INVESTIGATING THE FEASIBILITY AND EFFECTIVENESS OF A HYBRID BCI SPELLER USING A CONSUMER GRADE EEG HEADSET

by

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AUTHOR'S DECLARATION

I, Sunsun Kasajoo, declare that the research work carried out for this thesis was in accordance with the regulations of the Asian Institute of Technology. The work presented in it are my own and has been generated by me as the result of my own original research, and if external sources were used, such sources have been cited. It is original and has not been submitted to any other institution to obtain another degree or qualification. This is a true copy of the thesis including final revisions.

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ABSTRACT

Several paradigms have been utilized to create Brain Computer Interface (BCI) Spellers to assist individuals with neurological disorders in communicating. The current state of the art employs a hybrid technique that combines the Steady State Visually Evoked Potential (SSVEP) and P300 paradigms with the ensemble Task Related Component Analysis (TRCA) decoding algorithm. Existing research on hybrid spellers, however, relies heavily on expensive clinical-grade EEG devices (e.g., 64 channels, $>$1000Hz sampling rate), limiting their applicability in the real world. This work investigates the viability and efficacy of a hybrid speller utilizing a consumer-grade EEG device (e.g., 8 channel EEG, 250Hz sampling rate). The first study conducts engineering experiments, examining the internal parameters of the hybrid speller. The second study conducts user experiments, examining the model's long-term viability, i.e., whether it can still function after several days. In conclusion, although consumer-grade EEG is feasible, it has certain limitations, namely the number of targets (i.e., clinical grade can serve up to $>$100 targets, but we have trouble moving above 16 targets while maintaining at least 70% average accuracy) and speed (i.e., clinical grade requires less than 1s of stimulus duration, but we require at least 2s, likely due to the lower sampling rate). The results of this study will provide a practical foundation for practitioners and engineers to build upon on constructing a cost-effective, practical BCI speller. The outcomes of our investigation, including the results, data, and code are available in *https://github.com/sunsun101/hybrid-ssvep-p300-speller*.

Keywords: Steady State Visually Evoked Potential (SSVEP), P300, BCI Speller

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CHAPTER 1
INTRODUCTION

1.1 Background of the Study

The Steady State Visual Evoked Potential (SSVEP) and P300 paradigms have been used extensively to create Brain-Computer Interface (BCI) spellers. The current state of the art combines the P300 and SSVEP paradigms with sophisticated decoding algorithms such as ensemble Task Related Component Analysis (TRCA) to achieve higher performance and enable a greater number of target options. In a study conducted by Nakanishi et al. (2017), the TRCA-based approach was introduced and used to improve the accuracy of the SSVEP-based 40-target BCI speller. The results demonstrated that this method improves classification accuracy substantially in comparison to conventional methods such as extended Canonical Correlation Analysis (CCA). The impressive information transfer rate (ITR) for the online cue-guided task was 325.33 ± 38.17 bits/min, while the ITR for the free spelling task was 198.67 ± 50.48 bits/min. Xu, Han, Wang, Jung, and Ming (2020) proposed the implementation of ensemble TRCA, which introduced time-modulated SSVEP and frequency-phase-modulated P300, and obtained remarkable results. Even with a large number of targets (108), the online cue-guided task yielded an ITR of 172.46 ± 32.91 bits/min and the copy spelling task obtained an ITR of 164.69 ± 33.32 bits/min. These recent advancements emphasize the substantial benefits and improved results obtained by employing hybrid techniques, especially in conjunction with ensemble TRCA. Given the encouraging results, our ongoing efforts are focused on implementing a practical BCI Speller.

1.2 Statement of the Problem

However, past work on hybrid speller relies on costly, clinical-grade EEG headsets, which may not be suitable for widespread use. In general, higher-target BCI spellers were paired with clinical-grade headsets, whereas consumer-grade headset studies for hybrid BCI spellers were not well documented. By understanding the viability and limitations of using a consumer-grade EEG, we can potentially make hybrid spellers more accessible to the general public.

1.3 Objectives of the Study

This work examines the feasibility and efficacy of a hybrid BCI speller using a consumer-grade EEG headset (specifically, the g.tec Unicorn Hybrid Black EEG headset *Unicorn Hybrid Black* (2022) with 8 channels and 250 sampling rate). Following the success of Xu et al. (2020), we seek to emulate the same approach while solving engineering problems along the way and understand the limits of the consumer-grade headset. Secondly, despite the fact that numerous studies have proposed the use of ensemble TRCA, few evaluate the efficacy of the trained ensemble TRCA model after multiple days. This is an important perspective since it is impractical if the trained model cannot be used after multiple days, simply because the day changes or the location of the cap changes slightly.

Particularly, the objectives of this thesis are threefold:

1. Develop the hybrid BCI speller using the consumer-grade EEG along with the ensemble TRCA decoding algorithm
2. Perform engineering experiments to understand the limitations and provide a comprehensive account of our journey in identifying the optimal conditions and methodologies that successfully led to the development of the speller.
3. Perform user experiments to understand the long-term viability of the trained ensemble TRCA model.

The outcomes of our investigation, including the results, data, and code are available in *https://github.com/sunsun101/hybrid-ssvep-p300-speller*.

CHAPTER 2

LITERATURE REVIEW

2.1 Hybrid SSVEP-P300 Brain-Computer Interface (BCI) speller

Here we have to justify the reason we following Xu et al. (2020) We have to discuss how many hybrid variants are out there and their performance. Just very brief. The illustration might help, I guess. Then we review Xu et al. (2020) method and explain the different or how it works. With some detail. We save TRCA for the later part. At the end, we have to explicitly say Xu et al. (2020) hybrid speller is the current state of the art.

Nakanishi et al. (2017) proposed Task Related Component Analysis (TRCA) based target identification algorithm. This study presented visual flickers encoded by the joint frequency-phase modulation (JFPM) method using the sampled sinusoidal stimulation technique, similar to Chen, Chen, Gao, and Gao (2014). Nine electrodes over the parietal and occipital regions (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, O2) were used to record EEG data at a sampling rate of 1,000 Hz using a Synamp2 system (Neuroscan,Inc.). The monitor's resolution and refresh rate were 1920 $\times$ 1080 pixels and 60 Hz, respectively. The user interface consisted of visual stimuli containing 40 characters in a 5 $\times$ 8 matrix. These stimuli spanned a frequency range of 8 Hz to 15.8 Hz with a frequency interval of 0.2 Hz, and their phase value began at 0 and their phase interval was 0.35pi. Using MATLAB (MathWorks, Inc.) and the Psychphysics Toolbox Version 3, the stimulus program was developed. This study compared target identification algorithms such as Extended CCA, TRCA, and TRCA ensemble. In terms of classification accuracy and ITR, spatial filters based on TRCA outperformed the extended CCA-based method. Notably, they achieved an impressive ITR of 325.33 $\pm$ 38.17 bits/min for online cue-guided applications, with a classification accuracy of 89.83 $\pm$ 6.07%. Similarly, for online free-spelling tasks, they attained an ITR of 198.67 $\pm$ 50.48 bits/min and an accuracy of 36.17 $\pm$ 11.02 characters per minute (cpm).

