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Quantifying Brain Activity for Task Engagement

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***Abstract*—This paper addresses the potential of the Brain Computer Interface (BCI) for self-quantification through recording and analysis of brain activity. From the electroencephalographic (EEG) signal it is possible to quantify and investigate brain activity, allowing, for example, a measure of engagement with tasks to be derived, states of relaxation or anxiety to be determined, or levels of alertness to be assessed. This can be of particular use in areas such as immersive education, where an objective measure of task engagement would be of value. As such it may be possible to measure engagement but also to identify people who may not be able to engage fully, such as people with dyslexia.**

Keywords—BCI; usability; self-quantification; EEG

I. Self Quantification

Since the earliest times the need for documentation of 'self' has been apparent. The Roman philosopher Seneca in the first century AD and United States founding father Benjamin Franklin in the 18th century both recorded personal wellbeing data in their writings [1]. In the 21st century, the confluence of social networking and ubiquitous deployment of sensor rich gadgets has provided a dedicated group of 'Quantified Selfers' [2]; their mission – promoting healthier lives. The gadgets comprise smart phones' accelerometers, bespoke activity trackers, weight scales and pressure transducers. Typical measures have included location, physical activity, calories burned, steps taken, and even quality of sleep. Logging of data in the cloud and comparison of trends over time can be compelling in pursuit of one's personal lifestyle goals; be they reduction of weight for a healthier lifestyle or improving a plethora of activity metrics for competitive sport. In this latter case, heart monitors that link to smartphone apps have become popular training gadgets for long distance runners. Indeed processing capacity is such that feedback can be provided in real-time, allowing corrective action to be taken. Of course 'Generation Y' (those growing up with social media) have a need to share such information to their friends; and communities such as Nike Plus[1] have even introduced a completive aspect, with virtual coaches inspecting achievements and challenges issued between 'virtual' training partners, even in different continents.

So is the data useful or just a craze for the techno savvy?

Larry Smarr, the ultimate 'Quantified Selfer', was able to self-diagnose that he had Crohn's disease by laboratory analysis of blood and stool samples [3]. This may be only the tip of the self-quantification iceberg. Personal genome testing using saliva potentially allows consumer-oriented ($1000 dollars per test) genetic testing which can diagnose or reveal potential future health problems; paradoxically the United States company, 23andMe[2] has run into regulatory problems with the US Food and Drug Administration due to negative consequences associated with misdiagnosis [4].

As these two examples of self-quantification illustrate, the focus of such activity is primarily on health, utilizing mature technologies for physiological data acquisition and analysis. However, one of the least understood parts of the 'self' is the brain. It controls all our aspects of daily living; a spectrum ranging from the autonomic to intentional control, problem solving and artistic flair. Its structure and function can be investigated by powerful imaging techniques, and is the subject of huge research projects. Indeed one of the key objectives of the multimillion dollar 'Obama BRAIN' project is to: "Understand how brain activity leads to perception, decision making and ultimately action" [5]. The chemical interactions within the brain give rise to measurable electrical potentials at the scalp, which can be measured non-invasively by surface electrodes. As technology has improved this may be an opportunity for further self-quantification, and further understanding. Section II discusses the potential of brain computer interface (BCI) technology for measuring the electroencephalogram (EEG). Section III provides an evaluation of this technology as appropriate to easier measurement of EEG and associated potentials. Section IV identifies an application area of immersive education, where this technology may be appropriate for quantification. Further discussion is provided in Section V.

II. BCI for Self-Quantification

BCI is a technology that has traditionally been targeted as an assistive technology for the most disabled of user groups. By enabling a communication pathway between man and machine through a set of thought based paradigms or stimuli enriched user interfaces, defined activity within the EEG can be detectable, thereby providing a pathway for communication and control. However, advances in both hardware and software have given rise to the development of BCI systems as another non-invasive physiological sensor. Consequently, consumer-grade BCI systems for non-medical "lifestyle" applications, such as brain training tools and cognitive state monitors, are becoming increasingly prevalent [6], [7].

