ENHANCING SSVEP IDENTIFICATION TOWARDS PORTABLE BCI USING DISCRIMINATIVE FUSION AND DIMENSIONALITY REDUCTION

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ABSTRACT

Steady State Visual Evoked Potentials (SSVEPs) have been the most commonly utilized Brain Computer Interface (BCI) modality due to their relatively high signal-to-noise ratio, high information transfer rates, and minimum training prerequisites. Up to date Canonical Correlation Analysis (CCA) and its extensions have been widely utilized for SSVEP target frequency identification. However, reliable and robust SSVEP identification performance is still a challenge, particularly for portable BCI systems because of signal contamination factors, portable visual stimuli limitations, subject-to-subject variation, and the mental, emotional and physiological state of subjects. As such, we propose an innovative partition-based feature extraction method that entails partitioning the score spaces of CCA and Power Spectral Density Analysis (PSDA) in three cases, extract efficient descriptors from each partition, then concatenate the extracted measures to generate more discriminative fusion spaces. Moreover, we investigate transforming the fusion spaces to lower dimensions utilizing Linear Discriminant Analysis (LDA). Our experimental results report that our proposed method enhances the identification performance of our baseline system (i.e. CCA) from 63% to 78%. The performance is further improved to 98% after the discriminative transformation utilizing LDA.

***Index Terms*—** Brain-Computer Interface (BCI), Steady State Visual Evoked Potential (SSVEP), Feature Extraction, Fusion, Dimensionality Reduction

1. INTRODUCTION

Brain Computer Interface (BCI) systems provide direct communication channels between the users' brains and external devices [1]. Since the inception of BCI research in 1973 by Jacques J. Vidal, BCI technology has grown rapidly as a result of the scientific advancements in electronics, neurophysiology, and the computer science field in general [2]. In BCI paradigms, users think of a mental task that characterizes a specific command to be communicated. Thus, the BCI system receives the brain modulation of the user employing Electroencephalography (EEG) signal and utilizes the signal to recognize and communicate the desired commands [3]. In recent years, various BCI modalities have been proposed, and investigated, such as, selective sensation (SS) [4], steady state somatosensory evoked potentials (SSSEPs) [5], steady-state visual evoked potentials (SSVEPs) [6], P300 evoked potentials [7], and sensory motor rhythm [8]. However, SSVEPs are the most commonly utilized modality in BCI research due to their relatively high information transfer rates (ITR), high signal-to-noise ratio, and very low training requirements [9]. SSVEP is a phase-locked brain response that is evoked when a user's attention is focused on a flickering visual stimulus, such as flashing icons [10]. Thus, an SSVEP response is generated as a result of multiple neurons producing a signal that is similar to the visual stimulus's frequency, and is sustained throughout the fixation period.

Numerous studies proposed various SSVEP target identification techniques. Such studies include, but are not limited to, CCA [11], PSDA [12], Multiway CCA [13], Multi set CCA [14], task-related component analysis (TRCA) [15], and common and individual feature extraction (CIFE) [16].

In this paper, we investigate enhancing the SSVEP identification performance for portable BCI applications. As such, we propose combining the CCA and PSDA features at the score level via partitioning their score spaces into three different partitioning cases, extracting effective descriptors from each partition, and finally generate a more discriminative fusion space by combing the extracted measures. Subsequently, we transform each fusion space from each partitioning case to lower dimensions using Linear Discriminant Analysis (LDA).

2. METHODOLOGY

Figure 1 illustrates the block diagram of the proposed method. After filtering the signal, we partition the score spaces of CCA and PSDA in 3 different cases to evaluate the fusion spaces constructed from each case. Then we utilize LDA to discriminatively transform the fusion spaces to lower

