Do Weak Brain Signals Get Amplified When Strong Brain Signals are Evoked?

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***Abstract*—Brain-computer interfaces (BCIs) facilitate an unprecedented fusion between the human mind and pervasive computing systems, enabling users to engage with connected devices in their environment through neural signaling. Despite their potential, BCIs face certain challenges that hinder their widespread proliferation, such as low SNR and high noise levels in brain signals recorded via non-invasive techniques like EEG, high variability in signals among users that hinders generalization, usability challenges, etc. While brain signals like the error potential (ErrP) showcase low SNR and have lower detection accuracy, there are other kinds of signals that showcase high detection rates and resilience to noise. Motivated by this disparity, we ask ourselves if the abstract cognitive states involved in the evocation of such resilient signals be leveraged to amplify or augment the weaker signals, and thus provide them a performance boost. We investigate this hypothesis by designing an experiment to interface these two kinds of signals and collect EEG data in our lab through human trials. We evaluate our hypothesis and contrast our results with other datasets of isolated signals using spatial filtering and deep learning models. We obtain negative results and reflect on the insights and the lessons learned based on them and talk about plausible explanations and future work while also reassessing our initial hypothesis.**

***Index Terms*—BCI, ErrP, SSVEP, Hybrid BCI, ERP**

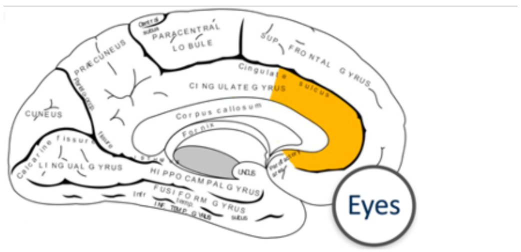
I. Introduction

Brain-computer interfaces (BCIs) have the potential to play a pivotal role in the domain of ubiquitous computing, where the seamless integration of technology in our lives is hotly pursued. BCIs provide us with a direct channel between our mental intent and connected systems without needing us to explicitly communicate, thus transcending the traditional modes of input like touch, speech, gestures, etc. This has profound implications in domains like healthcare, IoT, and augmented reality, security [1], where users can now interact with their environment effortlessly. In addition, BCIs also provide us with a foundation to access the valuable neurophysiological data of individuals, which facilitates the development of highly responsive systems that can respond to a user's immediate cognitive states in real-time. The seamless integration of BCIs with interconnected systems promises to radically change how we interact with the connected environment around us.

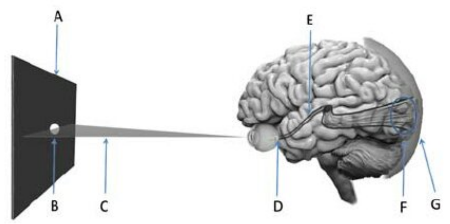
Despite the significant prospect, BCI systems also grapple with certain characteristic challenges. They suffer from extremely low SNR (Signal-to-Noise Ratio) and high interference from background brain activity, which makes the detection of certain brain potentials difficult resulting in low detection accuracy for systems designed for BCI. Aside from these technological challenges, there are also some usability challenges like attribution, attention, etc. Additionally, the level of attention a subject pays to the target stimulus greatly affects how reliably a desired brain signal is elicited. While, in general, BCI signals typically exhibit a low SNR and lower performance, there is significant variation in the detection accuracy among individual signals. Signals like the error potential (ErrP) are quite "weak" and harder to detect and are often very noisy, with average detection accuracies ranging between 60-70% [2] [3]. On the other hand, there are some prominent "strong" signals like the P300 and the Steady-State Visually Evoked Potential (SSVEP) which are significantly easier to detect and have their detection accuracy consistently in the range of 90-95% or higher [4].

