

Attention State Classification with In-Ear EEG

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Abstract—Electroencephalography entirely inside the ear (in-ear EEG) opens up exciting avenues for unobtrusive continuous physiological and cognitive state monitoring. This work presents techniques towards precise attention state classification based on data recorded from comfortable, binaural in-ear EEG instruments used during a vigilance task experiment. We recorded both on-scalp and in-ear EEG signals from multiple subjects, and we show that in-ear EEG offers comparable classification accuracy. Our work is the first adaptation of Common-mode spatial filtering techniques applied to signals acquired from sparse electrodes on untethered subjects. We demonstrate 90–95% accuracy (scalp-EEG with 30 electrodes) and 70–75% (in-ear EEG with 5 electrodes inside the ear canal and concha) in classifying attentive and resting states. We also show our approach to be lightweight for low-power on-chip classification with the capacity for few-shot learning. A necessity for wearable, continuous health sensors accommodating resource-constrained applications and adaptation to inter-subject differences and varying environmental conditions. This study suggests the future viability for a System-on-Chip (SoC) integration for user-generic and portable devices capable of closed-loop cognitive state monitoring and neuro-feedback.

Index Terms—BCI, in-ear EEG, cognitive state monitoring, vigilance task

I. INTRODUCTION

Brain-Computer Interfaces (BCI) are an important technology that bridge human brains and different types of functional devices. Clinically, BCIs are in use for people with motor disabilities to extend control of their real, or virtual, environment using just brain waves. The technology has also been applied to training, rehabilitation, and recreation. Electroencephalography (EEG) is a ubiquitous non-invasive, portable neuro-imaging technique foundation to most BCIs, responsible for providing the rich spatiotemporal neural information in mental state classification [1]. The conventional EEG acquisition methods acquire brain waves with attachment of metallic electrodes with ionic conductive pastes to the subject's scalp together with a cap or other wearable equipment. Practical use of conventional scalp EEG in everyday life is severely limited because of the long setup procedures and obtrusive head-worn apparatus.

EEG recorded from inside the ear (in-ear EEG) has emerged as a new type of sensing modality that slims down conventional scalp EEG brain monitoring methods by reducing electrode count and footprint to a discrete, comfortable device akin to wireless earphones [2]–[6]. In-ear EEG opens an exciting road map to wearable BCIs and continuous unobtrusive physiological and cognitive state monitoring. From normal everyday tasks like reading and driving, to critical tasks requiring sheer focus and self regulation like surgery, maintain attention on the task for enhanced safety and productivity becomes imperative. The requirement of continuous monitoring of attention during such tasks necessitates low-profile comfortable and portable EEG sensing. As the conventional bulky EEG headsets are unsuitable for wearable settings, in-ear EEG sensors offer a promising and convenient alternative. However, in-ear EEG devices have not been demonstrated yet to be practically suitable for real world applications as they can also have long wires and perform poorly compared to on-scalp headsets.

In particular, sensing in the ear canal produces not only new sensing locations other than the scalp and also proximity to brain sources, especially the auditory cortex, but also utilizes body real estate shared with everyday devices. In-ear EEG sensors have the potential to integrate with widely used earphones, hearing aids, and hearing prostheses. While in-ear EEG sensors have already shown great promises in the clinic and some daily applications, the main challenges of in-ear EEG sensing are weaker measured signals from smaller electrodes with reduced spacing and a lower signal-to-noise ratio compared to scalp EEG measurements. Specifically here, we only consider *in-ear* EEG for which all sensing, referencing, and active grounding (DRL) electrodes are placed only in the ear canal, concha cymba, or concha cavum [3].

There have been several studies on monitoring subject attention states through brain activity measurement techniques. There are various situations (driving [7], studying [8], exercising [9]) where we are often required to maintain attention to boost efficiency and prevent severe consequences such as traffic accidents and workplace fatalities. However, most

works involving mental state classification through in-ear EEG acquisition suffer from low accuracy or require higher epochs (in the order of 30 seconds to several minutes) [10] as compared to scalp-EEG, and the model is substantially prone to inter-subject variability, noise in the operating environments, and performance of the acquisition instruments. As a result, designing a robust in-ear EEG device capable of accurate cognitive-state analysis under various sources of noise and variability is challenging.