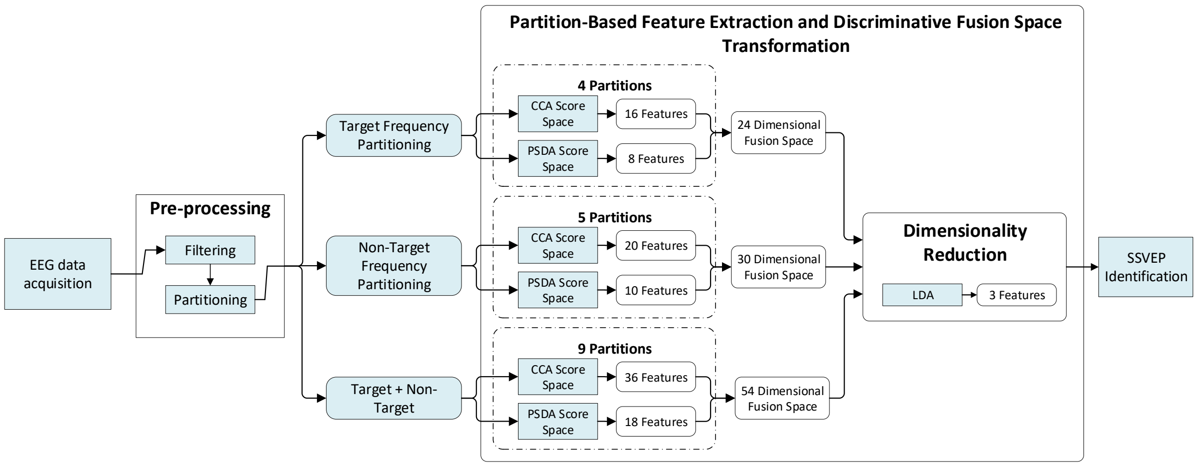

Fig. 1. Block Diagram of our proposed identification system

dimensions.

2.1. Experimental Setup and Data Collection

Our portable BCI system is comprised of the wearable Cognionics Bluetooth EEG device, and an Android tablet that serves as visual stimuli. In this study, 4 target frequencies were employed; 10Hz, 12Hz, 15Hz, and 8.5Hz. Ten healthy subjects, aged between 20 and 30 years of age, were recruited in this experiment. Our data acquisition was approved by the University of Michigan Institutional Review Board under the study ID: HUM00100788. Subjects were seated on comfortable chairs with a distance of $\sim$20 inches from the visual stimuli. The task involved focusing on one icon to record 10 successful icon selections (i.e. calls) per each target frequency. However, all subjects required approximately 75 calls to obtain the successful calls for all target frequencies. EEG data was collected utilizing 8 channels with a sampling frequency of 250Hz. The designated channels were PO3, POz, PO4, PO7, O1, Oz, O2 and PO8 (See Figure 2).

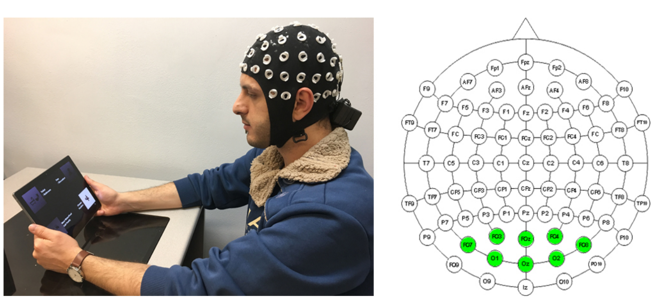

Fig. 2. portable BCI setup and designated channel locations

2.2. CCA and PSDA Score Space Partitioning

In addition to the drawbacks and challenges BCI systems face today, the performance of our portable BCI system is impacted by the imprecise generation of the SSVEP paradigm due to the insufficient screen refresh rate, and the recurrent interruptions of the Android operating system of our tablet-based visual stimuli. The impact of this limitation can be observed in Figure 4. From Figure 4 we note that the peaks of the SSVEP responses are not occurring precisely on the intended target frequencies. Moreover, we also hypothesize that there are subject-specific information and individual differences due to the imprecise SSSVEP paradigm generation challenge. As such, to mitigate the aftermath of this challenge and alleviate the impact of the subject variation and the effect of EEG signal contamination to some extent, we exploit the discriminative and analogous information extracted from CCA and PSDA utilizing three partitioning cases that span the frequency spectrum from 7Hz to 17Hz (See Figure 3).

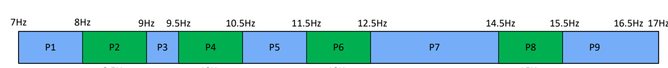

Fig. 3. CCA and PSDA score space partitioning

The first case entails utilizing the four partitions that encapsulate the target frequencies (i.e. P2, P4, P6, and P8). The second partitioning case involves employing the five partitions that encompass the non-target frequencies (i.e. P1, P3, P5, P7, P9). The third partitioning case on the other hand incorporates the previous partitioning cases and utilizes the nine target and non-target frequency partitions.