Intrigued by this variation in the resilience of different brain signals to noise interference, we attempt to surmise the factors contributing to the superior detectability of Steady-State Visually Evoked Potentials (SSVEPs) in comparison to Error Potentials (ErrPs). While pinpointing the precise catalyst for this enhanced performance is challenging, there can be several factors that may be influential. Although discerning the precise reason behind the enhanced performance of SSVEPs remains elusive, our investigation aims to ascertain whether the enablers conducive to SSVEPs superior performance can be invoked for ErrPs, potentially amplifying ErrP signals

In this context, we hypothesize that the cognitive states associated with the manifestation of robust neural signals may be harnessed to augment the less resilient signals. We design an experimental study where we simultaneously activate the regions of the brain responsible for both SSVEPs and ErrPs. In our IRB-approved data collection study performed in our lab, we design an experiment with stimuli engineered to elicit both SSVEP and ErrP signals concurrently and analyze our results in terms of ErrP detection accuracy for the concurrent evocation vs the case when ErrP signals are elicited in isolation. In terms of results, we observe that concurrent evocation of SSVEPs actually negatively impacts the evocation of ErrPs and thus adversely affects its detection accuracy. We present our findings, discuss the plausible underlying rationales behind the



(a)



(b)

Fig. 1. Brain regions responsible ErrP and SSVEP signal evocation. (a) ErrP source in the anterior cingulate cortex. (b) SSVEP response in the visual cortex. Figure taken from [5]. (A) display screen for stimuli, (B) centre of attention, (C) field of view, (D) retina, (E) optics nerves, (F) primary visual cortex, (G) scalp where electrodes are attached to capture the response.

negative results, and reflect upon the lessons learned from the results and insights obtained from evaluating our hypothesis. In this context, our research contributions are as follows:

- We investigate whether ”strong” brain signals can be used to modulate and amplify ”weak” signals so as to bolster their performance.
- We collect the EEG data of multiple human subjects using concurrent stimuli design.
- We provide experimental analysis using multiple detection models and plausible explanations of our results.

The rest of the paper is organized as follows. Section II elaborates on BCI background in more detail and lays out our hypothesis. Section III discusses the related work in the domain of hybrid BCIs as well as the work done to address some of the challenges faced by BCI systems. Section IV details our experiment methodology and data collection setup. Section V analyzes the result as well as reflects upon the negative results obtained and describes future directions, and finally, Section VI concludes the paper.

II. Background and Hypothesis

A. BCI Background, Error Potentials, and SSVEPs

Using non-invasive methods in BCIs, there are different methods to record a user's brain signals including EEG (Electroencephalography), MEG (Magnetoencephalography), NIRS (Near Infra-Red Spectroscopy), etc. While each of these techniques has its own respective utility, EEG remains by far the most popular method, arguably because it lies in a unique sweet spot of cost-effectiveness, portability, and user-friendliness [6]. Pioneering research on EEGs and BCIs started flourishing in the 1970s when many researchers worked on establishing direct brain-to-machine communication. In 1973, a Belgian researcher, Jacques C. Vidal talked about ”evoked potentials”, which were variations in brain activity as a response to a specific sensory stimulus or event. Research on evoked potentials, also synonymously used with ”Event-Related Potentials” (ERP), gained momentum in the ’80s. In 1988, Farwell demonstrated that subjects can communicate 12 bits per minute without talking, using the P300 ERP [7]. In 1991, Wolpaw presented a system to mentally control a cursor using the 8-12Hz μ-frequency band [8].

Despite their considerable potential, there are certain characteristic challenges that BCIs deal with. BCI signals are often very noisy and suffer from very low SNR. Typically, the voltage of the electrical neural activity inside the brain is of the order of μV, which is further attenuated as this signal travels through the cranial structures with different compositions and conductivities to reach the scalp. Combined with interference from competing signals from nearby regions of the brain, this signal is contaminated with high levels of associated noise by the time it reaches the top of the scalp to be recorded. Brain signals are also hard to obtain because collecting BCI data involves long and controlled sessions in a lab environment, which makes this process burdensome.