Another noteworthy study by Xu et al. (2020) focused on the expansion of BCI speller's instruction set. By integrating the steady-state visual stimulus (SSVS) into the P300 speller, they created a 108-instruction BCI system with 12 parallel 3 $\times$ 3 P300 sub-spellers. Time-modulated SSVEP and frequency-phase-modulated P300 were identified as two new, distinct EEG features for concurrent P300 and SSVEP features. Ensemble TRCA was employed as the decoding algorithm. Using the JFPM method, the frequencies and phases of the 12 flickering stimuli were also determined. The visual stimuli were displayed on a 27-inch liquid-crystal display (LCD) monitor with a resolution of 1920 by 1080 and a refresh rate of 120Hz. 13 electrodes were placed at Fz, Cz, Pz, PO3, PO4, PO5, PO6, PO7, PO8, POz, O1, Oz, and O2 according to the international 10/20 system and recorded using the Neuroscan Synamps2 system. In online cue-guided spelling and copy-spelling tests, their BCI system attained remarkable results with an average ITR of 172.46 $\pm$ 32.91 bits/min and 164.46 $\pm$ 33.32 bits/min, respectively. The average classification accuracy for online cue-guided spelling experiments was 81.67 $\pm$ 9.86%, while it was 79.17 $\pm$ 10.02% for online copy-spelling experiments.

2.2 Ensemble Task Related Component Analysis (TRCA)

Task Related Component Analysis (TRCA) is first introduced in Nakanishi et al. (2017) and later improved to ensemble TRCA in Xu et al. (2020). The model was shown to be effective in classification tasks on both SSVEP-based 40-target (Nakanishi et al., 2017) and hybrid SSVEP-P300 hybrid 108-target (Xu et al., 2020) BCI speller, where the later one achieved state-of-the-art performance.

Here we explained the ensemble TRCA algorithm briefly. TRCA is an algorithm that finds the projection matrix $\mathbf{W} = [w_{j1}w_{j2}...w_{Nc}]^T$ to maximize the covariance of task-related components between trials Tanaka, Katura, and Sato (2013). $j1$ and $j2$ refers to the index of channels. For the recorded Nc channels EEG signal $x(t) = \mathbb{R}^{Nc}$. Task related component is computed as a linear, weighted sum of those input signals as:

$$\begin{aligned} y(t) &= \sum_{i=1}^{N} w_i x_i(t) \\ &= \mathbf{W}^T x(t) \end{aligned} \tag{2.1}$$

Covariance between $h1$ and $h2$ trial is given by

$$\begin{aligned} C_{h1,h2} &= \text{Cov}(y^{(h1)}(t), y^{(h2)}(t)) \\ &= \sum_{j1,j2=1}^{Nc} w_{j1}w_{j2}\text{Cov}(x_{j1}^{(h1)}(t), x_{j2}^{(h2)}(t)) \end{aligned} \tag{2.2}$$

All possible combination of trials are summed as:

$$\begin{aligned}\sum_{\substack{h1,h2=1\\h1\neq h2}}^{N} C_{h1,h2} &= \sum_{\substack{h1,h2=1\\h1\neq h2}}^{N}\sum_{j1,j2=1}^{Nc} w_{j1}w_{j2}\text{Cov}(x_{j1}^{(h1)}(t), x_{j2}^{(h2)}(t)) \\ &= \mathbf{W}^T\mathbf{S}\mathbf{W}\end{aligned} \tag{2.3}$$

Here, the symmetric matrix $\mathbf{S} = (S_{j1,j2})_{1\leqslant j1,j1\leq Nc}$ is defined by

$$S_{j1,j2} = \sum_{\substack{h1,h2=1\\h1\neq h2}}^{N} w_{j1}w_{j2}\text{Cov}(x_{j1}^{h1}(t), x_{j2}^{h2})(t)) \tag{2.4}$$

To obtain the final result, the following restriction is applied:

$$\begin{aligned}Var(y(t)) &= \sum_{j1,j2=1}^{Nc} w_{j1}w_{j2}\text{Cov}(x_{j1}(t), x_{j2}(t)) \\ &= \mathbf{W}^T\mathbf{Q}\mathbf{W} \\ &= 1\end{aligned} \tag{2.5}$$

The optimization problem can be solved as:

$$\hat{w} = \underset{w}{\text{argmax}}\frac{(\mathbf{W}^T\mathbf{S}\mathbf{W})}{(\mathbf{W}^T\mathbf{Q}\mathbf{W})} \tag{2.6}$$

The optimal coefficient vector is obtained as the eigenvector of the matrix $\mathbf{Q}^{-1}\mathbf{S}$

Since there are N_f individual calibration data corresponding to all the visual stimuli,N_f different spatial filter can be obtained. An ensemble spatial filter

$$\mathbf{W}^{(m)} = [w_1^{(m)}w_2^{(m)}...w_{N_f}^{(m)}] \tag{2.7}$$

The correlation coefficient between projection of test data $\mathbf{X}^{(m)}$ and averaged individual template $\bar{\chi}^{(m)}$ is calculated as:

$$r_n^m = \rho((\mathbf{X}^m])^T\mathbf{W}^{(m)}, (\bar{\chi})^T\mathbf{W}^{(m)}) \tag{2.8}$$

The correlation coefficients in different sub-bands are weighted by:

$$\rho_n = \sum_{m=1}^{Nb} (m^{(-1.25)} + 0.25) * (r_n^{(m)})^2 \tag{2.9}$$

Finally the target can be identified by the following equation:

$$\tau_t = \underset{n}{\text{argmax}} \rho_n \tag{2.10}$$

2.3 Equipment

The Synamp2 system (Neuroscan, Inc.) cite (if you can) is used in the implementation of both Nakanishi et al. (2017) and Xu et al. (2020). The headset is capable of recording 64 channels with a 1000 Hz sampling rate. However, the recorded signals were sampled down to 250 Hz, and not all 64 channels were used in the analysis part. 9 channels, namely Pz, POz, PO3, PO4, PO5, PO6, O1, O2, and Oz, were used in both works and an additional 4 channels (Fz, Cz, PO7, and PO8) were presented in Xu et al. (2020). In comparison, the g.tec Unicorn EEG headset is capable of recording 8 channels (Fz, Cz, C3, C4, Pz, PO7, PO8, and Oz) with 250 Hz. The consumer-grade g.tec Unicorn should perform on par with the down-sampled Synamp2 system (Neuroscan, Inc.).

CHAPTER 3
METHODOLOGY

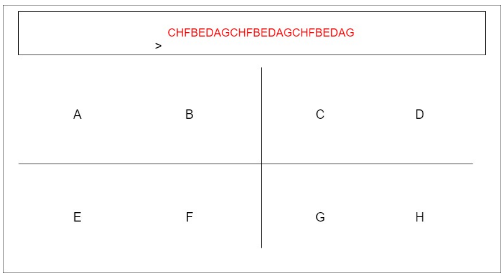
The methodology is structured into two parts. The first part involves a preliminary study (Study 1) conducted to determine the optimal parameters of the speller, while the second part (Study 2) focuses on examining the long-term viability of the trained ensemble TRCA model.

3.1 Study 1: Preliminary Study

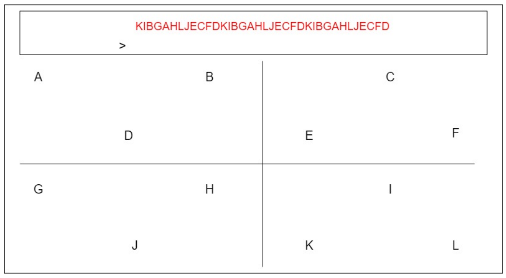
Figure 3.1

GUI design of hybrid speller.

