THINK : Toward Practical General-Purpose Brain-Computer Communication *

Mohit Agarwal
School of Electrical and Computer Engineering
Georgia Institute of Technology
magarwal37@gatech.edu

Raghupathy Sivakumar
School of Electrical and Computer Engineering
Georgia Institute of Technology
siva@gatech.edu

ABSTRACT

In this paper, we present **THINK**, a practical general-purpose brain-computer communication platform that relies on the OpenBCI and OpenViBE hardware and software platforms, and allows for a simple three-alphabet vocabulary. Specifically, we consider the scenario where a subject is wearing a sensor array (an electrode cap), and consciously manipulating her thoughts to communicate wirelessly with an external computing entity (a smartphone) without the aid of any external stimuli. Using **THINK**, we explore general aspects of brain computer communication that are application agnostic. In particular, we study the following questions: (i) what is the accuracy of the system? (ii) how fast can the subject switch thoughts corresponding to symbols; (iii) is there an impact on accuracy with learning time; and (iv) how does accuracy drop with decreasing number of sensors (electrodes)? Using purely experimental analysis, we present some results that provide preliminary answers for these questions.

1. INTRODUCTION

The brain is the seat of all human intelligence, cognition, and behavior [1]. Hence, for most of known history, humans have conceptualized, fantasized, and explored the notion of communication directly through thoughts in the brain [2]. With the discovery of electroencephalography (EEG) in 1929, obtaining a simple window into the functioning of the brain became a reality [3]. At a high level, any brain activity occurs through the synchronized electrical firing of millions of brain cells (neurons) communicating with each other. Such activity can be detected externally through appropriate sensors on the scalp on the brain that sense activity in specific portions of the electromagnetic spectrum (typically in the 0.5-100 Hz). Over the last century, there have been tremendous advancements into the understanding of which sections of the brain are responsible for what kinds of activities, in spite of there existing several aspects of the brain's functioning that are less understood or complete blind spots.

Having a window into the activities of the brain allows for both passive measurements (where the subject is not consciously manipulating the brain waves), and active measurements (where the subject is consciously thinking for the express purpose of manipulating the brain waves that are then picked up by external sensors). Within active measurements again, the synthetic thoughts of the subject can be aided by external stimuli (e.g. strobe light flashing at a certain frequency) or can be a function of purely the thought processes of the subject. *The context for this paper is active measurements without any external stimuli.* We specifically consider the scenario where a subject is wearing a sensor array (an electrode cap), and consciously manipulating her thoughts to communicate wirelessly with an external computing entity (a smartphone) without the aid of any external stimuli.

This is not the first paper to explore such a scenario. There have been numerous efforts over the last few decades to harness brain computer communication (BCC), especially for people with disabilities [4, 5]. The unifying thread across all such efforts though is the singular focus on enabling a very specific application of brain computer communication in each of the settings. The goal of this paper though is different. With the very recent advent of open brain computer interface (BCI) platforms and technologies, it has indeed become possible to consider BCC through a broader lens. *The focus of this paper is to consider BCC as a general-purpose communication platform, and study certain key properties such as accuracy rate, think rate, learn rate, scalability, etc., in an application agnostic fashion.*

Briefly, we develop and present an experimental BCC platform called **THINK** that relies on two open platforms - OpenBCI and OpenViBE. **THINK** allows for BCC through the imagined movement of limbs, has a vocabulary size of *three*, and uses Bluetooth LE for communicating out.
THINK is built as a general-purpose communication platform and can conceivably be linked to any application simply as an input mechanism. We then use **THINK** to study generic properties of BCC such as the rate of accuracy, the rate at which symbols can be thought and hence communicated, and the impact of learning on the accuracy. We also consider some practical questions such as the accuracy to form-factor trade-off that could inform future practical BCC platform designs.