Our signal of interest, the Error Potential signal (ErrP) is one of the signals that suffer from the aforementioned challenges. Error Potentials were detected in 1991 when Falkenstein showed their presence in humans when they detected that an error had been committed in an experimental trial [9]. ErrP signals in the brain are a measure of the brain detecting/processing an error (for instance, watching a robot perform a task incorrectly). ErrPs are extremely valuable for BCI applications as they provide a generalized notion of error detection in a diverse set of tasks across a wide variety of input modalities like audio, visual, somatosensory, etc. [9] [10]. ErrPs have a lot of promise and have been used in applications for improving the performance and reliability of BCI spellers [11], correcting and adapting AI systems, as well as aiding in learning for AI agents like correcting a robot's mistakes and accelerating learning for a reinforcement learning agent [12]. However, their detection accuracy is quite poor and is usually in the range of 60-70%. In contrast, certain other brain signals show considerably higher detection accuracies like the P300 ERP and the SSVEP signal [4].

B. Our Hypothesis for Amplifying a Signal

Upon observing this variation in the accuracy outcomes for both these signals, we try to delve into the fundamental differences between these two signals to better understand the factors contributing to this disparity, which can potentially be many.

- It is possible that the brain states or the activated regions linked with SSVEP (visual cortex, linked with vision processing) evocation as opposed to ErrP (anterior cingulate cortex, linked with reasoning and decision-making) ex-

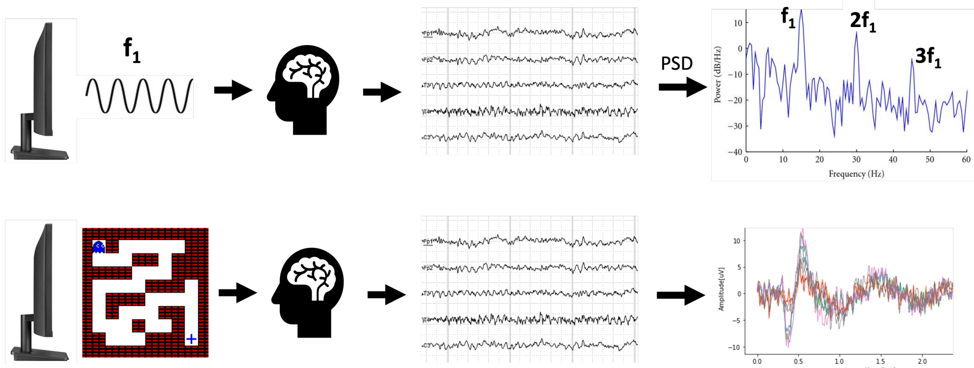


Fig. 2. SSVEP (top) and ErrP (bottom) stimulus and evoked signal profile

hibit resilience to noise, owing to the distinct functionality associated with different neural regions (Refer to Fig. 1).

- The SSVEP, which is primarily triggered by the visual processing system—a fundamental building block of the animal brain—may yield a more prominent amplitude compared to the region responsible for ErrP, associated with higher-level abstract reasoning and decision-making.
- Additionally, the stimulus for SSVEPs, which, as shown in Fig. 2, is a sequence of flickering light intensity, may prime the subject to pay more attention to the stimulus or focus more on the target compared to the stimulus for ErrP, which is an abstract decision making game.

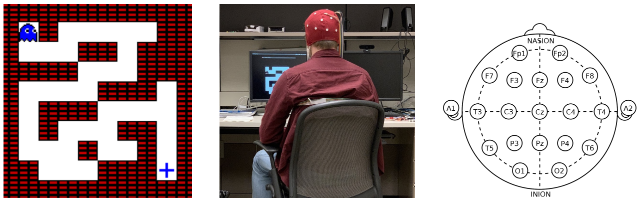
It is also plausible that there are certain other cognitive or neurophysiological states associated with SSVEPs that enable its better performance which are not activated for ErrPs. The specific causative elements remain elusive, prompting us to systematically manipulate all associated parameters. To this end, we orchestrate a concurrent experiment designed to elicit responses from both signals, to concurrently activate the associated neural cognitive states for both the signals. Specifically, we attempt to harness the abstract cognitive states associated with evoking a resilient signal like the SSVEP to see if it amplifies the ErrP response by ”modulating” ErrP with an SSVEP response.