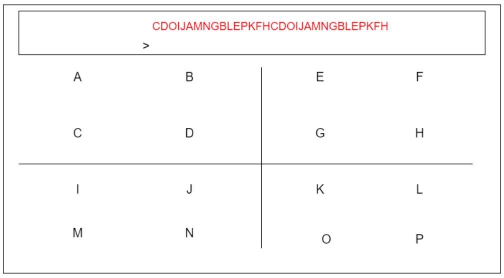
(a) *Distribution of 8 characters on the screen*



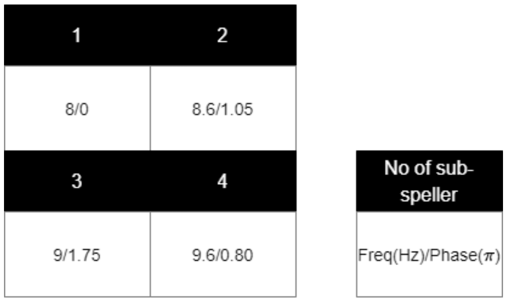
(b) *Distribution of 12 characters on the screen*



(c) *Distribution of 16 characters on the screen*



(d) *The selected frequencies and initial phase for each sub-speller*



This study focused on finding the optimal BCI speller parameters namely, (1) the number of targets (C), (2) flicker duration (T_{flicker}) and overlap (O) where $0 \leq O \leq 1$ where 0 means no overlap and 1 means fully overlap, (3) flicker frequency (F_c) and phase (P_c) where $c \in C$, and (4) trial size per target (S). The range of targets is 8, 12, and 16, and organized into four sub-spellers with an equal amount of targets in each sub-speller as shown in Figure 3.1. The range of flicker duration is between 1 and 2 seconds paired with either no overlap or half overlap. Two sets of flicker frequencies and phases [8.0/0.00, 8.6/1.05, 9.0/1.75, 9.6/0.80] cite which paper we copy Hz and [12.4/0.00, 13.2/1.40, 14.0/0.80, 14.6/1.85] cite which paper we copy Hz were used in the experiment. And, the effect of trial size ranges from 7 to 20 trials per target. The flicker size was constant at 100×100 pixels. The goal was to identify the most effective configuration to achieve reliable and accurate results.

3.1.1 Participants

A single participant (aged 26, female) with normal vision volunteered for this study.

3.1.2 Materials and Equipment

EEG data were acquired using g.tec Unicorn Hybrid Black EEG Headset with a sampling rate of 250 Hz. The headset is equipped with eight electrodes (Fz, Cz, C3, C4, Pz, PO7, PO8, and Oz) based on the International 10/20 system. The Unicorn Suite Hybrid Black application was used to ensure that the electrodes were working correctly after the participant wore the cap. A conductive electro-gel was used to enhance the conductivity and stabilize the signal. The visual stimuli were presented on a 27-inch liquid-crystal display (LCD) monitor with a resolution of 1920 $\times$ 1080 with a refresh rate of 60 Hz.

The experiments were conducted in a controlled environment. To eliminate external influences, the room was darkened by covering the windows and creating an undisturbed ambiance. The experimental procedures were approved by the institutional review board at the Asian Institute of Technology.

The speller was developed using Python version 3.8.3. For recording and processing the signal, the MNE library version 1.3.0 was employed. Additionally, the BrainFlow library version 5.6.2 was utilized to analyze the EEG signals. The stimulation system was developed using PsychoPy version 3. In our study, we utilized the ensemble TRCA code, which was developed based on the methodology presented in the work by Nakanishi et al. (2017). The code from the corresponding GitHub repository `https://github.com/mnakanishi/TRCA-SSVEP` was employed for our analysis.

3.1.3 Data Collection

One set of data is obtained from one session. The data is collected in blocks design with breaks in between each block. A block consists of $2 \times C$ number of trials. The number of blocks in one session (B) is $\frac{S}{2}$. The duration of a break (T_{break}) varied depending on

C using the following logic.

$$D_{\text{break}} = \begin{cases} 30 \text{ if } C = 8 \\ 40 \text{ if } C = 12 \\ 60 \text{ if } C = 16 \end{cases}$$

A trial consists of cue time (T_{cue}) and flickers. Time of a trial is $T_{\text{trial}} = T_{\text{cue}} + T_{\text{flicker}} \times (1 + ((1 - O) \times (\frac{C}{4} - 1)))$. Thus, the duration of a single block can be calculated as $T_{\text{block}} = 2C \times T_{\text{trial}}$. Finally, a session time T_{session} can be calculated with $(B \times T_{\text{block}}) + (B - 1) \times T_{\text{break}}$

In a trial, T_{cue} is set to one second. During this second, a red box is displayed on the screen over the target indicating the specific target that the participant needed to focus on. After that, a sequence of flickers following the order is presented. Please note that the order is random once at the beginning of the project for each sub-speller of each target number (C). These orders are used for all sessions.

How is the target order? The order of the targets is random in every session.

3.1.4 Task and procedure

There are two types of sessions in our experiment: an offline session and an online session. The data we obtain from an Offline session will be used to train the ensemble TRCA. Subsequently, the trained model will be evaluated against the Online session. The detail of how the model is obtained will be discussed later in Section 3.1.6

The preparation instruction was given to all participants. It instructed the participants to omit the use of hair products (e.g. sprays or gels) in the morning of the experiment day, and avoid eating or drinking anything containing caffeine for at least 8 hours before the test.

For each offline session, the participant was asked to sit comfortably in a chair, facing a monitor positioned at a distance of approximately 60 cm measuring from screen to eyes. The g.tec Unicorn Hybrid Black EEG Headset was put on together with monitoring the signal quality using the Unicorn Suite Hybrid Black application. The instruction on how to perform the BCI speller was reminded again. When ready, the data collection was started following Section 3.1.3. The data was obtained in a three-dimensional data $(C \times S, \texttt{n\_channels}, \texttt{n\_samples})$ where `n_channels` is 8 and `n_sample` is $250 \times T_{\text{trial}}$

continue here

In the online task, the experimental setup remained largely similar to the offline task. However, there was only a single block consisting of three trials for each target. Real-time predictions were generated using the previously trained and saved model. The system's output was displayed instantaneously on the screen, providing immediate feedback to the participant.

3.1.5 Preprocessing

The raw EEG signals obtained during both the online and offline tasks underwent band-pass filtering within the frequency range of 1 to 92 Hz, with an additional notch filter at 50 Hz. For the ensemble TRCA decoding algorithm, a filterbank of [[(1, 92), (0, 100)], [(7, 92), (6, 100)]] was utilized. Apart from these steps, no additional preprocessing was applied to the EEG signals.

3.1.6 Models

Ensemble Task-Related Component Analysis (TRCA) was used as the classification model. Using 5-cv. How to split, save best model.

All these parameters of the speller were varied and different experiments were conducted. To assess the offline accuracy of the system, a stratified 5-fold cross-validation methodology was employed. The model yielding the best performance across the folds was saved and utilized in the online experiment.

3.1.7 Evaluation metrics

Offline accuracy, online accuracy and information transfer rate (ITR) were used as the evaluation metrics. The offline accuracy of the system was computed using a stratified 5-fold cross-validation. Online accuracy was calculated by using the number of correct and incorrect prediction done by the speller.

$$\text{ITR} = \left[\log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right)\right] \times \left(\frac{60}{T}\right)$$

3.1.8 Result and Discussion

Effect of Number of Samples

Based on the initial experimental results with a single subject, it was observed that a higher number of data samples per class led to improved outcomes. Table 3.1 shows the positive effect of increasing the number of samples on the overall results. Specifically, when comparing the 8 target speller, the offline accuracy noticeably improved when the number of samples was increased from 12 to 15. Moreover, for the 16 target speller, similar improvements were observed as the offline accuracy increased when the number of samples was raised from 7 to 15. However, individuals can experience fatigue during prolonged data collection sessions, so we decided to set the number of samples per class to 20. To achieve this, we divided the experiment into 10 blocks, with 2 trials for each character within each block.