The primary motivation for this work is to develop efficient signal processing and Machine Learning (ML) methods for accurately determining attentive and resting brain states from unobtrusively, sparse electrodes placed in the ear for wearable and discrete electrophysiology measurement. Here we present the use of filter bank common spatial pattern (FBCSP), a spatial separation technique that we found to be most effective for cognitive state classification from time-series data [11]–[13]. Our FBCSP pipeline consists of a four-stage linear transformation and a robust feature selection algorithm. We observed that FBCSP is accommodating of inter-trials and inter-subject variability, as it enables the extraction of features at different frequency bands and eventually merges them into a final feature vector. FBCSP is also a lightweight training and test model which can be very reliably trained to various conditions and perform classification with ultra-low latency. Thus, this promises a better alternative to using multi-Layer perceptrons or recurrent neural networks [14], which have yet to be proven suitable for on-chip model tuning and low-power classification.

II. ELECTROPHYSIOLOGY HARDWARE METHODS

A. In-Ear and Scalp EEG Acquisition

Brain activity was measured in this study simultaneously from scalp electrodes and in-ear electrodes placed binaurally. Scalp recordings were made using a battery-powered 30-channel dry EEG headset (Quick-30r, CGX Systems, USA) sampled at 500Hz to a PC over a wireless interface. A total of five electrodes were placed in contact with each ear of the subject. As shown in Fig. 1, three electrodes per ear were sensing channels placed inside the ear canal with equal spacing around the canal circumference. Each sensing electrode has an ellipse profile with a height of ~ 1 mm, and a major and minor axis of 6 mm and 4.5 mm, respectively. One electrode placed on the concha cavum was the reference, and one electrode was placed in the concha cymba was the ground DRL. All ear electrodes were dry Ag/AgCl. The in-ear electrodes were attached to passive leads that were connected to an eight-channel electrophysiology acquisition system (BioRadio, GLNeurotech, USA) sampled at 500 Hz to a PC over Bluetooth.

III. VIGILANCE EXPERIMENTAL METHODS

A. Participants

The study consisted of three healthy subjects between the ages of 23 and 31, all male. The subjects did not have a history of neuropathy, neuromuscular disorders, cognitive deficiencies,

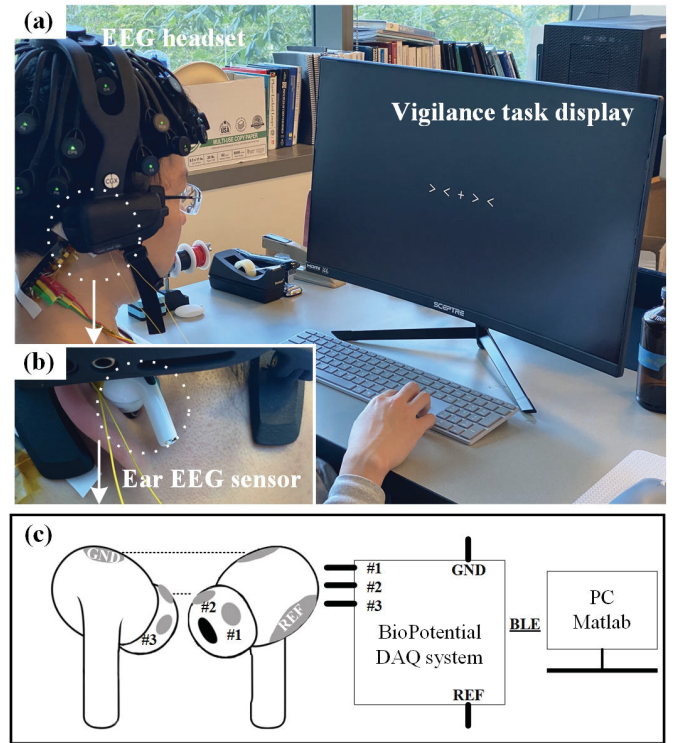


Fig. 1: Vigilance test setup and in-ear EEG sensor design. (a) Vigilance test setup, (b) Zoom in view of the in-ear EEG sensor inserted into the ear canal along with the earphone, (c) Design of the in-ear EEG sensor and the acquisition system.