Mathematically speaking, if we encapsulate all the enabling neurophysiological or cognitive variables that are activated for SSVEPs by ϕ_1 and the same for ErrPs by ϕ_2, we posit that the signal-to-noise ratio (SNR) given ϕ_1 exhibits a certain desirable characteristic which is not present in the SNR given ϕ_2. Our conjecture centers on the anticipation that the combined SNR given both ϕ_1 and ϕ_2 may yield a higher outcome. We aim to activate both ϕ_1 and ϕ_2 by designing an experiment setup where the ErrP response and the SSVEP response can be evoked simultaneously.

An ErrP response is evoked when a user observes an erroneous action being committed by themselves or another independent agent (like seeing an agent make the wrong move while navigating a maze). ErrP signals are characterized by a negative deflection in the EEG recordings roughly 200-300ms after the stimulus onset [9]. While ErrP signals consistently obey this, it is difficult to detect them using unsupervised methods owing to their low SNR as well as their considerable variability across subjects. On the other hand, the SSVEP is elicited in the brain when a human observes rhythmic variations of visible light (for instance, an LED light flickering with a certain frequency). The resultant SSVEP signals observed primarily in the occipital lobe, mimic the frequency of the stimulus and can be seen to have peaks around the said frequency in their frequency spectrum. The brain’s response to modulations of visible light and the resultant SSVEP has been modeled as an LTI system in literature [13] and its detection and characterization are also based on this. Thus, in order to elicit both these signals concurrently, we design an experiment where the ErrP stimuli are presented on a flickering screen.

III. Related work

Similar to BCIs in general, ErrPs have also been traditionally detected using spatial filtering techniques [14]. More recently, Reimannian-geometry-based methods have been very successful and have improved the accuracy to about 75% [2]. ConvNet also demonstrated the potential of shallow deep learning models to classify and generalize EEG signals [15] using very few parameters (91,602). With EEGNet [3], the authors brought the parameters further down to 1082 and 2290 (for two instances) and this showed promising numbers for ErrP detection. More recently, few-shot learning methods [16] and data transformation models [17] have also been shown to be effective. Similar to ErrPs, SSVEPs have also been detected using spatial filtering and other feature extraction methods. Some of these methods are supervised [18] while a considerable number of these methods are training-free and thus require no prior information about a subject or the data to detect SSVEPs. A few of the popular training-free approaches include PSDA [19] (power spectral density analysis), where peaks at the stimulus frequency in the signal spectrum are used to infer the presence or absence of SSVEPs, and CCA [20] (canonical correlation analysis), where signal cross-covariance matrices are used. More recently, deep learning models like EEGNet_SSVEP [4] have also been used for detecting SSVEPs. There have also been works where two or more BCI signal



(a) (b) (c)

Fig. 3. Experimental framework. (a) Game Environment. (b) Experiment Bench. (c) Electrode map

paradigms are used in conjunction and their combined input is used to enhance the performance of a system, also known as Hybrid BCI systems. [21] combined EEG and NIRS and observed enhanced classification of motor imagery signals, while [22] utilized SSVEP signals to complement P300 signal detection and classification accuracy. Note that while Hybrid BCI systems use the combined output of multiple signals to obtain performance enhancement in a task, our work deals with investigating the hypothesis of whether introducing a strong signal amplifies the characteristics of an otherwise weak signal.