The underlying concept of the partitioning scheme is to evaluate the discriminative capabilities of the fusion spaces

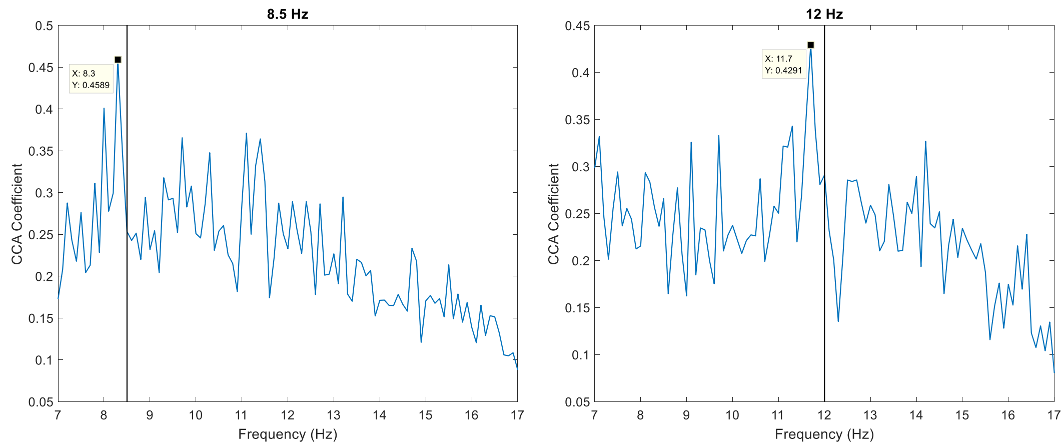

Fig. 4. Effect of imprecise screen refresh rate on the identification task

constructed from each partitioning case.

2.3. Partition-Based Feature Extraction

In this study, we extract four descriptors from CCA (Power, Mean, Standard Deviation, and Entropy), and two descriptors from PSDA (Mean, and Standard Deviation). PSDA inherently generates the power scores of the signal, which eliminated the need to extract it as a feature. However, because those power scores were infinitesimal in magnitude, extracting viable entropy measures was hampered. Subsequently, from the first case we construct a twenty-four dimensional fusion space (4 features x 4 partitions from CCA and 2 features x 4 partitions from PSDA), from the second case we construct a thirty-dimensional fusion space (4 features x 5 partitions from CCA and 2 features x 5 partitions from PSDA), and from the third case we generate a fifty-four dimensional fusion space (4 features x 9 partitions from CCA and 2 features x 9 partitions from PSDA) (See Figure 1).

2.4. Discriminative Fusion Space Transformation

LDA, which is a linear and supervised dimensionality reduction method, projects a dataset on a lower-dimensional space while preserving as much of the information about the separation between classes as possible. Furthermore, LDA seeks to find the linear discriminants, which are the axes that maximize linear class separability using the within-class scatter and the between-class scatter matrices. The within-class scatter and between-class scatter matrices are calculated as follows:

Within-class scatter matrix

$$S_w = \sum_{i=1}^{c}\sum_{j=1}^{n_j}(Y_j - M_i)(Y_j - M_i)^T \tag{1}$$

Between-class scatter matrix

$$S_b = \sum_{i=1}^{c}(M_i - M)(M_i - M)^T \tag{2}$$

LDA then generates a new transformation space where the within-class scatter is minimized and the between-class scatter is maximized:

$$J(U) = U^T S_b U / U^T S_w U \tag{3}$$

Thus, the projection matrix is:

$$\mathbf{Y} = U^T \mathbf{x} \tag{4}$$

3. RESULTS

In this analysis, we evaluate the effect of fusion spaces, generated from each partitioning case, on the identification performance. Hence, to accurately assess the models' performances we employ the leave-one-out Cross Validation, where we exclude one sample from the training set and utilize it for testing iteratively per each subject. For classification, we employ Decision Tree, Support Vector Machine (SVM) and K-Nearest Neighbor with K=1.

3.1. Feature Space Fusion

Table 1 illustrates the results of our proposed fusion method with the three partitioning cases. While our CCA-based system's average accuracy is 63% and PSDA's average accuracy is only 37%, the fusion space improves those accuracies to 75%. The first partitioning case further improves the accuracy to 78% utilizing SVM. However, partitioning

