Evaluation of Consumer-Grade EEG Headsets for BCI Drone Control

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***Abstract*—Brain-computer interface (BCI) allows people to control a computer system using their brain signals. The recent availability of consumer-grade electroencephalography (EEG) headsets enables this technology to be used outside the lab. In particular, there has been interest in controlling a drone using brain signals. We propose a system that allows users to manipulate the thrust of the drone using consumer-grade EEG headsets. Active concentration, represented by EEG band powers, was investigated as an input modality for the BCI system. Comparisons were also made between different approaches in data retrieval and processing, as well as headsets. It was found that using supervised learning with SVM and the Muse headset resulted in better performance (around 70%). Offline evaluation shows that while both Emotiv Insight and Muse had comparable accuracy, Muse had better usability and was thus adopted in our system. Online user testing with the implemented BCI system revealed variable performance across subjects. This highlights the need for incremental training of both classifier and users for improved efficacy.**

I. Introduction

Brain-computer interface (BCI) provides a new way of interacting with devices, by allowing people to control a computer system through their brain signals without the need for physical activity. [1] BCI has huge potential as an assistive technology, for enabling [2] and rehabilitative purposes [3]. Unmanned aerial devices (UAV) or drones have been gaining popularity in our daily lives, such as in photography. Research has also been done in designing BCI for drone piloting. Such BCIs provide users with a hands-free method to control the drone, This field has potential in allowing the disabled to reach and interact with objects via the drone [4].

Electroencephalography (EEG) is one of the principle methods of acquiring brain signals non-invasively in BCI control applications [5]. Most research in BCI drone control uses research-grade EEG headsets with 14 to 64 wet electrodes. While such devices provide the benefit of high accuracy, they have limited usability due to tedious set-up and clean-up procedures, high costs and restricted movement [6], [7]. On the other hand, consumer-grade EEG devices are cheaper and have better usability, but are more vulnerable to noise and have limited sensors at fixed locations [7]. Nonetheless, consumer-grade EEG systems have been shown to be able to demonstrate various neural phenomena [6], [7]. Our proposed system uses consumer-grade EEG headsets with dry electrodes to simplify the set-up for drone control.

BCI paradigms provide different interpretation of brain activity based on the corresponding stimulus or motivation for system control. They include P300, Steady State Visually Evoked Potentials (SSVEP) and Motor Imagery (MI). Mental concentration is investigated in this paper. Several EEG markers have been identified to be correlated with mental workload, task engagement and attention [8], which gives rise to various indices involving EEG frequency bands to measure the level of engagement [9]–[12]. Most studies about the application of BCI in drone piloting involve the MI paradigm and EEG [13]–[16], and multiple modalities [17]. While achieving high accuracy, many of these systems require long training time across multiple days for each subject. One important contribution of this article is to investigate if mental concentration can be used as an input modality for drone control to simplify the learning process. In addition, mental concentration is a high level executive function that the user can directly control without the need for external stimuli, which other modalities like P300 require.

In this project, we aim to design a BCI that is suitable for controlling the thrust of the drone (up and down movement) using consumer-grade EEG headsets. While other research mainly focuses on a single design and its implementation, this article investigates and evaluates different approaches in designing the system. We consider the model of the EEG headset (Emotiv Insight vs Muse), approaches in data processing (data-driven vs domain-driven), and methods for collecting data for model building (explicit and induced concentration).

II. BCI Drone Control System

We propose the usage of mental concentration for drone control. There are two states: inattention and concentration. The BCI system will increase the thrust of the drone when the user is detected to be concentrating, and reduce if the user is determined to not be concentrating or if contact quality is poor. The Crazyflie 2.0 (https://www.bitcraze.io/crazyflie-2/) is used in this project. It is a small quadcopter that supports real-time parameter setting from multiple platforms (e.g. Windows, Linux) via radio protocol. Two popular consumer-grade EEG headsets are evaluated in this paper: Emotiv Insight and Muse 2014 by Interaxon. Table I shows the differences between both headets.