IV. Methodology

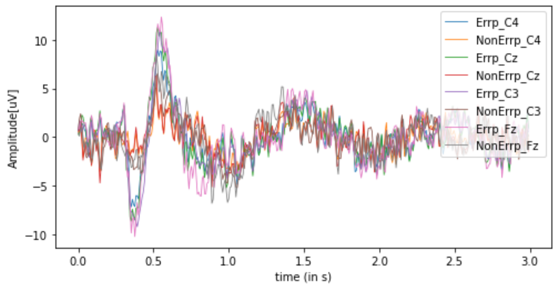
A. Experiment design to elicit ErrP

In 1991, Falkenstein [9] elicited error potential signals in an experiment involving a choice reaction task where subjects had to respond to a letter appearing on the screen by pressing one of two keys on a keyboard. In trials where subjects pressed the wrong key, a negative deflection in the EEG signal was seen, which was termed "Error-Related Negativity" (ERN) or "Error-Potential". In 1997, Miltner [23] postulated the existence of a general-purpose error-processing neural system and the ErrP signal to be a manifestation of it. ErrPs can be elicited in multiple ways, including but not limited to, committing errors [9], observing errors committed by other entities [12], or even receiving negative feedback in response to a given command [24], etc. To elicit ErrPs in our experiments, we chose the protocol where human subjects observed errors being committed by an AI agent on a computer screen while navigating an Atari-based maze game.

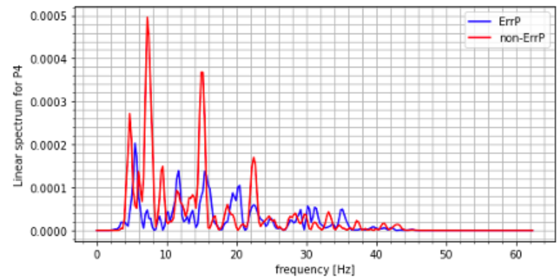
We utilize 3 different datasets to validate our hypothesis. The first dataset is a public ErrP dataset [25] consisting of 26 subjects containing 340 samples for each user. The ErrP signals in this dataset were elicited in response to detecting errors in a BCI speller software. We collect the remaining two datasets (one containing only ErrP and the other containing both ErrP and SSVEP) in our lab through our IRB-approved study. We use the BIOPAC CAP-100C electrode cap that has 21 electrodes spread across a user's scalp (refer Fig. 3(c)) with a sample rate of 125 Hz. This cap is connected with the OpenBCI Cyton platform, which is further connected to a desktop machine over the wireless channel. The game design was built using OpenAI Gym and was run on a screen in front of the user while minimizing any distractions. The OpenViBE software [26] was used to gather EEG data via a TCP port and accurately time the incoming signal with the movement of the computer agent. To elicit ErrP signals, we create an Atari-based maze game with a 10×10 grid containing obstacles that an AI agent navigates intending to reach a target (the plus symbol) as shown in Fig. 3(a). The agent is free to move along the top/right/bottom/left directions and it is possible to have multiple right or wrong actions. The agent makes a wrong move with a probability of 0.2. These wrong moves observed by a subject elicit the ErrP signal in their brain. The signal data of a user at any given state is linked to the game agent's location and the action taken. We utilized 12 human subjects (mean age 26.7, 2 female) with their consent to perform this experiment. The subjects were compensated for their time, and each subject performed 10 trials. Each trial starts with the AI agent at its initial position at the top left of the maze and terminating with the agent successfully navigating the maze. Each trial lasts roughly 2 minutes, and the entire experiment lasts about an hour on average per subject. All the requisite information about the agent's actions and the rules was communicated to the subjects before the start of the experiment, and the subjects were free to not continue with the experiment at any point if they wished.