eye or ear-related diseases, had normal hearing and normal eyesight, or wore corrective lenses. The ear canals of each subject were cleaned with Isopropyl alcohol 30 minutes before in-ear recording to removed cerumen. All subjects had an adequate sleep the night prior to their respective recordings.

B. Experiment Protocol

To validate the performance of the ear sensor, benchmark auditory steady-state response (ASSR) experiments were conducted before and after the vigilance task. ASSR is an electrophysiologic response to rapid auditory stimuli, and in-ear EEG sensor has been demonstrated to obtain ASSR and provide objective estimate of subject hearing threshold [2], [15]. During the benchmark ASSR experiment, auditory stimuli were generated using broadband uniform white noise amplitude modulated 100 percent by 40 Hz frequencies sinusoidal signal. A Blackman window algorithm was utilized to create the amplitude modulation pattern. A pair of earphones connected via bluetooth were used to present the sound stimulus to subjects at 75 dB for one minute. Characteristic power spectra were obtained based on the raw time series data measurement from each in-ear EEG sensing channel. Qualified ear EEG sensing channels were featured with an around $-130\text{dB}(\frac{\mu\text{V}}{\text{Hz}})$ noise floor and a corresponding 40 Hz ASSR peak with a signal to noise ratio of 5–10 dB.

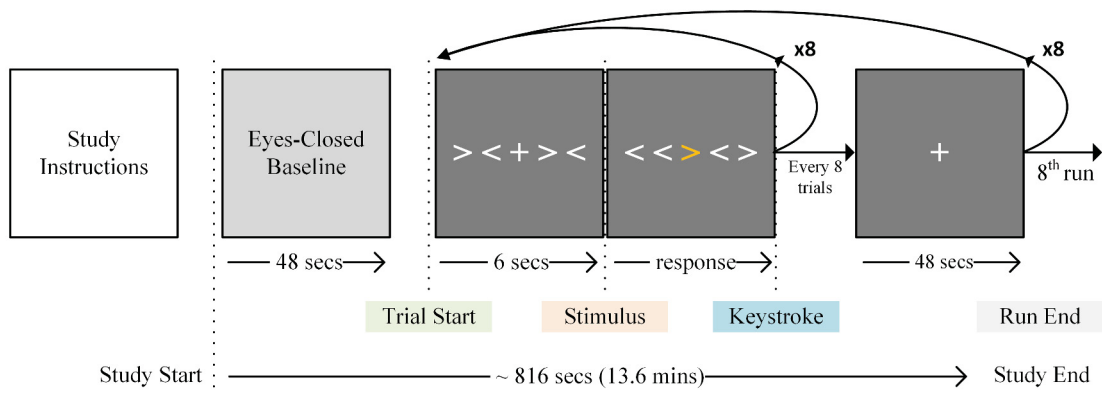


Fig. 2: Experimental protocol for visual vigilance study begins with a baseline period during which the subject is instructed by on-screen directions to close their eye while the neutral colored, static screen is displayed. A beep indicated the end of the baseline, during which the subject will open their eyes and read the prompts on the screen to begin the study. The fixation cross appears in the same location at the center of the screen for each trial. Subject must focus their visual gaze to that position for the duration of the trial (6 seconds) until a stimulus is presented in the form of a left or right arrow. Subjects will press the keyboard key corresponding to the presented stimulus as fast as possible. The key press and response times are recorded. The trials repeat until a rest phase is reached, during which the subject must maintain focus on a static screen with only a fixation cross and no stimuli. The study ends after predetermined runs.

