Computing, Brains and Geophysics?

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SUMMARY

Brain computer interface (BCI) systems emerging as a breakthrough technology of the 21st century. As is the case with other developing technologies, proof of concept must be demonstrated before advanced methods are pursued. This article presents the first published case study of a brain controlled geophysical software package. We show how brain computer interface systems can facilitate accelerated learning in the geoscience community. Our results show that processed brainwaves from the NeuroSky MindWave electroencephalography (EEG) device can be used to control various geophysical survey parameters with an acceptable degree of accuracy and to model the corresponding data in real-time.

Key words: BCI; CSEM; EM; Modelling; Software

INTRODUCTION

Brain computer interface (BCI) systems establish a connection between the brain and the computer. Progress in the area of computational neuroscience has exploded over the last 30 years. Accelerated development has been observed in the area of brain computer interface systems providing improved communication, recording and control capabilities (Ekandem et al., 2012). There is an increasing use and demand for BCI systems including applications such as lie detectors that use functional magnetic resonance imaging (fMRI), video games controlled using electroencephalography devices (Ekandem et al., 2012). The increase in use and development of BCI can be attributed to improved signal processing, electrical components and growing awareness of its capabilities. BCI works by measuring, processing and translating the electrical signals of the brain into a computer response. No geophysical software controlled by BCI technology exists to our knowledge.

The acquisition device we have used for our experiment is the NeuroSky MindWave (Neurosky, 2012). The NeuroSky MindWave is one of the first commercially portable electroencephalography (EEG) devices (Neurosky, 2012). It functions as a lightweight and wireless basic EEG device. An EEG measures the electrical activity recorded at the level of the scalp by electrical potentials generated from the firing of neurons during various levels of mental activity (Hall and Guyton 2011). It is commonly quoted that the human brain contains 100 billion neurons and ten times more glial cells, but the absolute number of neurons remains unknown (Azevedo et al. 2009) it is expected that the number remains in the billions. These neurons generate electrical signals which are propagated throughout the brain. This can be likened to a complex system of electrical wires. In order to generate recordable electrical potentials at the level of the scalp, an action potential (i.e. a voltage) must be generated. An action potential is a chemically induced process resulting in a rapid change in the cells membrane potential. This rapid change produces a voltage. The action potential allows the transmission nerve signals along nerve fibre membranes. A complex series of chemical changes must occur within a nerve fibre in order to generate an action potential, explained at length in Hall and Guyton (2011). This process begins with the normal resting membrane potential of approximately -90mV. An influx of positively charged sodium ions into the cell (approximately -55mV) to produce an action potential. The action potential is terminated by both the inactivation of the initial sodium channels opening and then the opening of potassium channels, allowing positively charged ions to escape out of the cell returning the nerve fibre membrane to its original state (Hall and Guyton 2011). Many action potentials occur throughout the human brain, which generate a potential difference, measured in voltage. An EEG device consists of several electrodes placed on the scalp that measures the potential difference between these electrodes (Schalk et al. 2004). The EEG records transient potentials generated from synchronous firing of individual neurons, the sum of which is sufficient to be recorded from the scalp (Hall and Guyton (2011) and Nunez and Srinivasan, (2006)). These transient potential differences are transformed into frequency bands via the fast Fourier transform (NeuroSky, 2009). Neurons acting together at a specific moment in time to perform a specific function or task, oscillate at particular frequencies (Demanuele et al., 2012) which have been grouped into frequency bands. The universally accepted EEG bands include

i. theta (4-8Hz),
ii. alpha (8-13Hz),
iii. beta (13-30Hz),
iv. gamma (30-49Hz) and
v. delta (0.1-3Hz)

(See Miller (2007), Demanuele et al. (2012), NeuroSky (2009), Hall and Guyton (2011)). Alpha, beta and gamma waves are found in the normal waking EEG (i.e. alert state), whereas theta and delta activities are rarely found in wakefulness (theory of normal waking EEG article). Alpha waves indicate relaxed consciousness (NeuroSky, 2009) or being awake but at rest (Hall and Guyton 2011). It has also been traditionally thought of as an "idling rhythm" Miller 2007). Beta waves represent a level of increased alertness (NeuroSky, 2009) and manifests when a person has their attention focused on specific mental activities (Hall and Guyton, 2011). The degree of alertness is differentiated by the amplitude level in sub-frequency bands within the greater beta frequency band. The higher the beta frequency spectra the greater the agitation, while the lower frequency spectra indicates wakefulness and alertness without agitation (NeuroSky 2009). The gamma band is of the highest frequency and is thought to represent motor functions and higher level mental activity (NeuroSky 2009). The theta band is thought to encapsulate creativity and imagination (NeuroSky 2009). Delta is associated with deep, slow wave sleep (Hall and Guyton 2011) and unconsciousness (NeuroSky 2009). Other research suggests that lower frequency osciallations of delta, theta and alpha waves are useful for integration across far flung cortical regions (Knyazev, 2011). Higher oscillations of gamma and beta are throught to handle localised computations, which do not require the same level of integration between various cortical areas (Knyazev 2011). We focus on the 'attention' and 'meditation' components of the brain wave.