B. Experiment design to combine SSVEP with ErrP

For the experiment where we elicit ErrP and SSVEP signals together, the protocol was the same as the ErrP-only experiment, except for an additional stimulus to evoke SSVEP signals. Stimuli combination to elicit two or more signals concurrently has been demonstrated to be effective in works like [27] where the authors combined SSVEP and P300 stimuli to improve the detection accuracy and target discrimination in a BCI speller application. To combine our stimuli for ErrP and SSVEP signals, we add a flicker component to the whole screen with a frequency of 7Hz. The AI agent navigating the maze evokes ErrP signals as before, while the added flicker also evokes SSVEP signals in the subjects simultaneously. We choose 7Hz as the stimuli frequency since it is sufficiently close to the Individual Alpha Frequency (IAF) of users, which leads to clearer SSVEPs [28] and lies in the low-range of frequencies for SSVEP elicitation, providing better performance compared to high-range frequencies [29]. We use *"Xrandr"* to alter the brightness of the screen as a step function with a 50% duty cycle. We perform 10 trials per subject. In the final trial, half the subjects were asked to blink every time they saw the agent take an action (irrespective of the action being correct. This trial was not used for training or evaluation). We also gauged the variation in our observations by altering the nature of flickers in our experiment, that is, flickering the entire maze (maze flicker) or only the AI agent (agent flicker). We only include maze flicker in this paper as agent flicker failed to reliably elicit SSVEP signals (details included in supplementary material). The time taken per subject was about 1 hour. For preprocessing the data, we pass the signals through a 4th order Butterworth filter with frequency ranges 0.5Hz and 40Hz and select 8 electrode channels that are located near the occipital, central, and parietal regions (where we expect

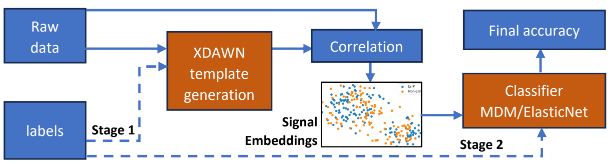


(a) A representative example of the ErrP response

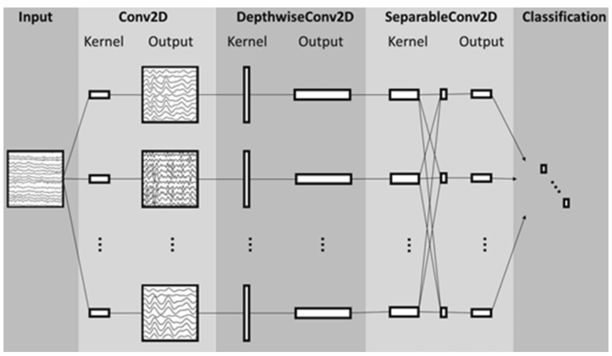


(b) A representative example of the SSVEP response

Fig. 4. Concurrent evocation of ErrP and SSVEP signals



(a) xDAWN + Riemannian Geometry model architecture [30]



(b) EEGNet architecture [3]

Fig. 5. Model architecture for EEGNet and xDAWN+RG

to find an interaction between ErrPs and SSVEPs) of the brain (C3, C4, Cz, P3, P4, Pz, O1, and O2 electrodes). The University Institutional Review Board reviewed and approved all the research protocols for all instances of our user data collection. We have not disclosed our dataset and code in this paper but plan to release them in the near future.

V. Analysis and Lessons Learned

A. Validation of coexitence of ErrP and SSVEP

We first analyze the signals obtained in ErrP+SSVEP dataset to ascertain that both the ErrP and SSVEP signals are simultaneously elicited. For the ErrP signals, we average all the signal samples for the fronto-central electrodes and visualize them. As seen in Fig. 4(a), we observe that the ErrP signal is distinct from the non-ErrP signal. Similarly, to check for the SSVEP signal, we average the signal samples for each user and plot the spectrogram. In Fig. 4(b), we see sharp peaks at the SSVEP frequency (7Hz) as well as its harmonics (14Hz and 21Hz), demonstrating that an SSVEP component is clearly elicited.

B. Evaluation over state-of-the-art detection methods

We evaluate all the datasets over three state-of-the-art detection methods: (1) Xdawn + tangent space classifier [2], (2) Xdawn + MDM (minimum distance to mean) classifier [30], and (3) EEGNet [3].