C. Stimulus Protocol

To evaluate the attentiveness of subjects, a visual vigilance protocol was designed similar to the one presented in [14], which incorporated an Eriksen flanker task [16] and a psychomotor vigilance task (PVT) [17]. The tasks evaluate the overall behavioral alertness during prolonged fixation and selective attention during reaction-timed button presses.

Subjects fitted with the EEG devices were seated comfortably in a quiet, naturally lit room at a desk in front of a 144 Hz monitor with a keyboard, as depicted in Fig. 1. They were directed by on-screen instructions to attend to a fixation cross at the center of the screen and press either the left or right arrow keys on the keyboard to indicate to which direction the fixation cross changed during each trial, according to the experimental protocol in Fig. 2. Each trial consisted of a fixation period of 6 seconds, during which time the subject was to pay attention to a cross on the screen flanked by a pair of static symbols. The second phase of each trial would change the screen such that the fixation cross became either a left or a right arrow, and the flanking symbols would also change at the same time to random left or right arrows. Phase 3 of each trial occurs when the subject presses the left or right key on the keyboard after seeing the cross change to an arrow. The key pressed is recorded and later compared to the actual direction arrow that was displayed. The reaction time from symbol change to key press is also captured in each trial. After eight trials, there is a 48 second rest period during which the subject is asked to attend to a static screen showing only the fixation cross and no flanking symbols. There are no direction arrows presented or key presses required during the rest period. The cycle repeats for eight runs until 64 trials and eight rest periods are completed, or sooner if the subject decides to end the study early. Subjects are asked not to move

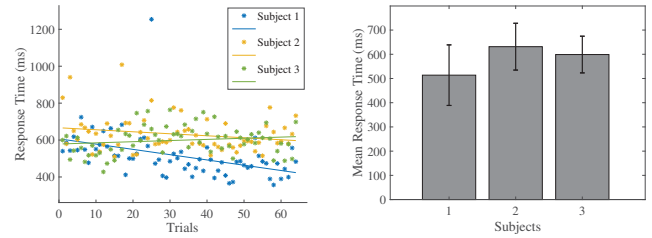


Fig. 3: Response time calculated between stimulus presentation and keyboard press across all trials.

during either fixation or rest periods.

D. Preprocessing

EEG data captured from the scalp headset and in-ear devices went through minimal preprocessing. Raw datasets were loaded into EEGLAB for visualization of time series data and LSL markers. Any channels that were not to be used, such as accelerometer and impedance, were removed, and a bandpass filter (FIR 1 to 58 Hz) was applied to all scalp channels. Data was exported in .edf format.

IV. DATA ANALYSIS AND ATTENTION STATE CLASSIFICATION

Both scalp and in-ear EEG data obtained from all subjects were analyzed using different techniques discussed below. In all of the techniques, around 85% of the trials were used for training and cross-validation while 15% were used for testing. We selected continuous trial intervals for train and test data (eight 6-second attentive, and a 48-second resting phase divided into 8 trials per run i.e., total of 64 trials) to completely separate the train and test data and avoid overfitting. As the total duration of the attentive and rest states is close, the train and test data have almost 50% of attentive and rest labels. We

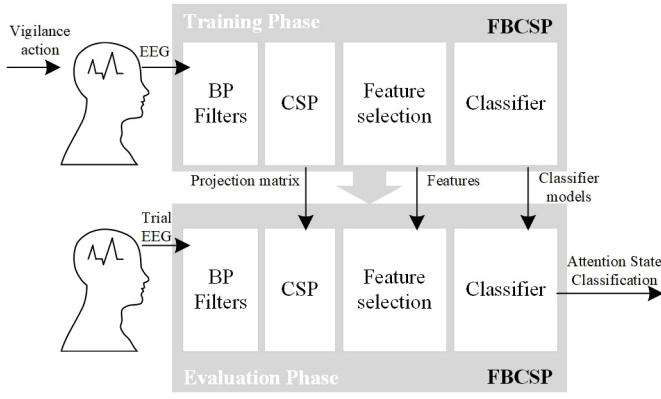


Fig. 4: The FBCSP processing pipeline.

examined the possibility of using baseline machine learning classifiers without feature extraction (i.e., on raw data with lightweight preprocessing as explained in Section III-D) and with feature extraction. Specifically, we implemented a filter-bank common spatial pattern (FBCSP algorithm) for feature extraction.