Table 3.1

Comparison of Number of Trials

No of Stimuli	Flicker duration (sec)	Trials	Overlap	Acc_{off}(%)
8	3	12	0	75
8	3	15	0	79
16	2	7	0.5	57.23
16	2	15	0.5	72.50

Effect of Stimuli Time and Overlap

Table 3.2 shows the comparison of accuracy when stimuli time and overlap were varied. For the 8 target speller, the highest online and offline accuracy was achieved with a flicker duration of 2 seconds and a 0.5 overlap of stimuli. As we decreased the flicker duration to 1 second with no overlap and 1 second with 0.5 overlap, the accuracy decreased.

However, for the 16 target speller, even with the 2-second stimuli and no overlap, the accuracy obtained was not significantly high. Furthermore, reducing the stimuli flicker duration to 1 second with no overlap and 1 second with 0.5 overlap further degraded the performance.

Finally, when considering the 12 target speller, a flicker duration of 2 seconds with a 0.5 overlap and 20 trials of each character resulted in an acceptable outcome.

Table 3.2

Comparison of Stimuli Time and Overlap

No of Stimuli	Flicker duration (sec)	Trials	Overlap	Acc_{off}(%)
8	2	20	0.5	90
8	1	20	0	88
8	1	20	0.5	81
16	2	15	0.5	72.50
16	1	15	0	44.58
16	1	15	0.5	57
12	2	20	0.5	79

Effect of Frequency range

Table 3.4 show the experiment conducted in two different days. All other parameters are kept constant except the frequency and phase of the subspeller. It was found that the performance of the speller was better when we used the lower frequency range.

Table 3.3

Comparison of Frequency range

No of Stimuli	Flicker duration (sec)	Blocks	Trial/Block	Overlap(%)	Freq (Hz)	Acc_{off}(%)
16	2	15	16	0.5	[8,8.6,9,9.6]	72.5
16	2	15	16	0.5	[8,8.6,9,9.6]	73.33
16	2	15	16	0.5	[12.4,13.2,14.0,14.6]	58.33
16	2	15	16	0.5	[12.4,13.2,14.0,14.6]	61.25

Moreover,it is known that not all participants can perform equally well when it comes to BCI experiment. Therefore, to accommodate a broader range of users, we selected the parameters as follows: flicker duration of 2 seconds, 0.5 overlap, 10 blocks, and 2 trials

Table 3.4

Comparison of Frequency range

No of Stimuli	Flicker duration (sec)	Trials	Overlap(%)	Freq (Hz)	Acc_{off}(%)
16	2	15	0.5	[8,8.6,9,9.6]	72.92±0.53
16	2	15	0.5	[12.4,13.2,14.0,14.6]	59.79±1.75

per character per block. This selection aimed to ensure that the system remains usable for a greater number of participants.

Other observations

Along the experiments, we also informally altered some parameters and here are some note worthy points to know:

Darker environment: We discovered that conducting the offline experiment in a darker environment yielded better training data. This allowed us to train the ensemble TRCA model with higher quality data, resulting in improved performance. However, once the model was trained with quality data, we observed that online experiments were less affected by variations in lighting conditions.

Time alignment: In our studies, we made an additional observation regarding the alignment of EEG signals in online experiments. We noticed that the received EEG signals during online sessions may not be perfectly time-aligned with the training data. To address this issue, we experimented with adding a specific offset to the online EEG signals.

By introducing this offset, we aimed to align the online signals more closely with the timing patterns learned during training, thereby improving the overall performance of the system. Remarkably, we found that incorporating the offset proved to be beneficial, resulting in enhanced results during online experiments.

This finding highlights the importance of accounting for temporal discrepancies between training and online data in BCI systems. By introducing the appropriate offset, we were able to mitigate the potential misalignment and optimize the system's performance. This further underscores the need for careful calibration and synchronization measures when deploying BCI technologies in real-time applications.

3.2 Study 2: Long-term viability Study

This study was undertaken to assess the long-term viability of the trained ensemble TRCA model. The objective was to investigate whether the model remains effective and practical after a considerable time.

3.2.1 Participants

A total of twenty-three healthy individuals with normal or corrected-to-normal vision participated in the final experiments, which were divided into three sessions.

In the first session, participants completed an offline experiment using the 8 target speller, followed by an online experiment. Out of the initial twenty-three participants, fourteen individuals demonstrated proficient performance on the 8 target speller, achieving a classification accuracy of 70% or higher on the best fold of the offline experiment. To evaluate the classification accuracy, stratified 5-fold cross-validation was applied, and the model from the best fold was selected and saved for further analysis. Participants who did not meet the performance criterion during the first session were excluded from subsequent sessions.

Prior to participating in the experiments, participants were provided with comprehensive information regarding the study. They were fully informed about the experiment's objectives, procedures, potential risks, and their rights as participants. All participants voluntarily consented to participate by signing the informed consent form, affirming their understanding and agreement to take part in the study.

3.2.2 Speller

Three different spellers were used for the experiments to compare their performance, feasibility and effectiveness.

The first speller consists of 8 targets. The design of the 8 target speller is shown in Figure 3.1.The design consists of 4 sub speller with 2 character each in the sub speller. The layout consists of 2×4 matrix showing 8 characters in a white background. The characters of the speller were highlighted by a visual flicker of size 100×100 pixels in a fixed random sequence. The stimulus duration for each character was set to 2 s. The flickering patterns of the stimuli had a 0.5 overlap, adding a degree of continuity to the visual presentation. To facilitate target selection, the targeted characters were distinctly highlighted by a red cue box. This cue box, also of size 100 $\times$ 100 pixels, remained visible for 1 second before the stimuli began flickering.

The sampled sinusoidal stimulation method Chen et al. (2014) was used to present the visual flickers. JFPM method Chen et al. (2015) was used to determine the frequencies and phases of the six flickering stimuli. Similar to Xu et al. (2020) 4 flickering frequencies were selected for the visual stimuli: 8 Hz, 8.6 Hz, 9 Hz, 9.6 Hz with phases 0, 1.05, 1.75, 0.80 respectively.

The second speller consists of 12 targets. The design of the 12 target speller is shown in Figure 3.1. It also consists of 4 sub speller and each sub speller had 3 characters each. All other parameters were consistent with the 8 target speller.Also the characters within the sub-speller utilize the same frequency and phase as those in the 8-target speller.

The third speller consists of 16 targets. The design of the 16 target speller is also shown in the Figure 3.1. It consists of 4 $\times$ 4 matrix of English alphabetical characters presented within 4 sub spellers. All other parameters remain consistent with the other spellers.

3.2.3 Task and procedure

The participants were instructed to sit in front of a monitor screen, at a distance of approximately 60 cm. The monitor displayed a layout consisting of English alphabets, organized in a specific manner as depicted in Figure 3.1.