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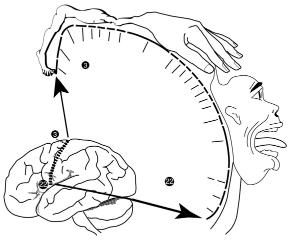


Figure 1: Motor Cortex and Cortical Homunculus

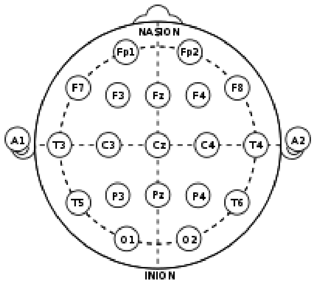


Figure 2: International $10-20$ System

We hasten to add that this is preliminary work and several of the results presented in the paper require further exploration and follow-up work. There are also several interesting avenues of exploration within BCC that the scope of this paper does not include. However, we do consider the contributions of this work as a key stepping stone to such deeper exploration. The rest of this paper is organized as follows: Section 2 provides a high level primer on the biology and physics of brain waves. Section 3 describes the two open platforms we rely on for our experiments. Section 4 presents the **THINK** architecture and prototype details. Section 5 discusses the experimental results and insights. Finally, Section 6 concludes the paper and presents future challenges.

2. BRAIN WAVES: A PRIMER

The presence of billions of neurons in the brain and their inter-communication through electrical impulses forms the basis of cognition in humans. Chemical activities inside the neuron cell body and dendrites result in depolarization and hyper-polarization of the cell membrane resulting in the generation of electrical activity. Neurons located in different parts of the brain are associated with different functionalities respectively. The electrical impulses produced are meant for either processing or transmitting information to the specific body part responsible for that functionality. *The superposition of a large number of electric pulses results in the generation of brain waves.*

Brain waves can be observed by planting electrodes either inside the grey matter (invasive) or on the scalp (non-invasive). Electroencephalography (EEG) is one of the most widely used non-invasive methods to record electrical changes on the brain scalp. EEG cannot capture a single neuronic activity. Instead, it measures electrical activity of a group of neurons (typically millions). It is similar to observing a wave arriving at a shore after it was generated in the heart of the ocean. EEG activity is generally measured in terms of frequency in *Hertz*. Brainwaves are categorized into six main categories: Delta ($<$ 4 Hz), Theta (4-7Hz), Alpha (7-14 Hz), Beta (15-30 Hz), Gamma ($>$30 Hz) and Mu waves (8-12 Hz). Each category (frequency band) has specific characteristics associated with different biological processes. An Internally or externally paced event leads to a change in EEG activity in the form of event-related synchronization (ERS) or desynchronization (ERD). ERS[6] and ERD[7] are characterized by an increase and decrease in the power spectrum of particular frequency bands respectively. *Mu and central beta rhythms display attenuation in power (a typical ERD) during imagination of specific limb movements [8].* These ERDs present contralateral spatial localization i.e. imagination of movement on the right side of the body is captured in the left hemisphere of the brain and vice-a-versa. The mu-rhythms are specifically localized over the motor and sensory areas of the brain, and hence are known as sensorimotor rhythms. A mapping of the primary motor cortex and the primary somatosensory cortex in the brain to motor and sensory body parts is illustrated in the *cortical homunculus* diagram shown in Fig.1. Left and Right hand movements are primarily concentrated over C4 and C3 positions respectively according to the international $10-20$ system shown in Fig.2.

A successful brain-computer communication system can be designed by capturing EEG and relying on modalities including Visually Evoked Potentials (VEPs), Mu waves, P300 and Alpha rhythms. Of these, Mu waves and Alpha rhythms do not require any external stimuli. As Mu waves are also theoretically capable of larger vocabulary sizes (unlike Alpha waves that differentiate only between rest and active states), for the platform presented in this paper, we rely only on detection and processing of Mu waves that are consciously manipulated by the subject through imagined limb movements.

3. OPENBCI & OPENVIBE PLATFORMS

The **THINK** prototype described later in the paper heavily relies on two related but independent open platforms, OpenBCI and OpenViBE, respectively for hardware and software. We briefly describe these platforms below.