A. Filter-Bank Common Spatial Pattern (FBCSP) Algorithm

Common Spatial Pattern (CSP) algorithm is an efficient method for classifying EEG data [18] and has been explored for multi-class feature extractions in BCI systems. However, the effectiveness of CSP depends on subject-specific frequency bands to precisely determine the features. Thus recently there have been some developments on Filter-Bank CSP (FBCSP) algorithm [12] [13]. FBCSP separately calculates the features in each relevant frequency band and combines them into the most significant CSP features based on a mutual information-based best individual feature (MIBIF algorithm) [12].

Our processing pipeline is detailed in Fig. 4. It consists of multiple stages of combined signal processing and machine learning techniques to enhance the feature extraction and classification in the presence of signal variability in different operating conditions, acquisition hardware mismatches, and inter-subject signal quality fluctuations. The first stage of FBCSP consists of a filter bank comprising multiple Chebyshev Type II band-pass filters between 4–40 Hz and in intervals of 4 Hz. The second stage performs spatial filtering using the CSP algorithm. Each frequency band has its own optimized CSP feature calculation. The primary purpose of CSP is to maximize the variance of class-specific samples in a specific spatial dimension. One typical discrimination of variance in different spatial dimensions is illustrated in Fig. 5 for in-ear EEG data (scatter plots of pre-CSP filtered and post-CSP filtered). Before CSP, the variance of samples related to attentive and resting class is approximately the same across Electrode 1 and Electrode 3. However, there is more variation observed across one particular spatial dimension after the CSP transformation. The CSP algorithm computes the spatial transformed signals $Z_{b,i}$ for each frequency band as,

$$Z_{b,i} = W_b^T E_{b,i} \quad (1)$$

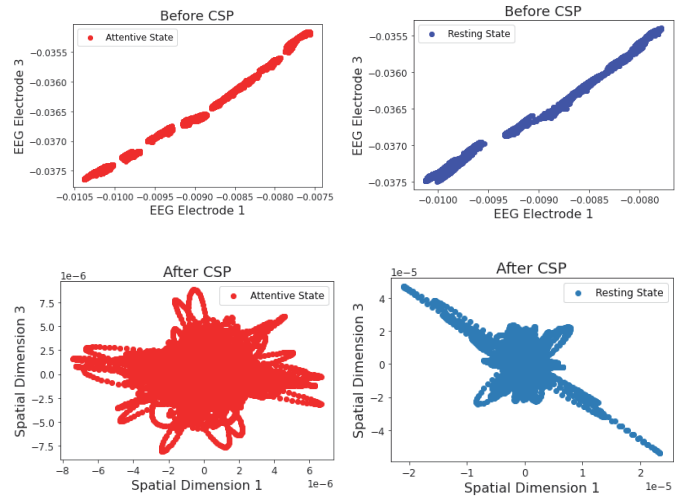


Fig. 5: Scatter plots of samples belonging to each class to demonstrate their variance in two spatial directions before-CSP and after-CSP transformation. After-CSP transformation plot is obtained by combining the transformed signals from all frequency bands.