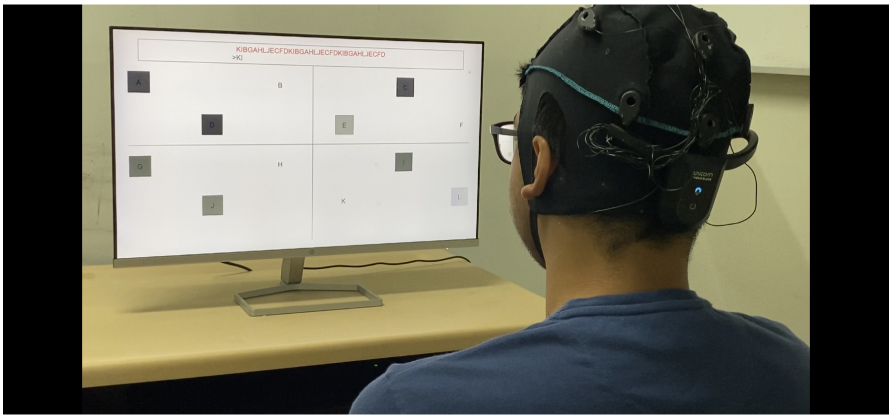
The participants were given a straightforward task: to maintain their focus on the targeted character highlighted by the cue with minimal blinking and mentally retain the target character throughout the flickering process. This approach aimed to ensure sustained focus and cognitive engagement during the task.

The experiment consisted of three sessions, each involving different combinations of offline and online experiments.

During the first session, the 8-target speller was used, and participants took part in an offline experiment, followed by an online experiment. Similarly, the second session involved the utilization of the 12-target speller, following the same offline and online

Figure 3.2

A participant performing online experiment



experiment structure as the first session.

The third session solely comprised online experiments, with one session dedicated to the 8-target speller and another session dedicated to the 12-target speller. Notably, the same model saved during the first and second sessions was utilized in the third session. After a minimum gap of one day following the second session, participants proceeded to the third session. This session aimed to assess the durability and stability of the trained model, examining its performance even after a gap of several days. By conducting experiments on different days, the study sought to evaluate the robustness and generalizability of the model over time and under varying conditions.

Further elaboration on the online and offline experiments is provided below.

Offline Experiment

The offline experiment was divided into 10 blocks. The character to be selected was indicated by a red outline for 1 second.

In the 8-target speller, each block of the offline experiment consisted of 16 trials, with 2 trials allocated to each of the 8 stimuli. The duration of each trial was 3 seconds. A 30-second break was provided between each block. Consequently, the entire offline experiment lasted approximately 12.5 minutes for each subject.

Similarly, in the 12-target speller, each block comprised 24 trials, with 2 trials assigned to each of the 12 stimuli. Each trial lasted for 4 seconds. A 40-second break was given between each block. Hence, the total duration of the offline experiment was approximately 22 minutes for each subject.

The 16-target speller offers a wider range of stimuli for participants to interact with. Each block in the 16-target speller comprises 32 trials, with 2 trials assigned to each of the 16 stimuli. Each trial was took 5 sec to complete. Following each block, there is a 60-second break to allow participants to rest and prepare for the next block. With a total of 10 blocks in the offline experiment, the entire duration of the 16-target speller is approximately 36.67 minutes for each subject.

$$T_{\text{total}} = N_{\text{blocks}} \times (N_{\text{trials}} \times N_{\text{chars}}) \times T_{\text{trial}} + (N_{\text{blocks}} - 1) \times T_{\text{break}} \tag{3.1}$$

T_{total} is the total time.
N_{blocks} is the number of blocks.
N_{trials} is the number of trials per character.
N_{chars} is the number of characters.
T_{trial} is the time taken per trial.
T_{break} is the block break time.

Online Experiment

The online cue-guided spelling experiment consisted of a single block with 3 trials of each character. For 8 target speller, each trial lasted for 3 sec. For 12 target speller, each trial lasted for 4 sec with 0.5 percentage overlap of stimuli flicker. The cue duration for online experiment was about 2 sec. The results of each trial were promptly displayed on the screen in real time, providing instant feedback.

3.2.4 Evaluation metrics

Same metrics have been used as in the study 1.

3.2.5 Result and Discussion

Table 3.6 and Table 3.7 shows the offline accuracy, online accuracy and online accuracy after at least 1 day for the 8 target speller and 12 target speller respectively. While the average accuracy decreased in the third session for the 8 target speller, it is important to note that individual participants displayed varied performance. Some participants demonstrated improvement in accuracy during the third session, while others experienced a decline. However, in the case of the 12-target speller, the overall accuracy increased yet it still remained true that certain participants exhibited enhanced performance, while others saw a decrease.

The absence of a consistent or clear pattern suggests that performance is not directly influenced by the passage of time. Instead, it is plausible that factors such as the participant's level of focus on a given day, their state of mind, and the amount of concentration exerted could have contributed to the observed variations in results. This result points out that combining recordings from multiple sessions could be a viable approach. It allows for a larger sample size without subjecting the user to excessive fatigue. By including data from different sessions, the model benefits from a more extensive and diverse dataset, capturing a wider range of conditions and performance variations.

In order to investigate the potential for improvement in participants' performance with the BCI speller, we conducted a specific training session with one participant. The objective was to determine if targeted training could enhance their ability to utilize the speller effectively.

During the training, various techniques were employed to assist the participant in maintaining focus. They were instructed to employ strategies such as counting the number of stimuli flickers and continuously mentally rehearsing the alphabet to sustain concentration. Furthermore, the participant exclusively participated in an online SSVEP experiment, employing FBCCA (frequency-based canonical correlation analysis) for classification. The online system provided real-time feedback, allowing the participant to ascertain whether their focus-enhancing techniques were effective.

The training spanned three consecutive days, with the participant actively engaging in the experiment. Following the completion of the training period, three offline experiments were conducted to evaluate the participant's performance. Surprisingly, despite the intensive training, no significant improvement in performance was observed.

These findings suggest that, in this particular case, the employed training techniques and the duration of the training period did not lead to notable enhancements in the participant's ability to utilize the BCI speller effectively. It highlights the complexity of individual variability in BCI performance and underscores the need for further investigation and experimentation to develop effective training strategies for improving BCI user performance.

Alzahrani (2021) Meshriky, Eldawlatly, and Aly (2017) Brennan et al. (2015)

Table 3.5

Comparison of accuracy of 8 target speller offline and online

Subject	Offline(%)	Best Fold(%)	Online 1(%)	ITR(bits/min)	Online 2(%)	ITR(bits/min)
S1	83.75	87.50	88.00	32	91.60	35.22
S2	85.00	**95.83**	81.00	26.47	87.00	31.16
S3	70.00	79.16	68.75	18.39	62.50	14.89
S4	76.66	83.33	56.25	11.74	66.66	17.18
S5	74.16	83.33	68.75	18.39	**100.00**	**44.97**
S6	85.62	87.50	93.75	37.3	87.50	31.58
S7	83.12	93.75	93.75	37.3	95.83	39.49
S8	87.50	90.62	87.50	31.58	95.83	39.49
S9	70.60	81.25	**100.00**	**44.97**	70.80	19.63
S10	73.00	81.25	91.00	34.66	70.00	19.15
S11	60.00	71.87	83.33	28.22	75.00	22.30
S12	68.12	81.25	87.50	31.58	83.33	28.23
S13	80.00	90.62	87.50	31.58	54.00	10.70
S14	**90.00**	**95.83**	91.00	34.66	87.50	31.58
S15	63.75	68.75	-	-	-	-
S16	48.00	56.25	-	-	-	-
S17	45.00	56.25	-	-	-	-
S18	47.00	59.37	-	-	-	-
S19	11.25	18.75	-	-	-	-
S20	34.50	43.75	-	-	-	-
S21	16.00	25.00	-	-	-	-
S22	27.00	34.37	-	-	-	-
S23	45.00	56.25	-	-	-	-