There are three main modules in the system (Figure 1):

TABLE I: Comparisons between two EEG headsets

Characteristics	Emotiv Insight	Muse 2014
No. of channels	5	4
Reference electrode location	Mastoid	Forehead
Frequency bands per channel	5	6
Data transmission rate	128Hz	220Hz
Raw EEG	Only with premium SDK	Yes
Cost	\$299	\$249

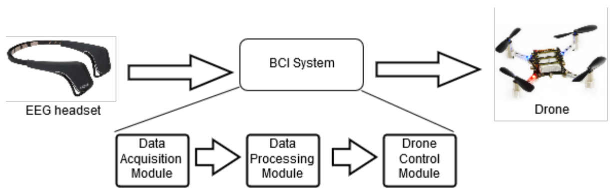

Fig. 1: Overview of proposed BCI system

1) Data acquisition that interfaces with the EEG device to acquire EEG readings
2) Data processing that performs feature extraction and converts the acquired data into a mental command (concentration state)
3) Drone control that converts the mental command to the parameters to pilot the drone

The modules have been implemented in Python. Communication between the different modules is established using the pub-sub protocol in the Zeromq library over TCP (zeromq.org).

III. Investigation of Design Approaches

Three experiments are designed to investigate different approaches of determining the state of intentional mental concentration using low-cost consumer-grade EEG headsets. In the experiments, the absolute EEG band power readings (extracted using Fast Fourier Transform (FFT)) provided by the headsets are used as representation of EEG activity.

A. Experiment Design

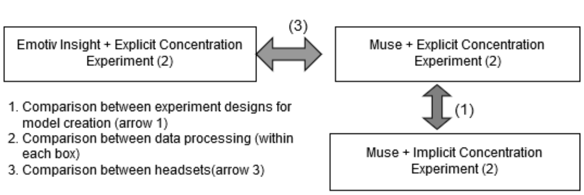

Fig. 2: Overview of Research Design

The experiments are shown in Figure 2. 10 participants were recruited for each experiment. They all have normal corrected eyesight and hearing, and do not have any psychological disorder.

Explicit Concentration Experiment (ECE) lasts 20 minutes with 20 iterations in total. A 2 mins break is given between the 10th and 11th iterations. Implicit Concentration Experiment

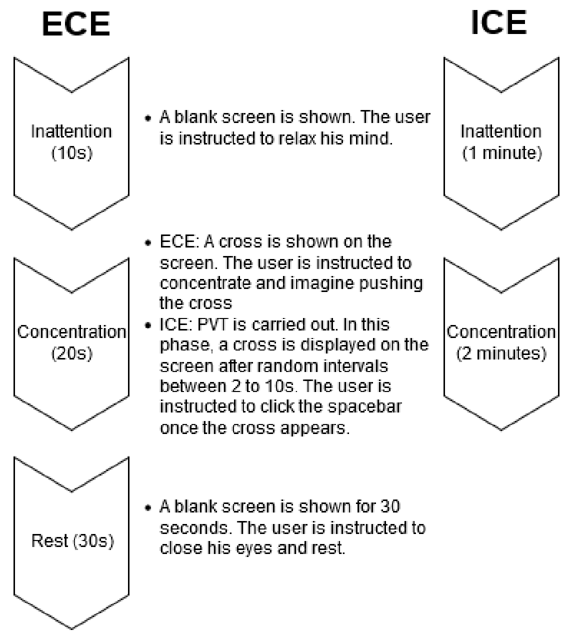

Fig. 3: Overview of Explicit Concentration Experiment (ECE) and Implicit Concentration Experiment (ICE)

(ICE) lasts 15 minutes with 5 iterations. No break is given during the experiment. The overview of the steps in each iteration is listed in Figure 3.

B. Evaluation Criteria

1) Comparison between experiment designs for model creation: We would like to compare between two data collection procedures for determining the threshold or building the model: explicit concentration and implicit concentration.

In explicit concentration, concentration is explicitly initiated by the subjects themselves by pushing the cross mentally; there is no external stimulus to induce them to concentrate. This is to simulate the scenario of actual drone control, where concentration is actively carried out by the user without any external stimulus to induce it.

In implicit concentration, Psychomotor Vigilance Task (PVT) is used in order to induce attention from the user in the concentration phase. It follows a reaction timed paradigm, where subjects are instructed to react whenever a stimulus appears on the screen. In this case, we are making the assumption that induced attention is the same as self-initiated attention, and that reaction time of the user is a surrogate measure of concentration. EEG activity has been shown to be be influenced by PVT [18].