Hardware Platform (OpenBCI). Before the launch of the OpenBCI board in 2014, all available BCI devices were limited in terms of limited access they allowed to raw EEG data, their closed architectures and costs. 'Open Source Brain Computer Interface (OpenBCI)' radically impacted BCI research by delivering a portable low-cost hardware interface to access raw EEG data. The OpenBCI platform is built with the ADS1299 IC at its core and a re-programmable 32-bit PIC micro-controller [9]. This low noise, 8-Channel, 24-bit analog to digital converter IC acquires, digitizes and amplifies the tiny EEG signals captured by the scalp electrodes. To enable the OpenBCI board to communicate outward, it is equipped with an RFduino and USB dongle that allows for a Bluetooth wireless link. Specifically, the RFduino present on the board is capable of communicating with smartphones or tablets over Bluetooth 4.0 Low Energy.

Software Platform (OpenViBE). OpenViBE is an open source software tool written in C++ and used for designing and testing BCIs [10]. It can acquire, filter, process, classify and visualize EEG data in real time. Its modular design allows for the processing and visualization of brain waves. It consists of several software modules/boxes that can be integrated and connected in order to design a signal processing chain. The latest version (1.0.0) comes with an OpenBCI driver to acquire signals from OpenBCI directly. It includes pre-configured scenarios for motor imagery and other BCI applications.

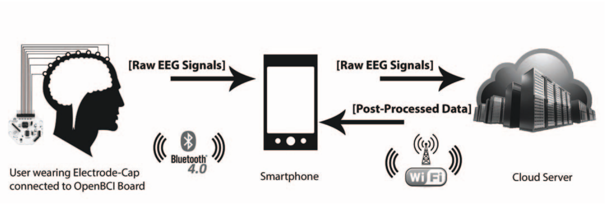


Figure 3: Workflow of **THINK** Prototype

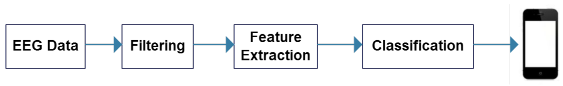


Figure 4: Signal Processing Architecture of **THINK** in OpenViBE

4. THE THINK PROTOTYPE

The goal of this work is to develop an interface to control handheld mobile devices via thought alone. **THINK** serves as a communication interface between the 'Human' and the 'Machine' with a vocabulary size of 3 ('Left', 'Right', 'Rest'). It transmits binary data (0 or 1) when the subject imagines the lifting of the 'Left 'or the 'Right' hand respectively. In 'Rest' state i.e. no imagination of limb movements, the system remains in idle state and does not initiate any data transfer. While exploration of a larger vocabulary size is out of scope for this work, we choose a vocabulary size of 3 for its balance of simplicity and usability (e.g. the system can support simple directives such as 'yes/no/no operation', 'left/right/no operation', etc.).

THINK is based on active measurements of the brain waves as the user consciously tries to manipulate the waves to effect control. The core mechanism behind **THINK** is motor imagery, since it does not require any external visual stimuli to operate and users can voluntarily control the system. **THINK** requires the user to wear an electrode-cap attached with the OpenBCI board, which is further connected to a smartphone over Bluetooth link[1]. The current prototype uses CAP-100C (by BIOPAC Systems Inc.) and 32-bit OpenBCI board. The OpenViBE application resides on an Internet server and receives raw EEG signals, processes them and labels them as one of the states out of 'Left', 'Right' and 'Rest' as depicted in Fig.3. The corresponding decoded state is transmitted as necessary to the smartphone on the same network through a vanilla TCP/IP session. The Smartphone application then displays the decoded state on the mobile screen. However, an observant reader would realize that the system can be modified to allow it to drive other third-party applications as well.