Note: 'Online 2' refers to the online accuracy obtained online at least one day later

Table 3.6

Comparison of accuracy of 8 target spellers offline and online

Subject	Offline(%)	Best Fold(%)	Online 1(%)	ITR(bits/min)	Online 2(%)	ITR(bits/min)
S1	83.75	87.50	88.00	32	91.60	35.22
S2	85.00	95.83	81.00	26.47	87.00	31.16
S3	70.00	79.16	68.75	18.39	62.50	14.89
S4	76.66	83.33	56.25	11.74	66.66	17.18
S5	74.16	83.33	68.75	18.39	**100.00**	**44.97**
S6	85.62	87.50	93.75	37.3	87.50	31.58
S7	83.12	93.75	93.75	37.3	95.83	39.49
S8	87.50	90.62	87.50	31.58	95.83	39.49
S9	70.60	81.25	**100.00**	**44.97**	70.80	19.63
S10	73.00	81.25	91.00	34.66	70.00	19.15
S11	60.00	71.87	83.33	28.22	75.00	22.30
S12	68.12	81.25	87.50	31.58	83.33	28.23
S13	80.00	90.62	87.50	31.58	54.00	10.70
S14	**90.00**	**95.83**	91.00	34.66	87.50	31.58
Mean±Std	77.68 ± 8.70	85.94 ± 6.96	84.15 ± 11.90	29.92 ± 9.74	80.00 ± 14.50	28.02 ± 9.78

Note: 'Online 2' refers to the online accuracy obtained online at least one day later

Table 3.7

Comparison of accuracy of 12 target speller offline and online

Subject	Offline (%)	Best Fold (%)	Online 1 (%)	ITR(bits/min)	Online 2 (%)	ITR(bits/min)
S1	72.00	77.77	70.00	19.99	83.33	28.30
S2	41.67	47.22	-	-	-	-
S3	57.50	58.33	44.44	8.06	58.33	13.96
S4	46.77	54.16	44.44	8.06	50.00	10.26
S5	62.91	72.91	55.50	12.65	66.66	18.16
S6	**84.50**	**90.62**	94.33	36.90	83.33	28.30
S7	81.66	87.50	72.20	21.25	72.22	21.26
S8	82.50	87.50	**94.44**	**36.99**	**97.20**	**39.65**
S9	75.00	87.50	86.77	30.76	77.77	24.62
S10	58.33	64.58	63.88	16.70	61.11	15.31
S11	53.00	60.41	72.22	21.26	47.77	9.35
S12	75.55	80.55	86.50	30.56	75.00	22.91
S13	53.75	56.25	52.77	11.44	58.33	13.96
S14	78.75	87.50	69.44	19.68	86.00	30.20
Mean± Std	65.99±14.28	72.34±15.11	69.76±17.33	25.24±10.42	70.54±14.98	24.51±10.04

Note: 'Online 2' refers to the online accuracy obtained at least one day later

Table 3.8

Comparison of accuracy of 16 target spellers offline and online

Subject	Offline (%)	Best Fold (%)	Online 1 (%)	ITR(bits/min)	Online 2 (%)	ITR(bits/min)
S1	39.37	45.31	18.75	1.29	-	-
S6	**67.50**	**73.43**	34.37	5.08	-	-
S12	60.31	68.75	**71.87**	20.43	59.37	14.38
Mean± Std	55.06±13.49	62.16±13.51	41.66±27.08	8.26±9.34	59.37±0.00	14.38±0.00

Note: 'Online 2' refers to the online accuracy obtained at least one day later

CHAPTER 4
DISCUSSION

4.1 Feasibility and effectiveness of Consumer-Grade EEG Headsets

Our study explored the feasibility of using consumer-grade EEG headsets for developing a hybrid BCI speller, and we found it to be a viable option. However, it is important to note that consumer-grade headsets come with certain limitations. We observed that a larger number of samples were required to train the model compared to studies utilizing clinical-grade EEG headsets, such as the work by Xu et al. (2020). This could be attributed to the noisy data obtained from the consumer-grade headset, which may not offer the same level of signal quality as clinical-grade devices. Additionally, we found that longer stimuli duration was necessary to achieve better performance. Shorter durations resulted in reduced accuracy, potentially due to the less prominent SSVEP and P300 signals captured by the headset. Furthermore, as the number of targets increased, we observed a decline in performance, which could potentially be attributed to the influence of each target on the others. The crowded nature of the stimuli on the screen, with less spatial separation between them, may have caused interference and resulted in poorer signal quality. By acknowledging these limitations and considering the specific requirements and constraints of consumer-grade EEG headsets, it can still be effectively utilized for hybrid BCI Spellers.

4.2 Long-term viability of the ensemble TRCA trained model

Based on the results of our study 2, we discovered that the TRCA trained model exhibited consistent performance even after a few days. We conducted an assessment immediately after the offline experiment and another assessment at least one day later, and found that the model's performance remained similar. This finding suggests that it is feasible to combine data from multiple sessions, enabling us to gather training data from a single participant across multiple days. By doing so, we can alleviate user fatigue and effectively train the model using a broader range of data.

This long-term viability of the TRCA trained model opens up new possibilities for developing robust and sustainable BCIs. By utilizing data collected over multiple days, we can enhance the overall performance and reliability of the system. Further research and experimentation in this area will be valuable in optimizing the training process and maximizing the long-term potential of TRCA-based BCIs.

4.3 Inter-individual Variability in Performance

The variability in participants' performance in our study can be influenced by several factors, including their level of alertness, ability to focus, sustain attention, and exhibit patience. Fatigue or drowsiness can impair concentration and performance, leading to lower accuracy. Participants who struggle to stay focused or experience mental fatigue may also encounter difficulties in maintaining consistent performance. Additionally, individual differences in attentional control can play a role in performance variations. Participants with better attentional control tend to perform more accurately and efficiently. Understanding these factors can assist in optimizing the design of BCIs, tailoring them to individual needs, and enhancing overall user experience and performance. Further research can explore additional subjective and objective assessments to gain a deeper understanding of these factors and their impact on BCI performance.

4.4 Guidelines

1. Utilize Wet Recording: Although the g.tec Unicorn Hybrid Black Headset supports dry recording, we recommend starting with wet recording. This method produces higher-quality signals that are less affected by participant movement or external disturbances. By opting for wet recording from the beginning, researchers can ensure optimal signal quality, leading to better results.
2. Maximize Sample Collection: It is advisable to collect as many samples as possible for each class when training the ensemble TRCA model. Increasing the sample size in the initial stages enhances the model's performance and generalization capabilities, improving overall results.
3. Begin with SSVEP-only Speller: Prior to delving into hybrid BCI spellers, it is beneficial to begin with an SSVEP-only speller. This approach allows researchers to better understand the obtained signals and validate the working of the model and presence of SSVEP component.
4. Utilize Time and Frequency Domain Plots: Employ time domain and frequency domain plots, such as PSD plots and Short Time Fourier Transform (STFT) plots, from the outset. These visual representations aid in assessing whether the desired features are accurately evoked by the stimuli.
5. Account for Interparticipant Variability: Recognize that performance may vary

among participants. To account for this variability, it is advisable to include multiple participants in the initial development phase rather than relying solely on data from a single individual. This broader sampling can provide valuable insights and enhance the generalizability of the BCI system.

4.5 Implications

From our study it is known that yes we can use consumer grade EEG for developing a speller but when the target is not too many. It can better support lower number of commands smoothly for example move left, right, down. So in case of lower number of targets this headset can give better performance.

