Improving CCA Algorithms on SSVEP Classification with Reinforcement Learning based Temporal Filtering*

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Abstract. Canonical Correlation Analysis (CCA) has been widely used in Steady-State Visually Evoked Potential (SSVEP) analysis, but there are still challenges in this research area, specifically regarding data quality and insufficiency. In contrast to most previous studies that primarily concentrate on the development of spatial or spectral templates for SSVEP data, this paper proposes a novel temporal filtering method based on a reinforcement learning (RL) algorithm for CCA on SSVEP data. The proposed method leverages RL to automatically and precisely detect and filter low-quality segments in the SSVEP data, thereby improving the accuracy of CCA. Additionally, the proposed RL-based Temporal Filtering is algorithm-independent and compatible with various CCA algorithms. The RL-based Temporal Filtering is evaluated using a wearable dataset consisting of 102 subjects. The experimental results demonstrate significant advancements in CCA accuracy, particularly when combined with the extended CCA (ECCA) algorithm. In addition to performance enhancement, the RL-based Temporal Filtering method provides visualizable filters, which can ensure the transparency of the filtering process and the reliability of the obtained results. By addressing data quality and insufficiency concerns, this novel RL-based Temporal Filtering approach demonstrates promise in advancing SSVEP analysis for various applications.

Keywords: Canonical Correlation Analysis (CCA) · Steady-State Visually Evoked Potential (SSVEP) · Reinforcement Learning (RL) · Temporal Filter.

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1 Introduction

Steady-State Visually Evoked Potential (SSVEP) is an electrophysiological brain response to visual stimuli presented at a constant frequency, often involving flickering or flashing stimuli. The main objective of SSVEP studies is to identify targets by representing them as various flickering stimuli. Using Canonical Correlation Analysis (CCA) [1] for SSVEP signals analysis has enjoyed major attention for researchers working on SSVEP data processing. CCA considers the frequency and phase of the flickering stimuli as reference signals and computes the correlation between the subject's EEG signal when they focus on a particular flickering stimulus and the reference signal associated with that stimulus. Although traditional CCA takes advantage of EEG's high-temporal resolution, leading to the high classification accuracy of above 90% [1], it is still limited by its sensitivity to signal noise ratio (SNR) and biases associated with subjects and sensor spatial positions. In attempts to improve CCA classification accuracy and minimize the duration of flickering stimuli, several studies have explored solutions focusing on (1) enhancing the SNR of EEG signals through various signal processing and filtering techniques, (2) improving EEG signal spatial accuracy via spatial filtering methods, and (3) employing individual templates as calibration data to mitigate subject-related biases in the EEG signals.

In [2], Poryzala utilizes the cluster analysis of CCA coefficients (CACC) method, which enables asynchronous SSVEP-based target identification through k-means cluster analysis to distinguish detection and idle states. On the other hand, the multi-way CCA approach [3] enhances target identification accuracy by utilizing optimization mathematics to correlate stimulus reference signals and the subject's EEG data. Similarly, in [4], the authors further optimize the correlation between reference and EEG signals by applying L1-regularization to penalize the correlation in incorrect trials. To address the limitation concerning EEG spatial accuracy, Zhang [5] proposed multi-set CCA methods, which utilize joint spatial filtering of multiple subject EEG training sets to derive an optimization function that maximizes the correlation among these sets. Additionally, to mitigate personally biased EEG signals, the Individual Template Based CCA (IT-CCA) [6] approach replaces the reference signals used in traditional CCA with individual templates. These templates are obtained by averaging subject EEG signals during multiple training trials with various flickering stimuli. Nakanishi [7] conducted a comprehensive comparison of various CCA methods, assessing target classification accuracy using different evaluation metrics, including stimuli duration, number of EEG channels, and number of trials. The study found that CCA performance stabilizes after 3 seconds of stimuli duration. Moreover, increasing the number of EEG channels and trials positively impacts CCA classification performance, and the individual template approach demonstrated notable advantages in enhancing CCA performance.