4.1 Signal Processing

For the signal processing component of **THINK**, the motor imagery scenarios present in OpenViBE are modified to suit the system requirements. Fig. 4 depicts the signal processing chain of **THINK** in OpenViBE. Briefly, the processing functions as follows:

1) EEG Data: Raw EEG data is acquired at the acquisition server running independently on an Internet server.
2) Filtering: The received EEG signals are digitally filtered in the 8-30 Hz band that includes Mu and central beta rhythm frequencies. The frequency filtered signals are allowed to pass through a *CSP Spatial Filter*. The *CSP Spatial Filter* generates new output channels by applying a linear combination to input channels (8-channels in this case) such that the variance for one class is maximized while at the same time the variance for the other class is minimized. The coefficient of the *CSP Spatial Filter* is learned by performing offline training sessions.
3) Feature Extraction: A signal epoch of the past one-second is generated every 1/16th of a second. The average power of epoch signals is computed and stored as features.
4) Classification: Finally, the features are classified into one of three categories ('Left', 'Right', 'Rest') using a Linear Discriminant Classifier (LDA). If the probability for decoded 'Left' and 'Right' classes is less than the preset threshold value, they are labeled as belonging to the 'Rest' class to boost the system accuracy.
5) Connecting with Smartphone: The decoded states from OpenViBE are finally sent to the smartphone through a TCP/IP session. The smartphone application plays the role of a client role and simply displays the result periodically.

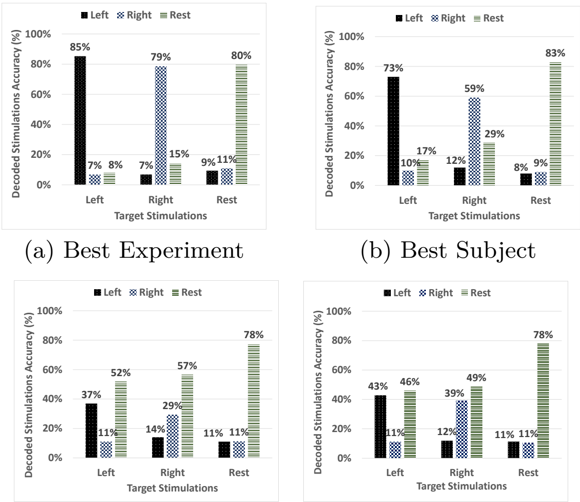
[1]Productized versions of the system can be more elegant and practical in terms of form-factor. We study the dependency on the number of electrodes to this effect later in the paper.

5. EXPERIMENTAL ANALYSIS

To evaluate the performance of the system, the 'Graz Motor Imagery BCI Stimulator' ([10]) script was modified to display 'Left', 'Right' and 'Rest' stimulation cues to the subject. Eight subjects were studied through trials that each lasted 11 minutes and 30 seconds. Each trial starts with the presentation of a fixation cross at the center of the monitor screen. After 3 seconds, a red arrow appears that indicates the corresponding stimulation cue. Users are required to imagine the lifting of limbs in order to initiate data transfer. **THINK** is capable of capturing different types of movements with different body parts, in this work we only evaluate **THINK** for the particular limb movements (Lifting of Left/Right hand). One experimental run consists of randomized distributed 30 'Rest' stimulation cues and 15 cues each for 'Left' and 'Right'. The rest of the settings are kept to the default values as in the script. During the imagination task, subjects were asked to remain motionless. The wireless data-rate of the system was measured to be approximately 64.45 Kbits/s. No optimization of this communication overhead was performed although there is scope for the same. The EEG Data was sampled using Biopac's CAP100C over T3, F3, F4, C3, C4, Cz, P3 and P4 positions according to the international $10-20$ system at 250 Hz. The ground and bias electrodes were attached to the left and right ear lobes respectively. The system is fully functional on its own without any requirement of external stimuli. External stimulations are used to evaluate the system performance.