Table 1. CCA and PSDA fusion accuracies

Subject	CCA	PSDA	Target Frequency Partitions			Non-Target Frequency Partitions			Target + Non-Target		
			Decision Tree	SVM	KNN	Decision Tree	SVM	KNN	Decision Tree	SVM	KNN
1	86%	67%	96%	96%	98%	81%	75%	71%	81%	96%	83%
2	77%	83%	86%	84%	87%	57%	44%	36%	82%	86%	77%
3	40%	26%	60%	42%	34%	49%	43%	45%	37%	47%	52%
4	59%	19%	77%	85%	78%	31%	54%	44%	75%	79%	59%
5	67%	41%	89%	76%	69%	31%	42%	32%	73%	71%	68%
6	55%	35%	88%	88%	75%	34%	45%	29%	86%	80%	71%
7	62%	29%	63%	80%	68%	42%	53%	46%	63%	74%	63%
8	71%	39%	71%	83%	75%	40%	49%	49%	76%	76%	68%
9	47%	17%	59%	81%	73%	34%	42%	40%	60%	79%	63%
10	61%	17%	49%	62%	55%	56%	44%	36%	49%	62%	41%
Avg	**63%**	**37%**	**74%**	**78%**	**71%**	**46%**	**49%**	**43%**	**68%**	**75%**	**65%**

the non-target frequencies yielded significantly lower identification accuracies. Thus, from the first and third partitioning cases we conclude that the effects of noise and different EEG contaminant factors are alleviated with our proposed fusion method to some extent.

3.2. Discriminative Fusion Space Transformation

To improve the performance of our BCI system, mitigate the effect of redundancy and avoid the curse of dimensionality, the high dimensional fusion spaces were transformed to lower dimensional spaces utilizing LDA (See Table 2). Table 2 reports that identification accuracies significantly improved from 78% to 90% with the twenty-four dimensional fusion space (case 1), and further improved to 98% utilizing the fifty-four dimensional fusion space (case 3). As such, we conclude that augmenting the non-target frequency partitions on the target frequency partitions improves the identification performance.

Table 2. LDA accuracies

Subject	CCA	PSDA	Target Frequency Partitions			Target + Non-Target		
			Decision Tree	SVM	KNN	Decision Tree	SVM	KNN
1	86%	67%	100%	100%	100%	94%	96%	94%
2	77%	83%	94%	97%	97%	97%	100%	100%
3	40%	26%	58%	71%	57%	91%	96%	93%
4	59%	19%	92%	94%	88%	99%	97%	99%
5	67%	41%	89%	92%	94%	92%	98%	98%
6	55%	35%	94%	92%	96%	96%	100%	100%
7	62%	29%	90%	86%	85%	91%	94%	93%
8	71%	39%	93%	90%	93%	100%	100%	100%
9	47%	17%	76%	89%	80%	95%	99%	100%
10	61%	17%	89%	87%	73%	100%	99%	100%
Avg	**63%**	**37%**	**88%**	**90%**	**86%**	**96%**	**98%**	**98%**

LDA's success is attributed to its ability to generate a linear mapping that maximizes class separability in the low-dimensional projection of the data. However, LDA assumes the dataset is normally distributed, and the covariance matrices of the various classes are the same. Thus, a log transformation of the PSDA power scores was performed to assess LDA's performance after the normalization concluding a very slight difference in performance (See Figure 5).

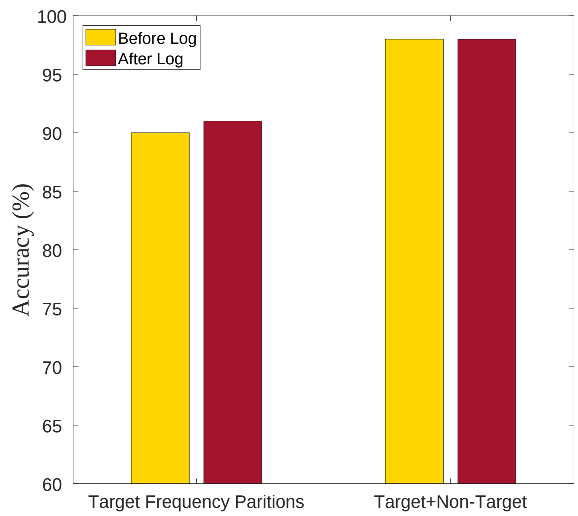

Fig. 5. LDA's performance before and after the Log transformation

4. CONCLUSION

Due to the advantages SSVEPs offer, they have been widely employed in BCI research. However, robust SSVEP identification performance is still an issue. While various studies introduced numerous methods to enhance the SSVEP identification performance, we proposed and investigated our partition-based feature extraction method, which involves partitioning CCA and PSDA score spaces, extracting information from each partition and concatenating the extracted measures in fusion spaces. Our experimental results demonstrated a performance improvement from 63% to 78% achieved by the fusion space from the first partitioning case. The accuracy is further improved to 98% utilizing LDA.

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