Researchers have made significant efforts to improve the performance of CCA by incorporating spatial filters. One typical example is the extended CCA (ECCA) [8], which defines three types of spatial filters for each trial. Additionally, the Sum of Squared Correlations (SSCOR) and ensemble sum of Squared

Correlations (eSSCOR) methods [9] adopt spatial filters but break them down into stimulus levels. Recent research [10–14] continues to focus on defining better spatial filters to enhance CCA accuracy, with some novel attempts emerging. For instance, the Spatio-Spectral CCA (SS-CCA) [15] includes both spatial and spectral filters, broadening the scope of improvements. Similarly, the Time-Weighting Canonical Correlation Analysis (TWCCA) [16] introduces a time-dimension weight to differentiate time periods during the analysis. In our research, we address data quality enhancement through the inclusion of a temporal filter. This idea arises from the observation that CCA tends to favor temporal aspects over spectral ones. To implement this temporal filtering, we employ a Reinforcement Learning (RL) agent, allowing the filter to learn and adapt to the unique characteristics of the data. The advantage of using RL is that it enables collaboration with any CCA algorithm, making our proposed method applicable and compatible with various CCA algorithms.

Another recent trend in SSVEP classification involves the adoption of machine learning methods for direct flicker class prediction. There are three major types of machine learning models commonly used for SSVEP classification. The first type is LSTM/RNN [17, 18], which effectively encodes temporal correlations of SSVEP signals. The second type, also the most popular one, is CNN [19–21], particularly EEGNet-based models. This method uses convolutional kernels to extract both spatial and temporal information. The last type, and the newest one, is the transformer-based method [22, 23]. This approach leverages the self-attention mechanism to extract correlations from both the temporal and spatial domains of SSVEP data. In this paper, our RL agent is built upon an EEGNet-based deep model, following the results of our experiments. In contrast to the aforementioned deep models, our proposed method combines deep learning with CCA algorithms to leverage information from the reference signal of CCAs. This design is also found in CCA-CWT-SVM [24] and [25]. While CCA-CWT-SVM combines a support vector machine (SVM) with CCA, [25] models both the reference signal and SSVEP data with CNN models. However, our proposed method is independent of CCA, allowing the RL-based Temporal filter to collaborate with any CCA algorithm, potentially enhancing their classification accuracy.

In summary, our contributions are as follows:

1. We introduce a unique filtering method that treats EEG data segments as an RL environment. By allowing an RL agent to explore this environment, we can intelligently determine the quality of each segment, making informed decisions about retaining or discarding specific parts of the data.
2. Compared to other deep CCA methods, our proposed approach is more explainable, providing a meaningful filter that can be reviewed, understood, and validated by domain experts, thus promoting reliability in the results.
3. To address the subject difference problem, we propose an EEGNet-based quality classifier. This classifier can accurately identify whether a subject's data quality is potentially risky or not, allowing us to decide whether data filtering is necessary for each individual subject.

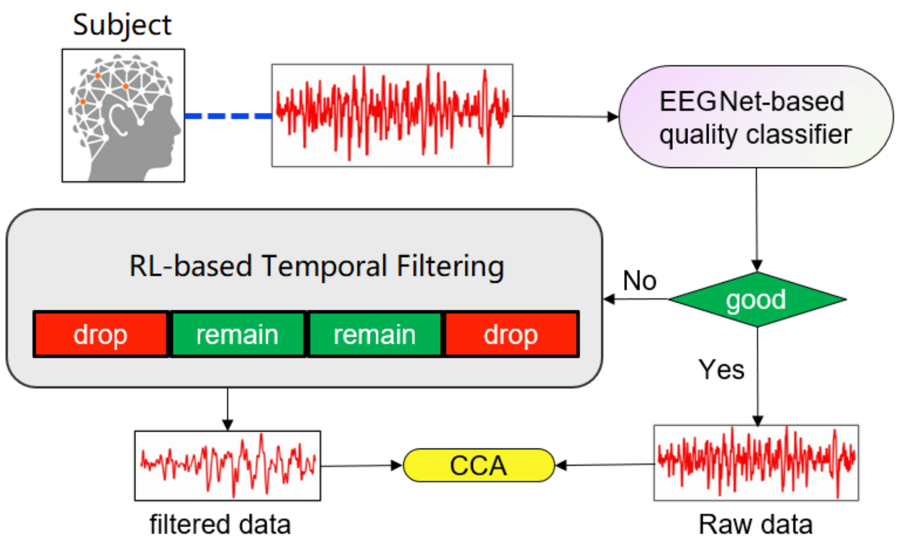


Fig. 1: The workflow of the proposed method. The "EEGNet-based quality classifier" and the "RL-based Temporal Filtering" components work together to enhance the classification accuracy of SSVEP signals.