With consumer neuroheadsets currently retailing for only a few hundred dollars, the sleeker designs, improved mobility and battery life has resulted in the scope for use of BCI reaching beyond assistive technology into domains such as

[1] http://www.nikeplus.com

[2] https://www.23andme.com

gaming, education, and health monitoring [8]. The improved accessibility of the technology, coupled with enhanced ease of use, has seen the technology employed within other domains of research where mental states and cognitive processes can inform on the subject's reaction to an environment or mental activity. For example, Aspinall et al. [9] used a consumer-grade BCI headset, specifically the Emotiv EPOC[3], to monitor the effect of the surrounding environment on the mental states of their subjects. They asked participants to walk through different areas of Edinburgh, which had been categorized as urban shopping streets, a green space, and a busy commercial district. From their recordings they looked for periods of excitement, frustration, engagement and meditation.

Crowley et al. [10] evaluated the use of the Neurosky's Mindset headset to measure the attention and meditation levels of a subject. They found that the device provided information about the user's change in emotions. Szafir et al. [11] present a system with an adaptive agent; the goal of monitoring and improving engagement. They also used the Neurosky Mindset EEG headset, gathering recordings from 4 electrodes. Reinecke et al. [12] separated out the EEG into the alpha, beta, theta, and gamma frequency bands and performed their analysis within these bands. Their results reinforced the capability of EEG as a suitable measure of user engagement and mental state, applied to sports science.

Zander et al. have also posited the use of such passive BCI; in [13] it has been suggested that passive BCI systems could be used to enable a greater understanding of important contextual information during mental tasks. Similarly, it has been proposed that electrophysiological patterns associated with specific cognitive processes, such as concentration, may be identified and explored using BCI technologies [14]. However, consumer-grade BCI technologies, such as the Emotiv EPOC headset, do not provide the full capabilities of research-grade amplifiers that are capable of 64-electrode placement; but these 'laboratory' systems are prohibitively expensive and would not meet the characteristics of a usable device in the wild! Consequently, this gives rise to the following question:

How can BCI devices with reduced specification but enhanced accessibility and usability enable another channel of information for the quantified self?

III. Evaluation of a Consumer-Grade Headset

In an attempt to determine an answer to this question, an initial pilot study was conducted, which evaluated a consumer-grade BCI device, the Emotiv EPOC, in order to assess its measure of EEG activity. Within this study four healthy participants were required to take part in a short recording session that lasted approximately 30 minutes inclusive of setup and data acquisition. In this preliminary experiment, an $N < 5$ was utilized to evaluate the usability, flexibility and EEG measurements of the Emotiv EPOC. Indeed, a larger sample size may have provided more conclusive results attaining to the ability of this device. Our goal, however, was to establish whether this device could be used pervasively and for the quantified self. A small sample size easily satisfied this requirement. The next phase of our work is to use this device within immersive education, which will consequently test its utility further thus rendering a larger N, in the preliminary experiment, unnecessary.

Before each session began the Emotiv EPOC was cleaned and prepared for use. The cleaning procedure involved a 50% diluted solution of white vinegar and a soft cloth. The rear of each sensor was gently agitated with this solution to remove any corrosion. Before each trial, all electrodes and felt pads were placed in a hydrator pack and a saline solution applied to each. After this, each electrode was secured to the device and positioned appropriately on the head of the participant. At the beginning of the session, the participant was required to undergo a training procedure facilitated by the Emotiv Cognitiv Suite, which employs various approaches such as EEG and electrooculography (EOG). It records and interprets a user's conscious EEG and intent so as to enable the user to manipulate virtual objects. The Cognitiv Suite was used to train a 'neutral' state plus four additional commands; left, right, lift, and drop. When training the neutral state the participants were required to relax, clear their thoughts and think of nothing in particular. To train the left and right commands, the participants were asked to focus their gaze on markers to the left and right of the screen. To train the lift command, the participants were required to clench their teeth, and to train the drop command the participants were asked to tap their left foot. Each trial commenced only after the individual participant had trained each command to an accuracy of greater than 70% (as advised by the Emotiv software). For all participants, each command had 3-15 training periods, with each training period lasting 8 seconds.

Once the session began, the participant was issued with twenty requests (e.g. move in one of four directions) and allowed ten seconds to complete each request. A five second rest period was given between each request in which the participant was asked to relax and simulate the neutral state.

