We Know it Before You Do: Finding Recognition Patterns in Brain Activity

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INTRODUCTION

Modern brain sensing technologies provide a variety of methods for detecting specific forms of brain activity. Only in recent decades advances have been made in neuroscience and brain sensing technologies in order to monitor the physical processes within the brain that correspond to certain forms of thought [1].

There are two types of Brain-body interfaces (BBIs), namely invasive (signals obtained by surgically inserting probes inside the brain) and non-invasive (electrodes place on body). Brain activity produces electrical signals that can be read by electrodes placed on the skull, forehead or other part of the body (the skull and forehead are predominantly used because of the bio-potential in these areas) [1].

The cost, size and complexity of many research systems obstruct evaluation with participants outside research laboratories. Thus most BBI evaluations have been laboratory exercises [2]. By using a non-invasive approach, research teams are able to get out from laboratories and medical facilities.

Primarily driven by growing societal recognition for the needs of people with physical disabilities, researchers have used these technologies to build brain-computer interfaces (BCI's), communication systems that do not depend on the brain's normal output pathways of peripheral nerves and muscles. In these systems, users explicitly manipulate their brain activity instead of using motor movements to produce signals that can be used to control computers or communication devices. The impact of this work is extremely high, especial to those who suffer from neurodegenerative diseases or other brain injury [1].

Although removing the need for motor movements in computer interfaces is challenging and rewarding, full potential of brain sensing technologies as an input mechanism lies in the extremely rich information it could provide about the state of the user. Having access to this state is valuable to HCI researchers because it may allow us to derive more direct measures of traditionally elusive phenomena such as task engagement, cognitive workload, surprise, satisfaction, or frustration. These measures could open new avenues for evaluating systems and interfaces. Additionally, knowing the state of the user as well as the tasks they are performing may provide key information that allow to design context sensitive systems that adapt themselves to optimally support the state of the user [1].

In this paper, we focus on the electroencephalograph (EEG), a technology used everyday in medical facilities and the most commonly used technology in contemporary BCI research. For general review of BCI research see [3,4,5].

Much EEG work related to the problem of task classification, which has received significant attention because BCI technology is most useful as an input control or communication device if the system is capable of discriminating at least two states within the user. With this ability, a computer can translate the transitions between states or the persistence of a state. Previous methods for accomplishing this can be divided into two approaches: operant conditioning and pattern recognition. Operant conditioning places the user in a tight feedback loop with the system output and the user must learn how to control their brainwaves in order to achieve the desired results. This approach is supported by Adaptive Brain Interfaces (ABI) that requires a training period [9]. On the other hand, pattern recognition places the burden on signal processing and machine learning techniques in order to recognize the signals associated with mental states or activities of untrained individuals without feedback from the system. The benefit of pattern recognition is that the tedious training and adaptation needed to bridge the gap between human and machine is performed by the computer rather than the human. From an HCI perspective, this approach is much more attractive because it can be applied to detecting and classification arbitrary states, rather than having the user generate pre-trained states on demand [1]. We utilized this basic approach in our work.

HARDWARE

This study required the monitoring of non-standard input (namely gaze and cognitive activity) as users completed the tasks. Specialized hardware was thus required to reliably capture the data.

In order to measure and record gaze information (or where the experiment participant is looking), we utilized eye tracking technology by Tobii [6]. This allowed us to monitor the focus of the participant's eyes as he or she scanned the provided images. Readings were made at an average rate of 70 readings-per-second.

To measure cognitive activity, we used the EPOC Headset distributed by Emotiv [7]. This device rests is worn on the head and has fourteen sensors to acquire neurological signals. The sensors make readings at an average of 150 samples per second. These readings are then wirelessly transmitted to a PC via Bluetooth.

SOFTWARE

We wrote three applications in order to capture and log the data and to present visual stimuli to the participants.

Both of the aforementioned specialized hardware devices required a dedicated program to capture input data. These programs were written in C++. After the data is read, it is transmitted over Ethernet. Each program uses a unique Ethernet port so that recipients can distinguish the source of the data.

The program that receives this data as input was implemented in Java. It acts as a server, receiving the data and logging it to a file in real time.