4.6 Limitation and Future Work

Currently based on the research so far we were able to support upto 16 target speller. However, since we found that the model is good for long-term performance exploring on combinind multiple session to better train the model and expand the speller could be possible. Furthermore, more techiniques can to

CHAPTER 5
CONCLUSION

The objective of this research was to develop a hybrid speller using a consumer-grade EEG headset, explore its limitations, document the development journey, and study the long-term viability of the ensemble TRCA model. Our findings revealed that replicating the exact work of Xu et al. (2020) with the consumer-grade EEG headset we had proved challenging. However, this led us to identify and understand the limitations of the consumer-grade g.tec Unicorn Hybrid Black Headset. Through alternative approaches, we were able to achieve positive results and make progress in developing a functional hybrid speller system. Additionally, we found that the ensemble TRCA model exhibited long-term viability, indicating its potential for practical applications.

The implications of this research are significant for the widespread use of speller systems. Consumer-grade EEG headsets offer a cost-effective and portable alternative to clinical-grade headsets. This research serves as a starting point for future improvements and advancements in the field. With further research and refinement, hybrid spellers using consumer-grade headsets can become more widely accessible to individuals, ultimately benefiting a larger population.

In conclusion, this research successfully tackled the challenge of developing a hybrid speller with a consumer-grade EEG headset. Despite the initial setback in replicating previous work, we identified the limitations of our equipment and devised alternative solutions. Through our findings, we demonstrated the feasibility of developing a hybrid BCI speller using a consumer-grade EEG headset. The long-term viability of the ensemble TRCA model further solidified its potential for practical application.

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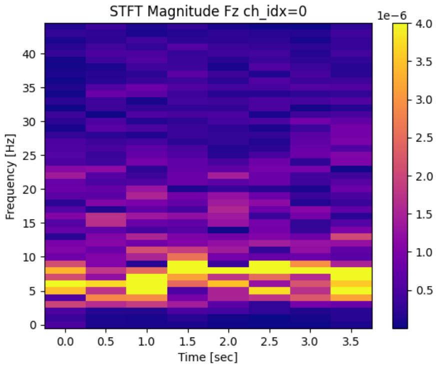
APPENDICES

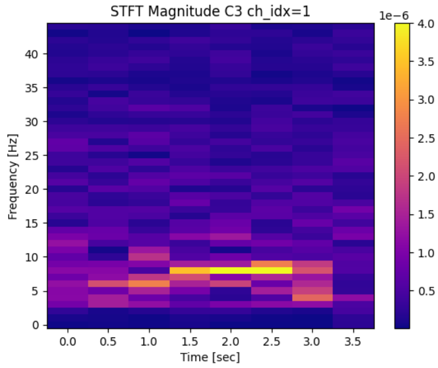
APPENDIX A: Time domain and Frequency domain plots

Figure 1 *STFT plot of character A flickering at 8Hz frequency*

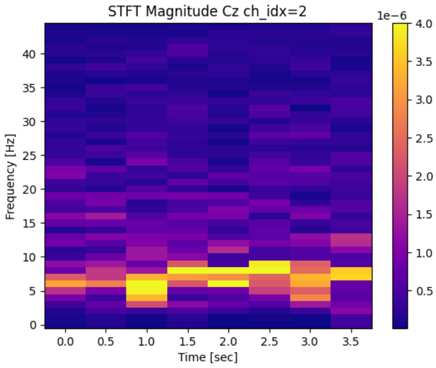
(a) *Fz*



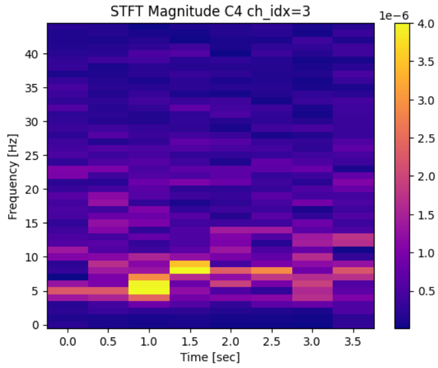
(b) *C3*



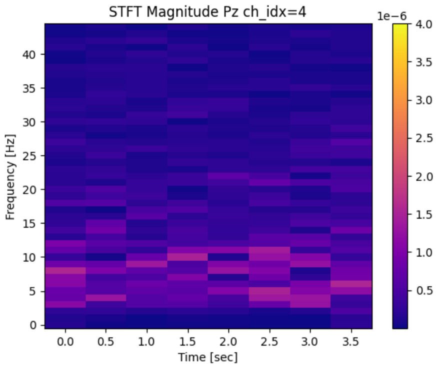
(c) *Cz*



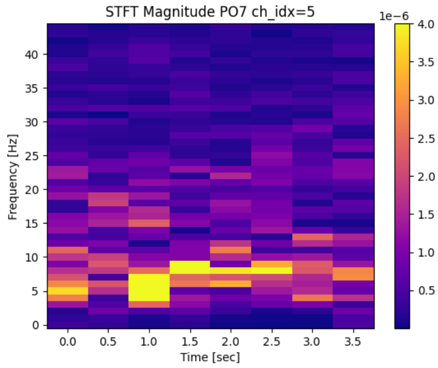
(d) *C4*



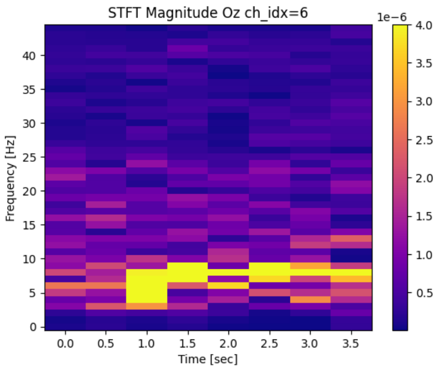
(e) *Pz*



(f) *PO7*



(g) *Oz*



(h) *PO8*

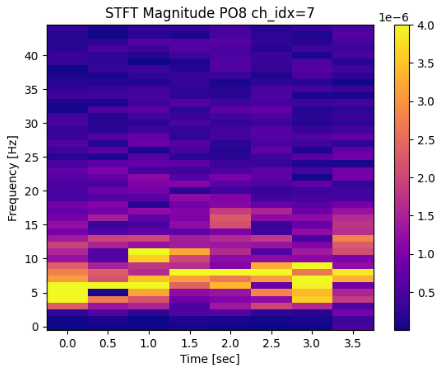
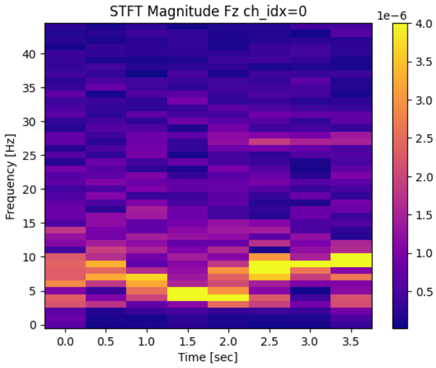
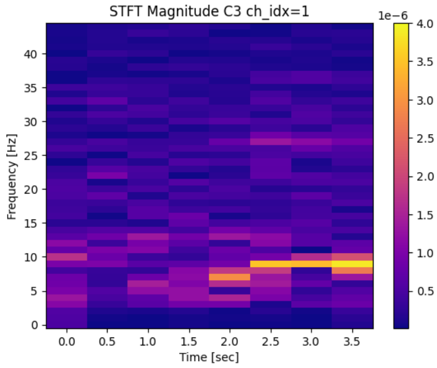