2) Comparison between data processing: Two approaches of processing the EEG band power data to determine the concentration state are investigated: the domain-driven approach and the data-driven approach.

For the domain-driven approach, we use the domain knowledge about concentration indices to determine if the user is concentrating. An absolute threshold for the concentration index is established, and the user is determined to be

TABLE II: Summary of indices used in domain-driven approach

Index	Source	Function
$\frac{\beta}{\alpha+\theta}$	Freeman et al. (1999) [19]	Task Engagement
$\frac{\beta}{\theta}$	Choi et al. (2014) [10]	Concentration
$\frac{\beta}{\alpha}$	Coelli et al. (2015) [9]	Engagement, Vigilance
Frontal asymmetry	Coan et al. (2003) [20]	Approach/Withdrawal

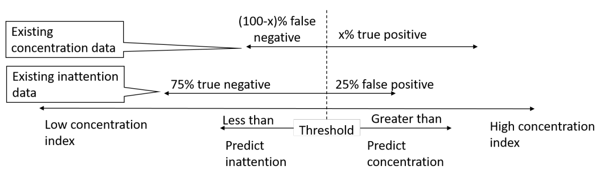

Fig. 4: Determination of concentration index threshold

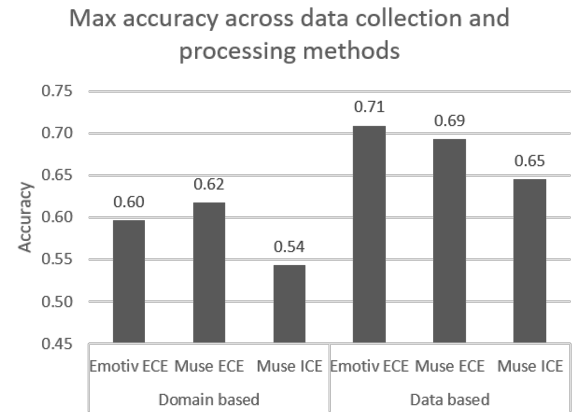

Fig. 5: Comparison of accuracy between data collection and processing methods

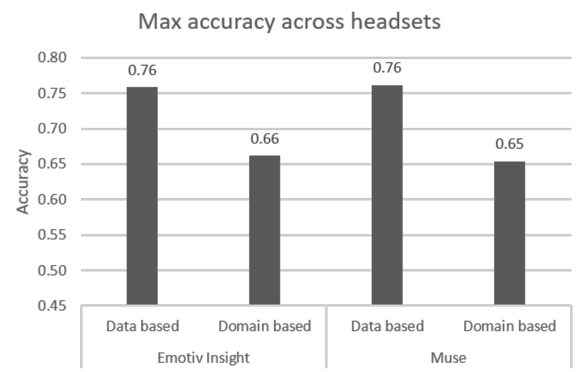

Fig. 6: Comparison of accuracy between Emotiv Insight and Muse

concentrating if the index exceeds the threshold. Existing indices proposed to measure attention and engagement are investigated in this section. These indices are listed in Table II. Frontal asymmetry is defined as $\frac{Power_{left}-Power_{right}}{Power_{left}+Power_{right}}$ or $\frac{Power_{right}-Power_{left}}{Power_{left}+Power_{right}}$, where $Power_{left}$ and $Power_{right}$ refer to the particular frequency band power at the left or right frontal electrode respectively.

In the data-driven approach, machine learning is used to build classifiers based on EEG band power data across different frequencies $(\alpha, \beta, \theta, \gamma)$ and electrode channels (AF3, AF4, T7, T8, Pz for Emotiv Insight; AF7, AF8, TP9, TP10 for Muse) as features. The relationship between EEG band powers and concentration is modelled via supervised learning, so that predictions on whether the user is concentrating can be made when the classifier is exposed to new data. The Random Forest Classifier and the Support Vector Machine (SVM) are evaluated in this paper.