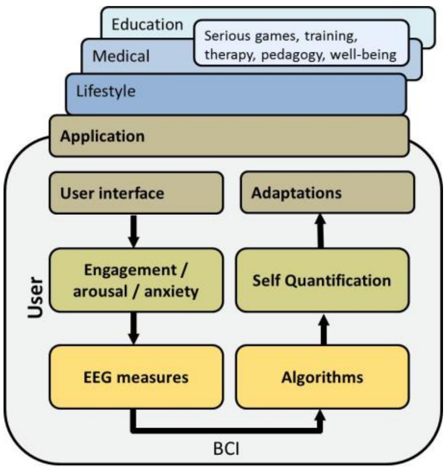

Fig. 1. Conceptual framework of EEG employed as a mechanism for self-quantification in education, medical and lifestyle environments.

For each of the twenty requests the participant had to concentrate on moving an object to one of four locations on the screen; top, bottom, left, or right. In order to move the object

[3] http://www.emotiv.com/epoc.php

right or left the participant was required to focus their gaze on a marker located to the left or right of the screen. In order to move the object up the participant was required to clench their teeth, and to move the object down the participant was required to tap their left foot. Including the training phase, each session took no longer than 30 minutes to complete. Curtailing a recording session to half an hour contrasts with normal laboratory-based recording, where set up time for electrode preparation and placement may take 15-20 minutes and cleaning time may add another five, yielding a total session time of approximately one hour. The easy to use interface with real-time feedback on the state of electrodes also improves usability, particularly where non-experts are involved. This has a significant impact on the user experience.

In this initial study, it was established that the use of a consumer-grade BCI headset (and accompanying software) for manipulating a virtual object based on gaze direction and actual movement is possible. Subsequently, the results are represented in Table I and Table II. These results suggest that the quality of EEG recorded using the EPOC is of an acceptable level, although further evidence is required.

TABLE I. TRAINING SKILL RATING

Subject	Sex	Overall Skill Rating	Left	Right	Lift	Drop
A	M	83%	86%	94%	76%	76%
B	M	79%	77%	71%	91%	78%
C	M	81%	74%	83%	87%	80%
D	F	81%	80%	95%	71%	78%
Mean:		81%	79%	86%	81%	78%

a. Skill ratings as a reported by the Cognitiv suite

TABLE II. SUBJECT ACCURACY

			Correctly Completed Requests			
Subject	Sex	Actual Accuracy	Left	Right	Lift	Drop
A	M	35%	1	1	5	0
B	M	85%	4	3	5	5
C	M	90%	5	3	5	5
D	F	45%	0	4	5	0
Total:		64%	10	11	20	10

b. Accuracy achieved for each subject for each request)

Over the initial training phases all four participants acquired a reported skill level greater than 70% for each command, which is displayed in Table I. Furthermore, it defines the skill rating of each individual command for all participants. In addition to this, Table II represents the actual accuracy and defines the number of each request that was completed correctly. Each participant exceeded the 20% accuracy expected by chance. The mean accuracy for all participants equates to 64%, with participant B and participant C performing greater than 85%. Each of the four commands was issued five times per participant in a stochastic order. All participants were able to correctly complete the lift command 100% of the time, the right command 55% of the time and the left and drop commands 50% of the time. However, some participants performed significantly better than others, indicating the inter-subject variability. Participant A and participant D were unable to perform the drop command successfully. This may be due to the vibrations caused from tapping the foot, which could have created noise in the scalp recorded EEG. The second least successful command was left since participant D could not complete it at all and participant A could only complete it once. Observation showed that inaccurate control of this command may be due to a difference in training and replication strategies, i.e. the participant trained the command on the correlated brain signal for eye movement but during the trial attempted to control the left command by turning their head to focus on the target. As both left and right commands are controlled by EOG, the software may have difficulties differentiating between the two, as a movement to the right is always followed by a return to the left, introducing the need for more considered synchronisation. Nonetheless, further investigation is required to achieve more conclusive results and provide a potential solution to this problem.