Figure 2 *STFT plot of character A flickering at 9Hz frequency*

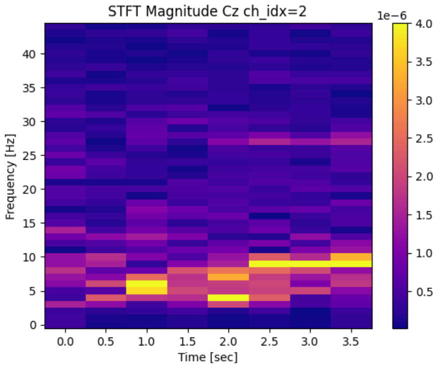
(a) *Fz*



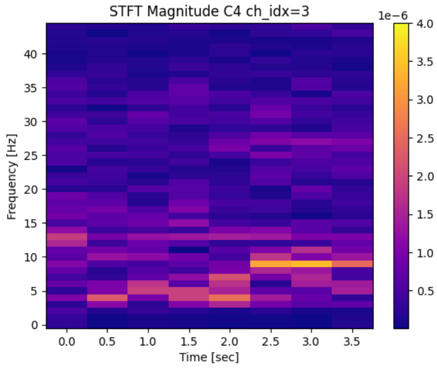
(b) *C3*



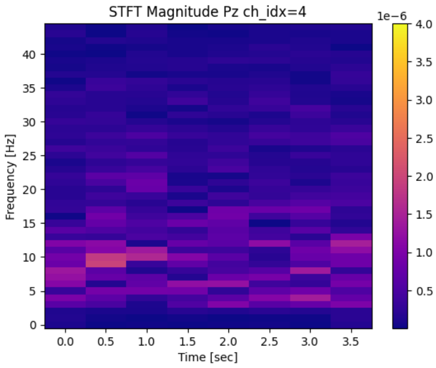
(c) *Cz*



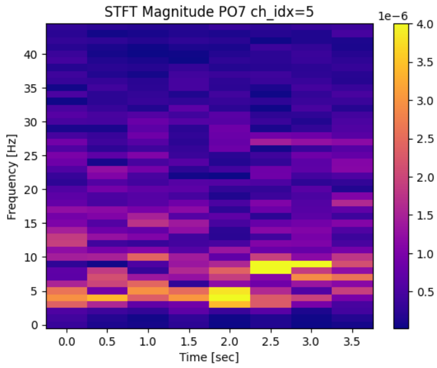
(d) *C4*



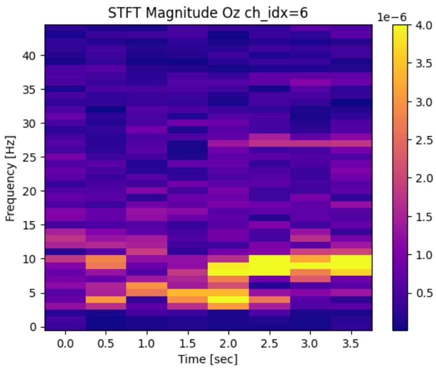
(e) *Pz*



(f) *PO7*



(g) *Oz*



(h) *PO8*

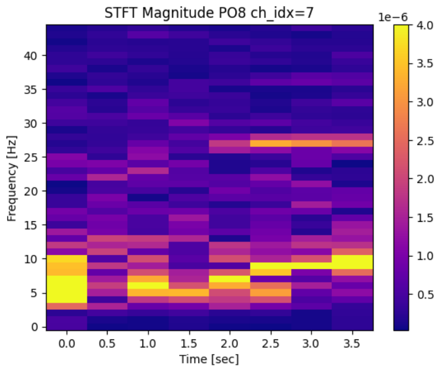
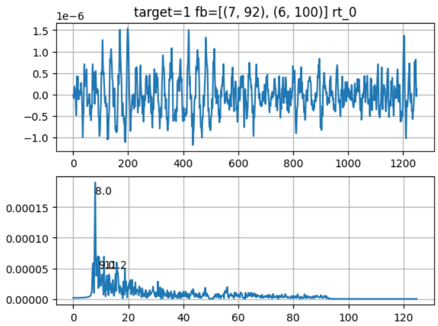
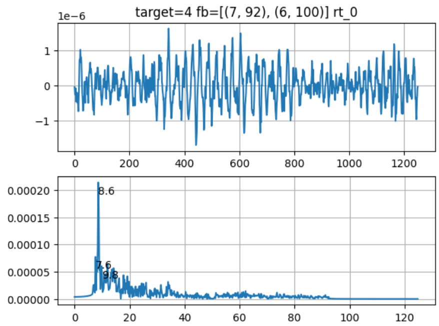


Figure 3 *Frequency and waveform plot of each subspeller of participant S8*

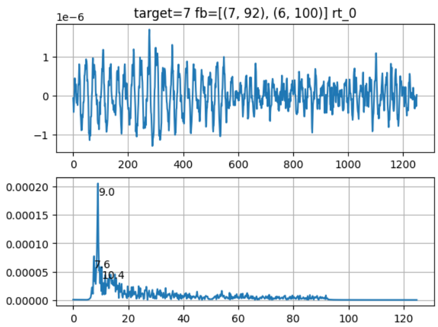
(a) *subspeller 1*



(b) *subspeller 2*



(c) *subspeller 3*



(d) *subspeller 4*

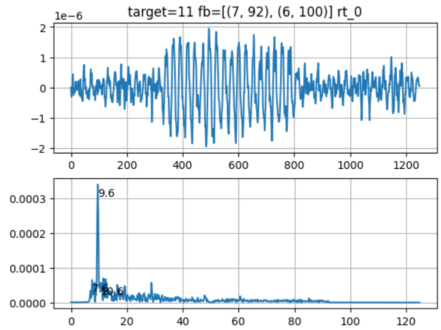
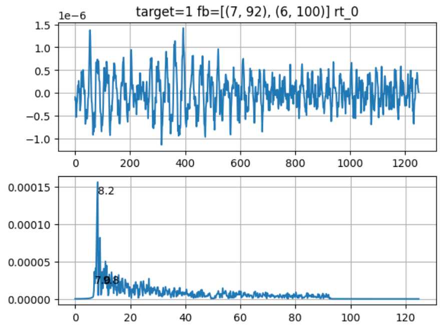
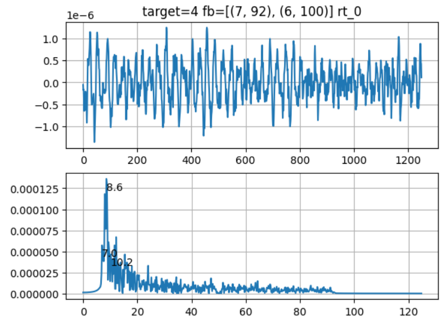


Figure 4 *Frequency and waveform plot of each subspeller of participant S4*

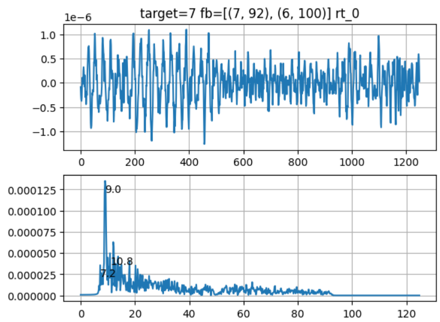
(a) *subspeller 1*



(b) *subspeller 2*



(c) *subspeller 3*



(d) *subspeller 4*