3) Comparison between headsets: These rubrics are used for the comparisons between the Emotiv Insight and Muse headsets:

- Accuracy: level of classification accuracy
- Usability: set-up time and ergonomics
- Extensibility: developer's ease of obtaining data from headset, ability to extend on the data provided

C. Results

Referring to Figure 4, the subject-specific threshold for the domain driven approach is established as the 75th percentile of the indices during the inattention phase. The true positive rate of the domain-driven approach for each subject is calculated as the proportion of indices during the concentration phase that exceeds the threshold. The accuracy for the domain-driven approach is therefore calculated using $\frac{x+0.75}{2}$. On the other hand, accuracy for the data-driven approach is calculated using 5-fold cross-validation accuracy over the combined data across all subjects.

1) Comparison between data processing: Considering the maximum accuracy achieved across the different indices and machine learning algorithms for the domain-driven and data-driven approach respectively (Figure 5), the data-driven approach (0.71 for Emotiv ECE, 0.69 for Muse ECE, 0.65 for Muse ICE) yielded better results than the domain-based approach (0.60 for Emotiv ECE, 0.62 for Muse ECE, 0.54 for Muse ICE). The poor performance of the domain-driven approach might be due to the difference in band power calculation and experimental methods. It also suggests that it may be too simplistic to determine the user's concentration state based on a sole index, for the relationship between EEG activity and concentration might be more subtle.

2) Comparison between data collection: Comparing between ICE and ECE using Muse headset (Figure 5), better classification accuracy in both the domain-driven and data-driven approaches was achieved for ECE (0.62 and 0.69 respectively) than ICE (0.54 and 0.65 respectively). This shows that absolute band power readings at Muse's electrode sites are more effective in distinguishing intentional mental concentration than induced vigilance. Our assumption that reaction time of the user can be used as a surrogate measure of active concentration might be unfounded too. In other research involving PVT, the level of vigilance is identified

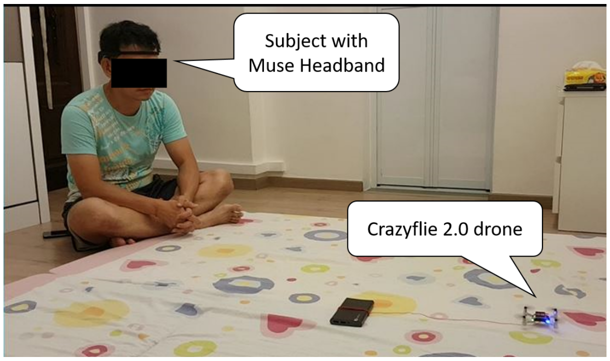

Fig. 7: Photo from non-cue-based experiment

using EEG activity measured using electrodes densely located at the posterior regions of the scalp [21], [22], or additional features such as raw frequency readings and variance [18]. This indicates that it may not be sufficient to solely use EEG band power reading from the limited electrodes in the Muse headset.

3) Comparison between headsets: Referring to Figure 6, both Emotiv Insight and Muse have approximately the same maximum cross-validation accuracy. However, the performance of the different classifiers vary greatly between Emotiv Insight and Muse. This difference is observed even when between features obtained from the same region of the scalp (such as AF3 and AF4 for Emotiv Insight, and AF7 and AF8 for Muse). This might be due to the differences in hardware and signal acquisition methods of the headsets.

With regards to usability, Muse received more positive feedback than Emotiv Insight headset. A higher level of comfort was reported the Muse headset, as the headset has an adjustable band which can cater to different head sizes. Furthermore, the set-up time required for Muse is much shorter than Emotiv Insight, for it is difficult to establish good contact quality with the latter. The ergonomics of Muse is more favourable, and contributes to better user experience.

For extensibility, the Emotiv community SDK has more non-EEG data available than the Muse, such as electromyography (EMG) and gyroscope data. With more input options available to complement the EEG readings, there is greater potential to build a hybrid BCI with Emotiv Insight. On the other hand, raw EEG data and FFT readings are freely available with the Muse, but not for the Emotiv community SDK. Therefore, enhanced EEG feature extraction is only possible with Muse, where we can access and process the raw data manually.

IV. Evaluation of Overall BCI System

In this section, we assess the performance of the overall BCI system in terms of its efficacy and usability. Table III lists the algorithm and parameters that lead to the highest cross-validation accuracy and are used in the final system.