4. Through our proposed method, we significantly enhance the tolerance of SSVEP data quality. Even with low-quality data, our advanced data filtering process ensures that the remaining information is sufficient for generating reliable outcomes, thus reducing data waste and increasing the efficiency of data analysis.

2 Method

Our proposed method consists of two major components: the EEGNet [26]-based quality classifier and the RL-based Temporal filtering (see Fig. 1). These components work in synergy to ensure that only high-quality data is fed into the subsequent CCA matching process.

In the initial step, the subject's SSVEP data is passed through the EEGNet-based quality classifier. This classifier evaluates the data quality and determines if it meets the required standards. If the data is deemed of good quality, it is directly used for CCA matching. However, if the quality is suboptimal, the RL-based Temporal filtering process is activated to identify and exclude problematic segments in the time domain. The filtered data is then used for CCA matching, ensuring that only relevant and high-quality information is considered.

2.1 RL-based Temporal Filtering

The RL-based Temporal Filtering component is at the core of our proposed method, aiming to enhance SSVEP data quality. We assume that during the experiment, subjects may get distracted or focus on the wrong flicker, leading to the inclusion of irrelevant segments in the recorded data. The RL agent is designed to explore the SSVEP data as a RL environment, deciding which segments to retain and which to discard, based on their contribution to CCA accuracy.

For each SSVEP data trial, represented as a 2D matrix with channel and time sample dimensions, the RL agent begins exploration at the first time sample and examines a window of time samples (state s). The agent then takes actions a (filtering options) at each step, determining whether to retain or drop segments. After fully exploring the training environment, the remaining parts of the data trail, combined with a reference signal under the same filter, are fed to the CCA algorithm. The agent's performance is evaluated based on CCA accuracy, and a reward r_a is calculated accordingly.

To prevent overfitting, we introduce a validating reward r_v, which minimizes the difference between training and validation accuracies:

$$r_v = |A_t - A_v|, \tag{1}$$

where A_t is the training accuracy, and A_v is the validation accuracy.

The final reward for the RL episode is computed as:

$$r = r_a + r_v. \tag{2}$$

The Proximal Policy Optimization (PPO) [27] framework is utilized to optimize the agent's policy based on the reward r. After several rounds of RL training, the final workable model is saved.

2.2 EEGNet-Based Quality Classifier

During the experiment, we observed that subject differences could influence the effectiveness of RL-based Temporal filtering. While some subjects' data quality can be substantially improved through RL-based Temporal Filtering, others already exhibit good enough quality without requiring such filtering. To address this variability and ensure CCA accuracy across all subjects, we introduce an EEGNet-based quality classifier.

The EEGNet-based quality classifier is a binary classifier, fed with one SSVEP data trail at a time, producing a binary decision of good or bad quality. We employ the EEGNet architecture for this classifier and train it using the results from the RL agent's performance. subjects whose data can be effectively improved by the RL method are labeled as "bad," while others are labeled as "good." After several epochs of training, the classifier achieves an accuracy of over 99%, allowing us to make informed decisions about whether data filtering is necessary for each subject. This approach ensures that the method generalizes well across diverse datasets and guarantees the quality of data delivered to the subsequent CCA analysis.

Algorithm 1 (Learning Scheme)

Input: $\mathcal{T}$ (all subjects trails data), N (number of subjects).
 for $i \leftarrow 1$ to N **do**
Step 1: select t_i from $T_i \in \mathcal{T}$, train a RL agent on t_i
Step 2: $l_i \leftarrow q$ (q is the subject quality found from RL agent)
 $L \leftarrow l_i$, store subject label in L
 end for
Step 3: Train the EEGNet-based classifier H with T and L
Step 4: **for** $i \leftarrow 1$ to N **do**
 if l_i="Bad" **then**
 Train a RL agent A_i on T_i
 $\mathcal{A} \leftarrow A_i$, save agent
 end if
 end for
Step 5: Combine saved models: $\{H, \mathcal{A}\}$

2.3 Learning Scheme

In our proposed method, both major components rely on deep models that require training, and the classification head depends on the labeling results from RL-based Temporal Filtering. To facilitate this process, we have defined a 5-step learning scheme outlined in Algorithm 1.