We designated a single program to log data for two key reasons. First, this method yields a comprehensive log file with data from different sources interspersed according to time. Secondly, this method avoids concurrency issues that can arise when multiple independent processes write to the same file.

The same server program is responsible for displaying images to the participant and advancing images when the user clicks the mouse button.

EXPERIMENT DESIGN

In our research, we were particularly interested in cognitive response to visual stimuli. Because perception necessarily comes before any report of perception, we took special interest in the moment of perception. We made it our goal to find recognition patterns in brain waves which preceded the physical act of reporting.

In order to prompt recognition patterns, we chose to ask participants to find errors (or "bugs") in computer code. This task suited our needs because bugs are not immediately apparent and require critical thinking to recognize.

First, we needed to write sample code which we could intentionally populate with errors. We chose to use the C programming language because of its relative simplicity and its ubiquity (C and C++ together are used in more than 25% of today's software projects [8]). We chose to write functions instead of full-fledged programs in order to minimize language-specific initialization code (i.e. including packages, declaring program entries, etc.) which could confuse participants.

We defined three distinct types of errors to insert into our code: lexical, syntactical, and logical. Lexical errors are instances of misspelled variables or functions. Syntactical errors include missing parenthesis or invalid characters. Logical errors are any errors which result in syntactically correct code but which do not serve the intended purpose.

The sample code was segmented into three equally-sized sections. We created a test instance for each of the three error types in each of the three sections, resulting in nine distinct test cases. (Please refer to the appendix for an example task.) Each test case was repeated three times so that the experiment contained twenty-seven tests in total.

STUDY

Participant demographics

The study comprised a total of 9 college-educated participants--7 males and 2 females. The age range for the participants was 21-35 years, and their backgrounds ranged like Computer Science, Human Computer Interactions and Psychology.

Problems encountered

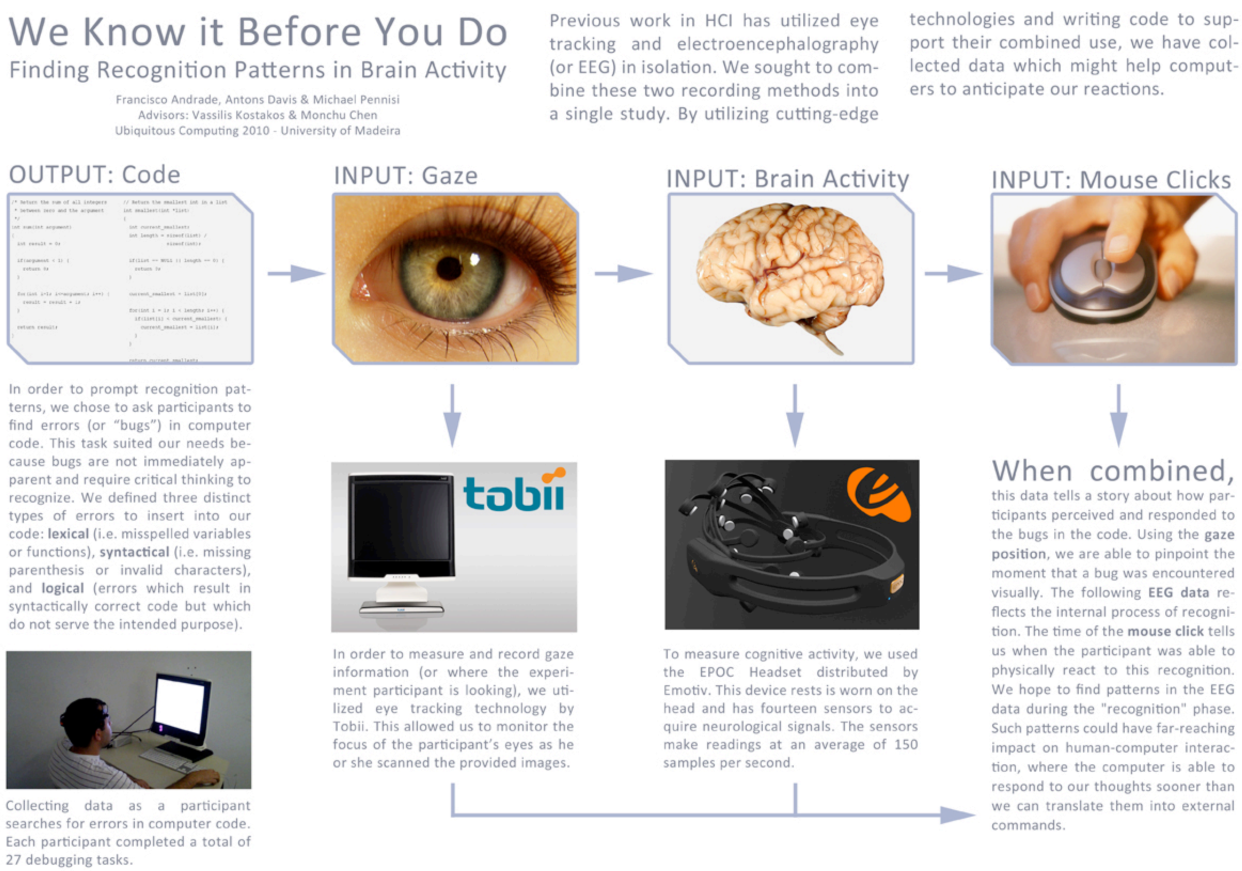
The Emotiv headset required elaborate setup procedure which required significant time and effort for the moderators as well as the participants of the study. Often the electrodes were not sufficiently lubricated to obtain EEG readings, or the electrodes failed to make sufficient contact with the participant's scalp while wearing it. It can be fairly speculated that the frustration in setting up the Emotiv headset may have had an impact over the initial set of EEG readings. It was also interesting to note that allowing the participants to place the Emotiv EPOC headset yielded better results, despite their not knowing anything about the headset itself.