TABLE III: Parameters used in implemented BCI system

Approach	Data Driven
Algorithm	Support Vector Machine (SVM)
Parameters	Kernel=RBF, C=0.25, gamma=0.1
Experiment	Explicit Concentration Experiment
Headset	Muse 2014
Features used	Absolute α, β, γ, θ band powers from AF7, AF8

A. Experiment Design

Four experiments were conducted to achieve these aims: the cue-based and non cue-based experiments, each repeated twice with subject-independent and subject-dependent classifiers.

1) Cue-based Experiment: The aim of the cue-based experiment is to measure the accuracy of the classifier given out-of-sample data, without influence of the drone. It consists of 10 iterations. The outline of each iteration is shown in Figure 8.

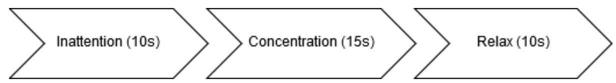

Fig. 8: Overview of each iteration in cue-based experiment

- Inattention: The user is instructed to relax his mind.
- Concentration: The user is instructed to concentrate.
- Rest: The user is instructed to close his eyes and rest.

6 participants were recruited, and the classifiers were built according to the data collected from them in the ECE. Each subject is given 5 minutes prior to the experiment to practise with the classifier. The predicted concentration state is displayed on the screen throughout the experiment.

2) Non-cue-based Experiment: The suitability of the system for drone control is evaluated. Subjects who managed to achieve an accuracy of more than 50% in the cue-based experiments participated in the non cue-based experiment. They are given the goal to make the drone fly for 5s, before landing it onto the ground. This is done twice: with the user looking at the feedback screen on the computer, and the other with the user looking at the drone directly. Feedback about the setup process and usability of subject-independent and subject-independent classifiers was seeked for in the questionnaire.

3) Classifiers: The subject-independent classifier is a single classifier built based on the combined data across all subjects, and is used for all subjects. On the other hand, the subject-dependent classifier is built for each individual based on his or her own data.

B. Evaluation Criteria

1) Out of sample performance: We assess the performance of the classifier in the data processing module given new testing data through the cue-based experiment.

2) Comparison between classifiers: We compare if a general subject-independent classifier or a personalised subject-dependent classifier would have a better out-of-sample performance. If the subject-independent classifier has a better

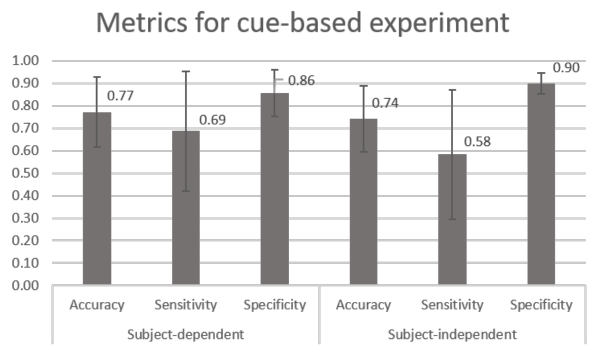

Fig. 9: Mean accuracy, sensitivity and specificity for cue-based experiments

performance, it suggests that EEG activity across the users share similar statistical patterns, so that a single classifier is able to represent it with adequate accuracy. However, if EEG activity is statistically unique for each user, we would expect the subject-dependent classifier to perform better.

3) Usability: This is assessed through the non cue-based experiments, via practical trials of controlling the drone in the non cue-based experiment. A questionnaire is given so as to get their feedback about their experience controlling the drone and wearing the headset.

C. Results

The performance of the classifiers in the cue-based experiments was evaluated using the accuracy, specificity and sensitivity metrics.

1) Out of sample performance: Referring to Figure 9, mean accuracy metrics for the subject-independent and subject-dependent models are 0.74 and 0.77 respectively, showing that the classfiers are able to perform reasonably well on out-of-sample data. For both models, specificity was the highest, followed by accuracy and finally sensitivity. This shows that the models are able to predict inattention more precisely than concentration. While a higher sensitivity would have been ideal, it is more desirable to have poor sensitivity than poor specificity for practical drone control, as false positives (that comes with poor specificity) resulting in powerful, uncontrolled drone movement may cause injury to people. However, the susceptibility to false negatives is still a limitation of the system.