Xdawn + tangent space and Xdawn + MDM follow a similar signal decoding pipeline which can be summarized as follows (more details can be found in [2] and [30]):

- Estimating two sets of xDAWN spatial filters, one for each class (ErrP and non-ErrP), and using these filters to transform the signal data into covariance matrices [31].
- Using backward elimination to only keep the most significant 15 channels in the transformed data.
- MDM classifier performs classification on this matrix data using the Riemannian distance as a distance metric [30].
- The tangent space classifier projects the covariance matrices to their tangent space and then classifies the data using an ElasticNet classifier [32].

The detection pipeline of xDAWN + MDM classifier is shown in Fig. 5(a). On the other hand, EEGNet [3] is the state-of-the-art deep learning classifier for ErrP detection based on convolutional neural networks (CNNs) with its architecture shown in Fig. 5(b). For EEGNet, we used the optimal parameters listed in [3] for ERP decoding. The only change were the number of input channels (which were 56 for the public ErrP dataset but 8 for both the datasets collected in our lab). The class weight was roughly 4:1 (Non-ErrP vs ErrP) and was input to the network before training. To investigate our hypothesis on whether any amplification for the ErrP has occurred compared to the datasets containing only pure ErrP signals, we evaluate the detection performance over the three classifiers in Table I. Throughout this evaluation, we use per-user evaluation instead of ensemble methods used in preceding works (ensemble approaches generally perform better due to the availability of more data, which is why we preferred individual user evaluation to see performance w.r.t limited data). We also use balanced accuracy ((TPR + TNR)/2) (where TPR = True Positive Rate or Sensitivity, TNR = True Negative Rate or Specificity) for evaluating our models because it is an excellent and wide-accepted metric for unbalanced classes which eliminates biased models which excessively favor either the positive or the negative class. For every user, we use k-fold cross-validation with $k = 5$ and each instance is simulated 4 times, thus yielding 20 simulations per user. The final average balanced accuracy is the average of the per-user balanced accuracy for all users.

TABLE I
COMPARISON OF AVERAGED BALANCED ACCURACY OVER ALL THE TRAINING USERS (MODEL TRAINED ON A PER-USER BASIS).

Datasets	EEGNet	Xdawn + tangent space	Xdawn + MDM
Public dataset (ErrP)	73.54%	64.32%	65.18%
Lab dataset (ErrP)	67.0%	64.9%	65.4%
Lab dataset (ErrP+SSVEP)	**63.5%**	**58.9%**	**57.11%**

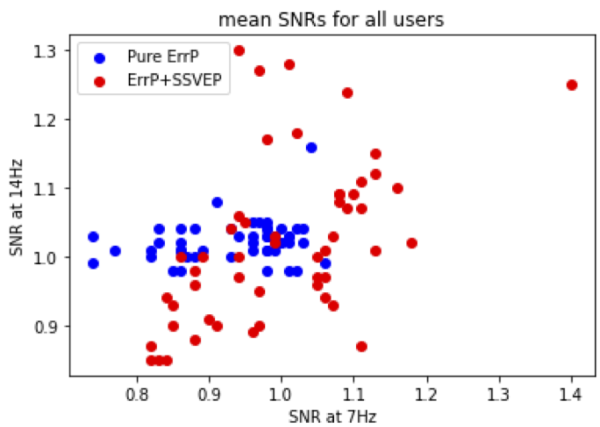


Fig. 6. SSVEP average SNR and correlation between harmonics for the ErrP and ErrP+SSVEP dataset

In Table I, the balanced accuracy for ErrP+SSVEP dataset is lower compared to the standalone ErrP datasets for both the public dataset as well as the lab dataset. Introducing SSVEP into ErrP datasets brings about 12% to 15% of degradation in detection performance. These results are in contrast to our expected results based on our hypothesis. Moreover, the substantial degradation enlightens us in the opposite direction of the hypothesis: the combination of ErrP and SSVEP may lead to destructive interference between each other, instead of enhancing SNR and constructive detection result.