Within this study, it is evident that reasonable control can be achieved with little training. Nevertheless, there are a number of previous studies that suggest that the EPOC's performance is lower than that of a research-grade BCI [15]. These studies, however, do not address usability and flexibility, and it is clear from initial feedback that the EPOC was readily accepted and better in terms of usability. All participants had experience of research-grade devices and stated that the EPOC was much more comfortable and less difficult to setup. All participants agreed that, as with any BCI device, prolonged use causes fatigue. However, this preliminary study demonstrates that specific users are able to gain reasonable control with little effort, though suggests that this will not be the case for all users. A number of previous studies have conveyed that healthy participants are able to gain better control of BCI systems than severely disabled participants [16]. Consequently, if an adequate level of control can be achieved with a device of this nature, acting as an *active* BCI within an office setting, then it is reasonable to suggest that such a consumer-grade device may be more easily utilized to passively monitor EEG activity, thus increasing its feasibility for the Quantified Self movement. If this is the case, less accurate consumer-grade BCI devices could be used to acquire data that is representative of an emotional state such as stress, frustration or even attention span. Such a device is easily portable and may require no experimental assistance (if initial training is given), which reduces the barriers to entry for quantified self.

IV. IMMERSIVE EDUCATIONAL ENVIRONMENT AND SELF QUANTIFICATION

In order to address the effectiveness of any immersive environment, it is desirable to measure the level of engagement that a subject has with some computer-generated content being played. There are many possible use cases in which measuring the engagement of the user can be of benefit. It could be examples where safety critical factors are of key concern, such as flying an aircraft, or surgery. Our initial interest however, lies within the education domain. The results from our evaluation study suggest that the Emotiv EPOC is applicable in this domain, due to its usability, flexibility and EEG measures. Indeed, it may be appropriate to implement this BCI as a passive monitor in multiple use cases: 1) the lecturer; 2) the marker; and 3) the student. In each of these cases the goal may be to monitor attention levels and therefore, in the case of the marker, for instance, provide an alert to identify when a break is required. This is particularly interesting, as conventional objective measurement approaches involving visual (e.g. eye tracking) or aural sensing (e.g. speech analysis) does not necessarily indicate engagement with thought and reasoning. Collaborating EEG with eye tracking and/or other physiological signals such as blood pressure, it may be possible to measure engagement unambiguously.

To first evaluate suitable mechanisms for extracting such useful information it is important to understand how physiological signals, such as EEG, can be used to determine a measure of engagement. There is a significant body of evidence on the role of EEG in tasks such as determining levels of alertness, attention and cognitive tasks, suggesting strongly that measuring brain activity can form a valuable input to such a system [11]. The architecture illustrated in Figure 1 can provide an objective assessment of the behavioural state of a user (such as alertness, engagement or anxiety) and from this adaptively augment what the user perceives in the physical world. Using EEG, alone or combined with other sensor inputs, for behavioral assessment, it is possible to evaluate the degree of engagement (the active process of being "engaged" in solving a problem) or immersion (the passive process of being "immersed" in a particular material) that a user has with different types of digital content. The content can then be updated in reaction to the user's response.

V. Discussion and Concluion

In this paper we have argued that the 'quantified-self' paradigm can be extended to that of EEG acquisition and analysis. One domain that could benefit from such quantification would be immersive education. The key factor for the feasibility is whether the recording of the brain signals can be done 'in the wild' through inexpensive, portable, comfortable and relatively aesthetic headsets that offer a suitable level of robustness and capability. To date there is some evidence that such commercial headsets may provide enough capability. The aesthetics and usability of the recording headsets have improved in response to significant BCI research efforts and we have inferred from our initial work that such devices may be sufficiently accurate for passive BCI applications. An important educational 'use case' could be the automated assessment of learning for children with special educational needs such as sensory impairments, ADHD, autism, etc. Part of this could be the assessment of comprehension and assimilation of information provided to the subject. However there are many further possibilities. Over 1 million people in the UK alone are estimated to be living with the long-term effects of brain injuries. A sufficiently accurate EEG headset could provide ongoing monitoring for 'self-management' of this long-term condition; possibly even the monitoring of rehabilitation progress such as those recovering from stroke. Indeed, for the healthy population, in the longer term it may be possible to utilize passive BCI in order to assess general mood and wellbeing as an additional facet of self-quantification.

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