The study relied on a client-server model for communicating with the eye tracker as well as with the Emotiv headset. It was noticed that when the eye tracker client was started after the Emotiv client, the server program was prevented from reading further data from the Emotiv client. To avoid this, the eye tracker client was run before the Emotiv client.

Preliminary findings

Of the 323 megabytes of data that was obtained from the participants, all the successful cases were narrowed down and the following data was summarized:

- Only 65 errors from a total of 216 errors were found by the 8 participants.
- Of these, 15 errors were syntactical, another 15 errors were logical and another 35 errors were lexical in nature



FUTURE WORK

Our next steps involve interpreting the corpus we have generated. There are many ways to do this, and we have begun planning various approaches.

One approach involves searching for trends within the successful trials. We use the compiled list of all successful cases, where the users were able to identify and locate errors. We plot the EEG data for a particular participant to show the brain activity, specifically looking at the time of identification of a problem to the time he takes an action and clicks the error. From here 2 approaches can be taken. Either we can try to trigger an action immediately on identification of the problem and thus minimize the time involved in explicitly taking an action on the user's side. Or, the brain activity can be analyzed to find points where the user subconsciously recognizes the error without explicitly realizing it. If such points can be correctly identified, the user can be aided in quickly seeing the exact errors minimizing the time involved in conscious recognition.

The data obtained show the electrical signals of the participant's brain from the time he is presented with the problem until he clicks for the next image. This can be plotted over time to analyze how his brain reacted to a specific problem. The brain patterns can be further analyzed to see the difference in reaction to cases he was sure of the solution, cases he was making a guess, or other cases where he had was unable to determine the solution.

Further study designs

While this study revolved around a debugging task, completely different tasks could be constructed to collect further data.

One such task is recognizing a slightly out-of-place feature of an otherwise-normal image. For instance, the user may be presented with an image of coffee beans where a human face is disguised to blend in amongst them. Completing this task would involve the user to identify face shapes and distinguish them from the coffee beans.

A related task involves finding slight anomalies in patterns. For instance, the user may be presented with a field of the letter N repeated many times over. He would be tasked with locating the single occurrence of the letter M amongst them. This is a simpler task than the former study as the user to has only to focus on the structure of the letters to find the solution

These proposed tasks are more diverse in nature compared to the somewhat rigid debugging task. However they require less use of tacit knowledge and are primarily based on pattern recognition.

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