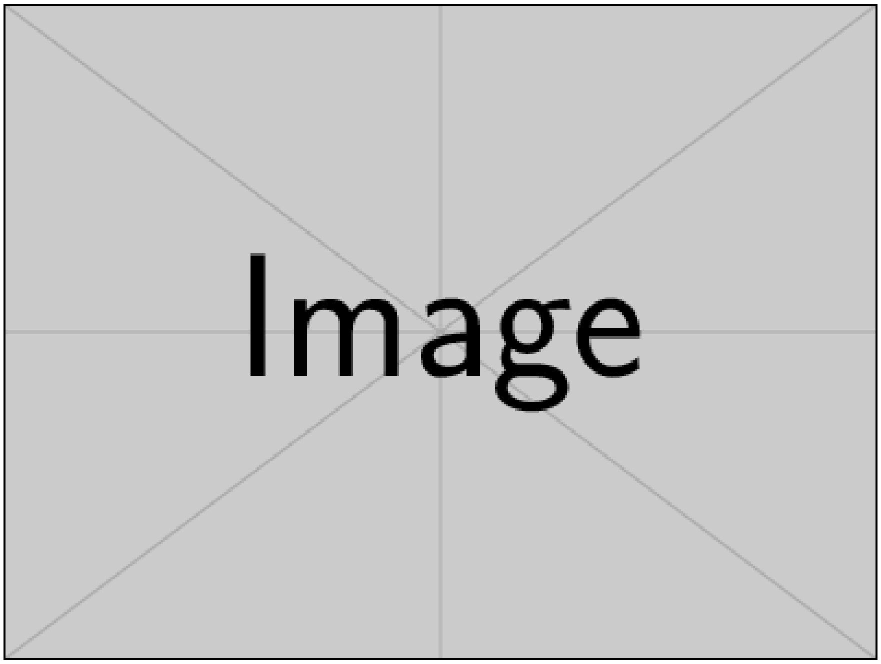

(a) (b) (c)

FIGURE 6 Recognition accuracy of CCA(a), FBCCA(b), and TRCA(c).

Figure 6b unfurls the recognition accuracy comparison between the SF_FBCCA methodology, as introduced by Yan et al. [5], and the ERLLP_FBCCA approach of the present study. Drawing from the findings of [15], the demarcated corner frequencies for the passband and stopband for the initial group are registered at [6, 90] Hz, for the second assembly at [14, 90] Hz, and for the third cluster at [22, 90] Hz. As is manifest in Figure 6b, when measuring over stimulus durations spanning 1, 1.2, 1.4, 1.6, 1.8, and 2 seconds, the ERLLP_FBCCA methodology manifests recognition accuracy enhancements of 2.07%, 1.17%, 2.23%, 1.65%, 2.03%, and 1.88%, contrasted against the SF_FBCCA paradigm.

Figure 6c portrays the recognition accuracy contrasts between the SF_TRCA approach, as articulated by Yan et al. [5], and the ERLLP_TRCA methodology elucidated in this manuscript. The data scrutiny ensues over intervals from 0.5 to 0.8 seconds, incremented by 0.1 seconds. In gauging the recognition accuracy for individual subjects, an exhaustive leave-one-out cross-validation methodology was harnessed, leveraging five from the sextet of blocks for indoctrination and sequentially probing the recognition efficacy on the solitary sixth block.

As illuminated in Figure 6c, over stimulus durations of 0.5, 0.6, 0.7, and 0.8 seconds, the recognition accuracy of ERLLP_TRCA method witnesses surges of 2.40%, 2.82%, 1.02%, and 0.98%, respectively, in juxtaposition with the foundational SF-TRCA protocol.

In summation, through the judicious integration of the ERLLP technique, which exhibits a proficient capability for SSVEP signal enhancement, with established methodologies such as CCA, FBCCA, and TRCA, we have witnessed a notable elevation in the recognition accuracy metrics. This convergence elucidates the synergistic potential of combining advanced signal enhancement with classical recognition techniques in the realm of neuroscientific research.

| DISCUSSION AND CONCLUSION

In this study, we have presented a novel approach for enhancing the analysis of steady-state visual evoked potentials (SSVEP) signals. Our method, termed Enhanced-RL based on Laplacian pyramid (ERLLP), combines the benefits of fractional-order differentiation and Laplace pyramid to enhance the features of SSVEP signals. We have demonstrated the effectiveness of ERLLP in improving the recognition accuracy of SSVEP target identification, using three well-known algorithms: Canonical Correlation Analysis (CCA), Filter Bank Canonical Correlation Analysis (FBCCA), and Task-Related Component Analysis (TRCA).

Our results indicate that the application of ERLLP leads to a significant enhancement of SSVEP signal analysis. By leveraging fractional-order differentiation, we successfully enhance the fine details of SSVEP signals, effectively mitigating the influence of trends and noise. Importantly, ERLLP consistently improves recognition accuracy across various stimulus durations for CCA, FBCCA, and TRCA algorithms. The significance of the ERLLP approach extends beyond improved recognition accuracy. The integration of image processing techniques and hierarchical enhancement introduces a novel perspective in brain signal analysis. Through the combination of fractional-order differentiation and pyramid structures, we achieve effective noise reduction and trend elimination in SSVEP signals. This novel approach not only advances SSVEP target identification but also offers promising applications in the broader field of brain-computer interface research. Despite the promising outcomes, it is important to acknowledge challenges and potential refinements associated with the ERLLP approach. Parameters such as the fractional-order differentiation order and the number of pyramid levels warrant further optimization and investigation for optimal performance. Additionally, the algorithm's robustness across individual variations and real-world scenarios requires further exploration.

In conclusion, the ERLLP algorithm presented in this study introduces innovative strategies for SSVEP signal analysis. By employing image processing and hierarchical enhancement techniques, we enhance signal quality and recognition accuracy. Future research can explore the adaptability and applicability of this approach in diverse brain signal analysis tasks. Moreover, the optimization of algorithm parameters and its extension to various real-world scenarios hold potential for further advancements in brain-computer interface research.

AUTHOR CONTRIBUTION

Zenghui Li: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Software; Validation; Visualization; Writing—original draft; Writing—review & editing. Saijie Yuan: Conceptualization; Formal analysis; Methodology; Resources; Validation. Junpeng Pei: Conceptualization; Investigation. Qianqian Yang: Conceptualization; Investigation. Yousong Wang: Conceptualization; Investigation. Wei Wang: Conceptualization; Resources; Supervision

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVALIABILITY STATEMENT

The data that support the findings of this study are available from the author, [Zenghui Li], upon reasonable request.

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