5.1 Accuracy

Fig.5 shows the confusion matrix (where each row represents the predicted class while the columns represent the instances of actual class) for target and decoded stimulations in a graphical form for (a) best experiment, (b) best subject, (c) worst subject, and (d) all subjects. The 'best experiment' results show the performance for the best individual trial (Fig.5(a)) across all subjects. Out of the total of 80 trials (8 subjects, twice a day for 5 days), an average of 10 trials for each subject is calculated, and the best and the worst performances amongst the subjects are presented



(a) Best Experiment

(b) Best Subject

(c) Worst Subject

(d) All Subjects

Figure 5: Accuracy Measure

	Best Exp.	Best Subject	Worst Subject	All Subjects
Correct Classification	81.2%	72.3%	47.9%	53.4%
Mis Classification	11.3%	12.5%	15.9%	15%
Neutral Classification	7.5%	15.2%	36.2%	31.6%

Table 1: Accuracy Metric

in Fig.5(b) and Fig.5(c) respectively. Fig.5(d) presents the averaged performance across all 80 trials. For the best experiment, the system outputs 85% of time correct stimulations for 'Left' cue, 79% for 'Right' and 80% for the 'Rest' cues. We define the accuracy measure using three different quantities which are presented in Table 1.

1. Correct-Classification: Counts all target stimulations that were decoded correctly.

2. Misclassification: Stimulations corresponding to the following target-decode pair, *'Left' to 'Right'* or *'Right' to 'Left'* or *'Rest' to 'Left/Right'*. This quantity hurts the performance of the system.

3. Neutral-Classification: Counts instances when 'Left' or 'Right' target stimulations are decoded as 'Rest'. This reduces the data rate of the system by keeping system in idle state when a transmission is intended.

For the best experiment, the three defined accuracy measures are 81.2%, 11.3% and 7.5% in order.

A relatively large variation in the accuracy measures for different subjects across different experiments can be observed in Fig.5. The averaged correct classification accuracy obtained for best subject, worst subject and all subjects is 72.3% , 47.9% and 53.4% respectively , which is significantly lower compared to the highest (81.2%) indicating a large variance value. Even with the 53.4% accuracy rate, a practical system can be realized as misclassification occurs only 15% of the time (the rest of the errors are due to the Neutral-Classification (31.6%) status that simply lowers the data rate of the system.). Note that a completely random decision process would have an accuracy rate of 33%.

The system accuracy is highly dependent on the user's performance. Among all experimental trials, the accuracy metric attained a maximum of 81.2%. The same metric turns out to be 53.4% if averaged for all trials. Even a low accuracy rate (53.4%) is sufficient for practical BCC systems as long as there are few misclassifications (15%) occurring in the system.

5.2 Learn Rate

In this section, we evaluate the effect of training on individual's performance. Eight different subjects were studied twice a day over a course of five days. Their correct classification accuracy was averaged for each day and reported in Fig.6. It should be noted that these experimental runs did not involve providing of any kind of neurofeedback (a technique for training of brain) to the users.

From Fig.6, we can see that although performance metric improves for subject S2, S3 and S6 but there is no fixed pattern for the other users. Accuracy for subject S7 lies in 65%-80% block and rest of the subjects lies in 40%-60% block. From this, we can conclude that the mu-rhythms are indeed characteristic property of different individuals.

Evaluation of impact of biofeedback on learning rate would be part of our future work. We plan to design a system that can learn classification parameters simultaneously with allowing user to adapt to the system during experiment.

There is no considerable effect of training on learn rate without biofeedback. Performance for S7 varies in 65%-80% range while rest of the subjects lies in 40%-60% range, indicating mu-rhythms as characteristic property of an individual.

5.3 Think Rate

This particular experiment investigates the system performance as the time between thinking states is varied. *Think duration* is defined as the period of time a user is required to imagine the limb movements. This quantity controls the data rate of the system and could be impactful in developing a practical BCC system.

For the experiments, the *Think duration* was varied from 4 down to 0.5 seconds. It was not reduced below 0.5 seconds due to practical issues with a human responding to a fleeting stimuli. Experimental results were calculated keeping the epoch rate fixed to 0.25 seconds and the results are plotted in Fig. 7 for subjects S3 and S7. We observe that the performance metric increases with a decrease in the think duration. The performance curve increases from 46.1% to 66.9% and 51.4% to 68.6% in case of S3 and S7 respectively, accounting nearly 20% increment in the correct-classification accuracy in both the cases. An explanation for this trend is that subjects usually tend to think moving limbs for a fixed amount of time even if the stimuli duration is longer due to focus issues. Hence, all averaged signal epochs would not necessarily contain corresponding stimuli features resulting in mislabeling of data and a dip in performance for the longer think durations.