2) Comparision between classifiers: Referring to Figure 9, the mean improvement in accuracy and sensitivity in the subject-dependent model was higher than the loss in specificity for the subject-dependent model. This shows that the overall performance of the subject-dependent model is better than the subject-independent model. This seems to suggest that the brain activity and method of explicit concentration may not be universal among individuals. The general model may thus be less able to capture the differences in the ways the subjects concentrate, which indicates that having a personalised classifier for each subject may contribute to better control of the drone.

However, individual performance varied, as not all subjects had better accuracy with the subject-dependent classifier. This shows that the subject-dependent classifier itself may not be an accurate representation of the individual's overall brain activity across different attempts, since the data used to train the model was only collected from one session for each individual. The variation in accuracy might also be due to insufficient representative features, for which further feature engineering is required in order to investigate this discrepancy.

3) Usability: Favourable reviews were received for the set-up process, highlighting the strengths of consumer-grade EEG headsets in allowing for quick set-up and comfort in using the headset. However, the subjects indicated that it was taxing to alternate between concentration and relaxation when controlling the drone. This was exacerbated when they were looking at the drone directly, for the movement of the drone acted as a distraction. The excitement and pressure that the subjects felt while trying to control the drone also made it hard to explicitly focus or relax, which affected both the accuracy and the mental workload experienced by the subjects.

V. Discussion

From Section III, we have determined that it would be the most suitable to use the Muse headset with data-driven approach in the BCI drone control system. In particular, SVM had the best performance out of all the classifiers, with the EEG band powers at AF7 and AF8 used as features. However, through validating the classifier on a test set, and user testing of the BCI system (Section IV), while the system received positive reviews about the set-up process and comfort, there were concerns about the high mental workload, and the variance of performance across the subjects.

The difference in performance between the subjects highlights the weaknesses of having insufficient representative data to train the classifier. In order to increase the accuracy across different individuals, subject-dependent classifiers can be created for each individual. An interactive machine learning model [23] can be introduced to allow designers to train and correct the errors of the classifier with new data across separate sessions. In addition, an incremental and interactive training process can be implemented for users to learn to produce a consistent brain activity. This will also reduce the mental workload of the user, by training them to the mechanism of the system. Other input modalities can also be considered to complement the BCI and allow for multi-parameter control. For example, we can introduce an eye-tracker in the existing system to build a hybrid BCI that allows people to move the drone left or right using their gaze.

More research can be done to improve the accuracy of the domain-driven approach. This can be done by utilising raw EEG data, and constructing our own indices by considering subsets of the frequency bands (e.g. alpha activity of a lower frequency which is known to increase with inattention [24]). Regression analysis can also be used to create more complex index from the existing indices. Such indices may be more representative of the EEG activity following active concentration.

To investigate the observed differences between the headsets, the band powers derived by the headsets can be compared with that obtained by independent control sensors. This will also aid in determining which headset is more accurate in distinguishing concentration from inattention. We can also consider investigating other BCI platforms, such as OpenBCI. OpenBCI has 8 electrodes that can be placed at any locations, which allows us to explore other modalities (e.g. SSVEP), and how they can be used for drone control.

VI. Conclusion and Future Work

BCI has great potential in providing a hands-free method for controlling a drone. Not only does it benefit the disabled as an option to reach remote objects, it is also a novel approach for recreational drone piloting. However, there is a need to balance between the accuracy and the usability (cost, set-up process, training) of the system. Using a consumer-grade EEG headset, we designed and implemented a BCI system for 1-dimensional drone control based on the user's concentration. Reviews of the usability were generally favourable, highlighting the strengths of consumer-grade EEG headsets in ease of use.

However, the actual efficacy of the system varied between the subjects, which shows the weaknesses of having insufficient representative data to train the classifier. Although this study has highlighted the potential of using consumer-grade EEG headsets for drone control, it would be fruitful to compare the consumer-grade EEG headsets with independent control sensors in order to accurately evaluate its EEG acquisition ability. To improve the usability of the system across all individuals, we can also look into implementing an iterative training process and evaluate other input modalities to complement the existing system.

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