The learning process begins with labeling the data quality of subjects. We achieve this by running agents in RL environments with a small amount (10%) of trial data, which provides an overview of subjects' data quality. This overview is then used to label the subjects in the second step. In the third step, we train a reliable distinguisher, an EEGNet-based quality classifier, for subjects' data quality. Our experiments show that this classifier can easily achieve 99% accuracy with just a few epochs of training. With the help of the pre-trained quality classifier, we can now use all data trials for those labeled as "Bad" quality to train dedicated RL agents in step four. This approach avoids unnecessary training for subjects who are already determined to have good data quality, which provides a solution for subject difference issue in SSVEP experiments. Once all RL agents are optimized, we integrate the entire architecture of the method, comprising one shareable classifier and multiple RL agents dedicated to different subjects. This integrated model can then be used for unseen data.

3 Experiment Results

To evaluate and demonstrate the advantages of our proposed method, we conducted experiments using a wet wearable dataset kindly provided by 2020 International brain–computer interface competition [28]. This dataset comprises SSVEP data from 102 subjects, each recorded with 8 EEG channels: POz, PO3, PO4, PO5, PO6, Oz, O1, and O2. The data was recorded with a sampling rate of 1000 Hz and then down-sampled to 250 Hz without any other processing. Each

Table 1: Network Architecture Summary and Learning Settings of PPO.

	Architecture/Settings
EEGNet	CNN kernel size 1×8, 2×1, 1×15 Activation: Exponential Linear Unit (ELU)
PPO settings	Total learning step: 10000 Steps of update: 128 Feature extractor: EEGNet (with 128 latent dimension) Policy network: 2 layers of FFN Critic network: 1 layers of FFN

subject's data consists of 120 trials, with 12 targets/classes and 10 blocks. For each trial, we collected 500 time samples, which were treated as individual runs of the RL environment. To process the data and facilitate RL exploration, we set the RL agent with a window size of 50 time samples. In other words, the input provided to the RL agent's EEGNet-based deep model is an 8×50 matrix, representing the 8 EEG channels over a segment of 50 time samples."

To clarity our experimental settings and the design of EEGNet, which was utilized both as the Quality Classifier and the PPO feature extractor, we have meticulously outlined all relevant configurations in Table 1. To tailor the EEGNet architecture to our wearable dataset, we made adjustments to the kernel size and activation functions. It's important to emphasize that these modifications were guided by empirical findings. Furthermore, we imposed specific constraints on the PPO training process: the total training steps were capped at 10,000, and updates were performed every 128 steps. This deliberate approach was chosen to ensure a swift and efficient learning trajectory for the PPO agent. In the subsequent subsection, we include discussion of the outcomes derived from our experiment.

3.1 Performance Comparisons

In order to demonstrate the advantages of our method, we conducted a comprehensive comparison with several existing CCA algorithms, namely ECCA, SSCOR, and ESSCOR. The results are summarized in the following table, which presents the improvements achieved by our RL-based Temporal Filter:

Table 2: Accuracy improvement summarizing of adopting the proposed method. This experiment includes three CCA algorithms, which are ECCA, SSCOR, and ESSCOR.

CCA Algorithms	#Improved	Acc without filter	Acc with filter	Acc lift
ECCA	44	53.1%	76.7%	23.6%
SSCOR	5	0.0%	8.8%	8.8%
ESSCOR	2	0.0%	17.5%	17.5%

The first column of the table indicates the number of subjects (out of 102) whose performance improved using our approach. The second and third columns compare the average accuracy of these improved subjects before and after applying our method, respectively. The last column summarizes the improvement percentages achieved with our RL-based Temporal Filter. One key advantage of our method is its ability to selectively target problematic subjects. The classification head accurately identifies subjects that stand to benefit from the RL filter's intervention, allowing us to consistently enhance CCA accuracy. This adaptability ensures that our method can improve CCA accuracy across varying scenarios and datasets. In particular, we observed a significant improvement when combining our method with ECCA. Our filter yields enhancements in nearly half of the subjects' data, with an impressive average improvement of 23.6%. Conversely, SSCOR and ESSCOR showed limited improvements with our approach. The 0.0% accuracy for some subjects indicates that SSCOR and ESSCOR struggle to make correct predictions for all trial data. However, our method still demonstrates we can utility 8.8% and 17.5% of the subjects trail to yield correct prediction.