An additive increment of 20% is obtained in the system accuracy when the think duration is reduced from 4 seconds to 0.5 seconds. This enables the system to be more accurate when run on the faster think rates.

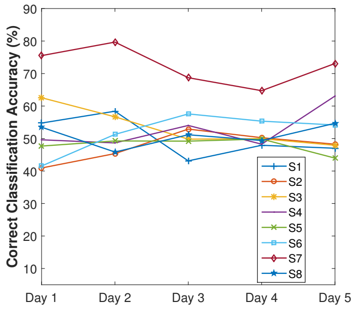


Figure 6: Learn Rate

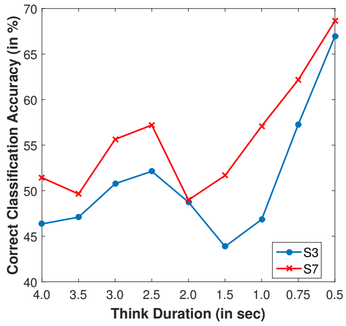


Figure 7: Think Rate

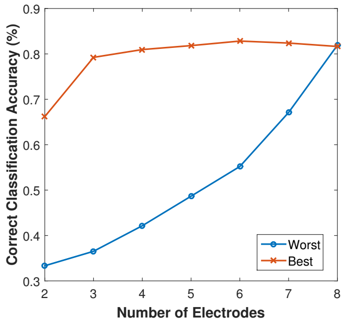


Figure 8: Number of Electrode

Electrode Count	Electrode Combination
2	C3,C4
3	C3,C4,Cz
4	C3,C4,Cz,F4
5	C3,C4,Cz,T3,F3
6	C3,C4,Cz,P4,F4,T3
7	C3,C4,Cz,F43,P4,F3,T3
8	C3,C4,Cz,P3,P4,F3,F4,T3

Table 2: Electrode Selection for Best Performance

5.4 Number of Electrodes

The form-factor of the electrode cap is a direct function of the number of electrodes required. Hence, the total number of electrodes and their selection are key aspects in designing BCC systems. Fig.8 presents the best and the worst obtained classification accuracies when the electrode count is varied from 2 to 8. The best and worst case scenarios are identified after a brute-force search of all possible accuracies with a given electrode count. The accuracy increases from 66.19% to 79.24%, and attains steady state afterwards. This shows that only 3 electrodes are sufficient if chosen optimally. Table 2 presents the best combination of electrodes against the electrode count. 'C3', 'C4' and 'Cz' being substantial positions in motor imagery context are subsets of electrode-sets for higher number of electrodes.
An exponential increase can be noticed for the worst case scenario with increasing number of electrodes, ranging from 33.33% to 82.39%. The considerable gap between the worst and best performance curves highlights the importance of electrode selection.

Three electrodes are sufficient to design a practical system with accuracy up to 79.24%. The performance metric varies from 36.52% to 79.24% depending on the approach for electrode selection.

6. CONCLUSION

This paper considers the potential of BCC as a general-purpose substitute for current Human-Computer Interaction Systems. We demonstrate that a simple motor imagery scenario can improve the communication experience of users with a machine whether it be a smartphone, a tablet or a laptop. The accuracy results obtained through the experimental runs is promising enough to advance research in the field. BCC has historically been considered for the challenged and disabled people and EEG has been looked at for medical purposes only. We believe that the presented **THINK** platform and the associated experimental analysis serve as a valuable starting point for several new research directions in the area of brain-computer communication. There are a slew of challenges that we will explore as part of future research, including the following: (i) how large can the vocabulary size be for practical brain-computer communication? (ii) can other modalities of brain waves (e.g. VEPs, alpha rhythms, etc.) be used in tandem with Mu waves for better performance? (iii) what are the usability issues (e.g. wet vs. dry electrodes, perceived appearance when wearing electrode cap) with brain-computer communication systems? and (iv) how intense and in what form does training need to be to elicit better accuracy rates?

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