C. Lessons Learned and Future Work

The universal degradation of detection performance among all three state-of-the-art classifiers contradicts our hypothesis that SSVEP could enhance the detection of the ErrP signal. One possible explanation for this could be that the ErrP signal degraded the SSVEP signal and as a result, the evoked SSVEP signal itself was not strong enough. To explore this explanation for the reduced performance of the composite dataset and gauge the SSVEP strength, we calculate the SNR and the correlation between the first and second harmonic components for the SSVEP signal. SSVEP signals are known to exhibit a high correlation between the SNRs at their harmonic frequencies [29]. We denote SNR as the ratio of the power in a given frequency bin to the average power in its neighboring bins. The SNR at any given frequency bin is given by the following:

$$SNR(f) = \frac{2K * P(f)}{\Sigma_{i=1}^{K}(P(f+i*b) + P(f-i*b))}, \tag{1}$$

where $P(f)$ denotes the power spectral density of a signal at frequency f, b denotes the frequency bin size, and K denotes the total number of neighboring frequency bins on either side of the harmonic frequency taken into account. For the purpose of our experiments, we set $K = 4$. For all the users in the ErrP+SSVEP dataset as well as the ErrP dataset collected in our lab, we calculate the mean SNR at the first and second harmonic (7Hz and 14Hz respectively) for the channels Pz, Cz, O1, and O2. We then plot these values and calculate the Pearson correlation coefficient between the SNRs for each dataset. We obtain a correlation coefficient equal to 0.246 (p-value 0.04) for the ErrP dataset and 0.721 (p-value 0.006) for the ErrP+SSVEP dataset. The plot for the SNRs for both the harmonics is shown in Fig. 6. While we observe a higher correlation for the dataset where SSVEP is present compared to that where it is absent, the average SNR for our composite dataset (0.99, 1.02) is not sufficiently high compared to the dataset where SSVEP is absent (0.93, 1.03). This suggests that the magnitude of the elicited SSVEP is not as prominent as we had expected.

Using the results obtained for evaluating our hypothesis, we chalk the observations down to the following potential causes and corresponding future countermeasures:

1) **Destructive interference**: The most direct explanation for the performance degradation is that the two signals engage in a form of destructive interference where the evocation of one signal inhibits the intensity of the other. This behavior might also explain why the average elicited SSVEP SNR in our ErrP+SSVEP dataset is not sufficiently high compared to the average SNR in our ErrP dataset. If so, this behavior needs to be studied in detail so valuable insights can be derived from this.
2) **Subject distraction**: Another explanation to the performance degradation is that the competing stimuli for the two signals distracts the subject observing the screen, thereby decreasing their attention and leading to diminished accuracy of the elicited signal. If that is the case, we need to research better ways to reconcile the two competing stimuli so that they do not adversely impact the subjects' neurophysiological states.
3) **SSVEP elicitation**: The third possible explanation to the performance degradation is the way to elicit SSVEP. Current elicitation method is limited by the maximum brightness of the screen. This might also explain the poor SNR observed in the elicited SSVEP in our dataset. We will experiment with better models of eliciting SSVEP signals like LED flickering (as opposed to screen flickering) as that has been shown to provide better SSVEP amplitudes.

VI. Conclusion

In this paper, we investigated a hypothesis as to whether weaker brain signals can be "modulated" or influenced by stronger and more resilient brain signals, thus getting amplified in the process. We put forth this idea after being intrigued by the variation in brain signals w.r.t. their SNR and their resilience to noise and conjecturing that perhaps it is because of the different neural states specific to different kinds of signals that dictate this behavior. We then explored if characteristics like resilience to noise be transferred to a weaker signal by using a stronger signal with it concurrently. We collected two datasets in our lab following this postulation and evaluated our results using state-of-the-art detection models. We obtained negative results implying that concurrently eliciting a strong signal with a weak signal does not amplify the latter. We then put forward some plausible explanations for our results and reflect on the insights and reassess our initial hypothesis.

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