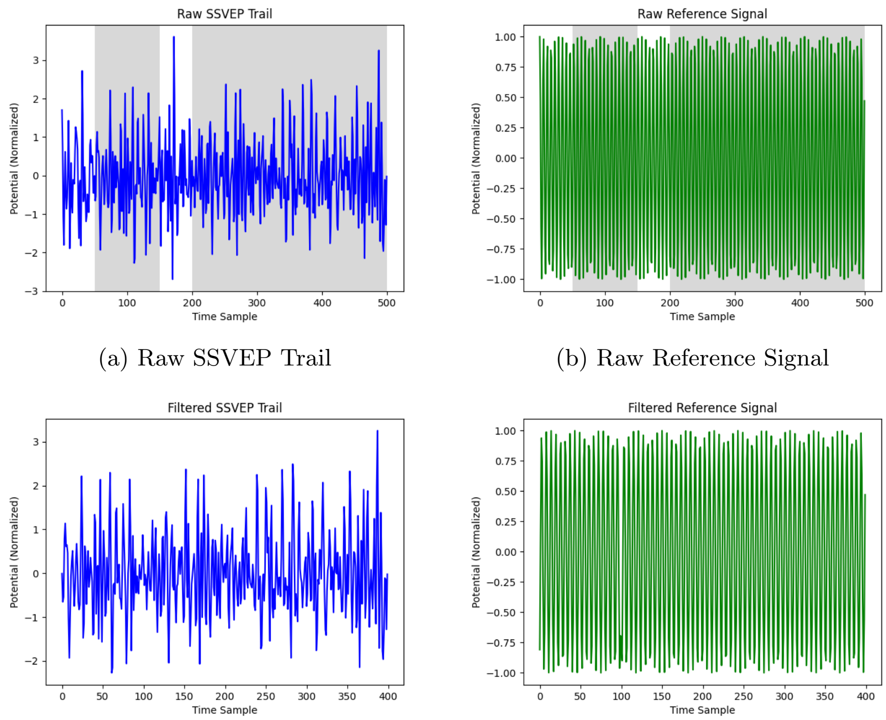
3.2 Filter Explanation and Visualizations

We present a data filtering technique to elucidate the mechanics of our proposed approach. In Fig. 2, we have chosen a single trail of SSVEP data from a subject to analyze its CCA classification results. In Fig. 2(a), the displayed SSVEP trail data exhibits low quality, and when used with its corresponding reference signal (Fig. 2(b)), the CCA classification yields an incorrect result. In this instance, CCA predicts a label of 8, while the true label indicated by the reference signal is 9.

To address this issue, we introduce our RL based filter, as detailed in Section 2.1. The RL filter systematically scans the problematic trail and identifies segments that require retraining (depicted in grey). Upon applying the RL filter, the trail data undergoes transformation into a filtered trail data, as illustrated in Fig. 2(c), from 500 time samples to 400 time samples. Simultaneously, the same filter is applied to the reference signal (Fig. 2 (d)). Subsequently, both the filtered trail data and the filtered reference signal are utilized to calculate CCA correlations.

4 Conclusion

This paper presents a novel RL-based Temporal Filtering approach that can be used in CCA for SSVEP classification task. The proposed RL-based Temporal Filtering effectively identifies and filters out low-quality segments from raw SSVEP data, leading to significant improvements in CCA accuracy. To validate its efficacy, we conducted experiments with three CCA algorithms using the wearable datasets. Additionally, the proposed approach provides an intuitive view of how the RL agent interacts with SSVEP data by visualizations that allow



(a) Raw SSVEP Trail

(b) Raw Reference Signal

(c) Filtered SSVEP Trail

(d) Filtered Reference Signal

Fig. 2: Example of one trial data applied with the RL-based Temporal Filter, visualizing the Oz channel of the SSVEP trial along with the ground-truth of the reference signal.

users to interpret the results of filters, thus ensuring transparency and reliability. An important advantage of adopting the RL-based Temporal Filtering method is its ability to leverage even low-quality subjects' data. This addresses the common challenge of data insufficiency frequently encountered in SSVEP-related research, making the approach more robust and practical for real-world applications. This novel combination of RL and CCA provides additional explainability and a solution for the subject difference issue. Our future research objectives involve conducting in-depth analyses of the behavior of these filters. It aims to uncover the underlying reasons behind incorrect CCA classifications on SSVEP data, leading to further advancements in our understanding of SSVEP signals and refining our proposed approach. We would also like to extend our experiment with more SSVEP data without quality selection. When conducting online SSVEP classification, the tolerance of low-quality data plays a more important role than offline analysis.

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