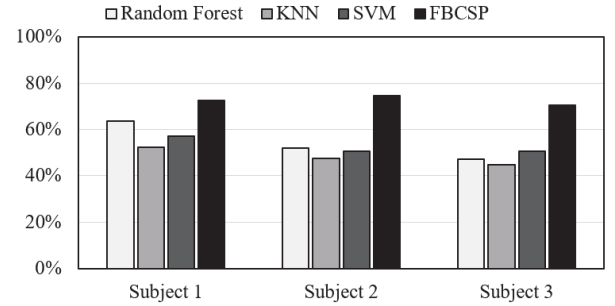


Fig. 6: Accuracy of *in-ear* EEG signals (with 3 electrodes) using different classification techniques such as RF, KNN, and SVM without any feature extraction, and comparison with FBCSP feature extraction + classification method.

where $E_{b,i}$ denotes single-trial (i-th) EEG measurement from which is a filtered input signal through b-th band-pass filter and W_b denotes the corresponding CSP projection matrix. The projection matrices are computed to behave optimal for distinguishing between two cognitive states. This is done by solving the eigenvalue decomposition from the covariance matrices of the measurements of different cognitive states. The spatial filtered signal maximizes the differences in the variance of two classes of measurements. After this, FBCSP feature vectors $v_{b,i}$ are calculated from the transformed signals.

The third stage implements a feature selection algorithm which selects most discriminative CSP features from $v_{b,i}$. This is accomplished by a Mutual-Information based Individual Feature (MIBF) where mutual information of each feature is computed and sorted in descending order. Finally, the first k features are selected to be used for classification. The fourth stage is the classification step, for which we use a Support-

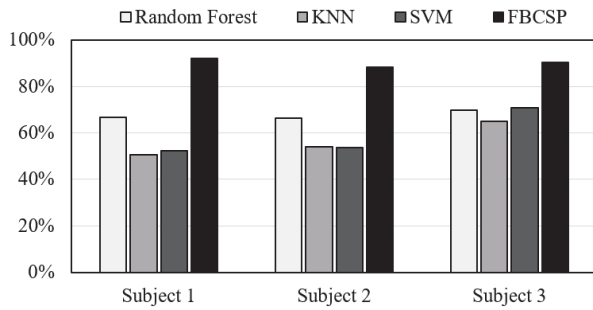


Fig. 7: Accuracy of *on-scalp* EEG signals (with 25 electrodes) using different classification techniques such as RF, KNN, and SVM without any feature extraction, and comparison with FBCSP feature extraction + classification method.

Vector-Machine (SVM)-based method with a Radial-Basis-Function (RBF) kernel.

B. Classification Accuracy

Fig. 6 and Fig. 7 show the accuracy of the FBCSP and conventional ML techniques on the, respectively, in-ear and on-scalp signals for all the three subjects. There is a significant accuracy gap between Filter-Bank CSP feature extracted classification and baseline methods such as Random Forest (RF), K-Nearest Neighbor (KNN) and Support-Vector Machine(SVM). For the *in-ear* signals, the conventional techniques achieve no better than 54.3% on average. FBCSP, on the other hand, achieves 72.6% average accuracy for the three subjects with a standard deviation of 1.96%. It is noteworthy that for the FBCSP we used a support vector machine (SVM) classifier which, as shown in Fig. 6, achieves as low as 52.7% when working on simple preprocessed data.

For the on-scalp data, the FBCSP achieves an average accuracy of 90.2% (1.95% standard deviation), which is 17.6% higher than the in-ear device accuracy. Without feature extraction, the random forest classifier (the best among the conventional techniques) achieves 67.6%. The FBCSP accuracy on our in-ear EEG dataset is promising, especially it is trained over only 64 trials. This promises a very lightweight training model that can be often trained on the fly. Our FBCSP model is expected to provide higher accuracy (upto 80–85%) when trained with larger datasets and through further experiment trials.

V. CONCLUSION

We presented a low-profile user-generic and portable in-ear EEG instrumentation device with just 5-electrodes capable of classifying cognitive states using a multi-frequency band feature extraction, feature selection, and classification algorithm. We demonstrated up to 75% accuracy with a minimal in-ear EEG training dataset. This work paves the path for a complete system-on-chip closed-loop brain-state monitor that can be reliably used irrespective of the operating conditions.

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