We utilise the Neurosky derived values of alpha and beta waves. The Neurosky Mindwave records a 12 bit voltage at 512Hz with the measurements recorded as raw voltage. These signals are processed by the proprietary NeuroSky Mindwave drivers and processing algorithm, 'eSense', into values labelled as 'attention' and 'meditation', the neuroscience defined frequency bands are also computed (NeuroSky, 2009). These 'eSense' readings are recovered at 1Hz intervals and attention and meditation values are derived from the alpha 1 and 2 (attention) and beta 1 and 2 (relaxation) waves respectively. Attention is related to focus whilst meditation is related to relaxation. BCI systems have been used throughout the world at an ever increasing rate and we are only truly beginning to see its full potential. BCI systems have traditionally been used in medical settings, for example in assisting patients with severe motor disabilities (Dornhege et al. 2007), in assisting wheelchair navigation (Leeb et al. 2007) and even controlling a virtual keyboard through spontaneous EEG Activity (Obermaier et al., 2001). BCI systems have also been implemented in the field of geophysics. The experiments involve the application of understanding geophysical data interpretation (e.g. Sivarajah et al. (2012)). The continued development of this technology suggests a possible future where BCI systems would be able to control computer interfaces at unprecedented levels. Intel Corp. research scientist Dean Pomerleau suggests that users may be able to surf the web and open documents by the year 2020 (Gaudin 2009). Our goal is to perform the first proof of concept experiment to show that brain controlled geophysical software is possible. Using the developed BCI software we believe that BCI technology can assist in the training of geophysicists through associating a particular geophysical data state with a thought pattern (i.e. classical conditioning). Participants are in direct control of survey parameters through varying levels of focus via the BCI system. The survey parameters are linked to real time survey execution framework which updates on-screen synthetic survey data. This learning method is similar to Pavlovian associated style (Baeyens et al. 1995) where the amount of mental effort required is remembered to achieve a particular stimulus (i.e. the visualised data). We propose that brain controlled geophysical software packages can provide an accelerated learning environment.

METHOD AND RESULTS

Achieving brain controlled software is possible by developing a BCI system which enables communication between the brain and the software. The recording apparatus used is the NeuroSky MindWave EEG device. The device is a non-invasive head piece which consists of a dry electrode placed on the forehead skin above the prefrontal cortex of the brain and a dry bipole electrode clip that attaches to the right earlobe. Standard EEG systems have reference points, many located either at the earlobe or on the mastoid process (NeuroSky, 2009). In the case of the Neurosky, the signals are collected from the forehead site are compared with the reference point (i.e. the earlobe). These points are chosen as reference points as they are unaffected by cerebral activity (NeuroSky, 2009). The Neurosky Mindwave EEG then measures the difference in the activity between what is known as the 'active site' (i.e. forehead) and the reference point (i.e. earlobe). As a result, it mainly captures activity at the prefrontal cortex. Alpha and Beta waves are recorded from the frontal region of the brain during activation, although the alpha waves tend to occur more intensely at the occipital region (Hall and Guyton, 2011). We are using the ThinkGear Communications Driver (TGCD) written in C/C++ programming language. These drivers are connected to Java through JNI (JNI, 2012). These drivers reads serial device output and parse the incoming data stream. A training program was also created using The ThinkGear drivers. The training program allows users to control an on screen virtual ball. The ball's position was dictated by the amount of user concentration (i.e. the NeuroSky derived attention value). The training program allows users to practice controlling their 'thoughts'. These drivers were integrated into our CSEMoMatic EM forward modelling engine. CSEMoMatic (Pethick and Harris, 2012) is an interactive 3D electromagnetic forward modelling engine built for marine controlled source electromagnetic investigations. The interactive modelling engine ran the Dipole 1D MCSEM modelling algorithm (Key, 2009), providing real time feedback to the user. The CSEMoMatic engine computes and visualises data from 1D CSEM surveys in real time. Survey and geo-electrical parameters updates invoke recalculations and visualisation of MCSEM data. Selected parameters are linked directly to the processed NeuroSky attention stream. As the neurosky input value varies, the on screen data continuously updates. The 1Hz limitation in attention calculation (i.e. updates to the attention stream occurs every one second). To overcome the slow and potentially 'jarring' updates the attention stream is sub-sampled to 10Hz (i.e. 0.1s). The stream is linearly interpolated between each recording to produce smoother forward modelling updates. Our BCI CSEMoMatic build was then executed on an ASUS EP121 tablet. To reduce this experiment's complexity we used the touchscreen, removing the need for keyboard input. Our experimental setup is described below in Figure 1.

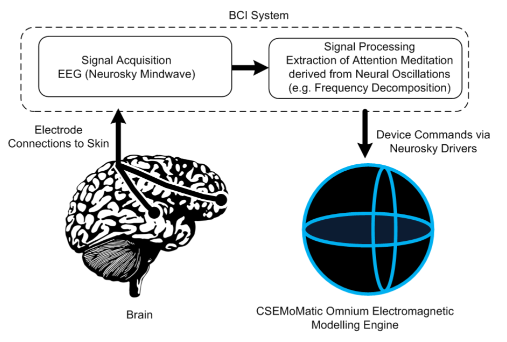

Figure 1: The brain controlled interface system (Derived from Schalk et al., 2004)

This configuration is found in most BCI setups (e.g. Schalk et al. (2004), Xu et al. (2004) and and Guger et al. (1999). We tested our BCI geophysical modelling program with eight subjects, each having varying levels of geophysical knowledge. Each person was given a training exercise for about 20 minutes to control the virtual ball using the training program (Figure 2). The ball was raised and lowered in direct relationship to the user's concentration. Once the user was able to sufficiently control the ball they were asked to control the CSEMoMatic software. A screenshot of the CSEMoMatic engine running with the NeuroSky drivers can be seen in Figure 3. The interface has three components, the parameters, data viewer and Neural and eSense recorder. Figure 3 has two visualised panes, the survey layout showing electromagnetic receiver locations, earth model and the electrical bipole transmitter position and orientation. The experiment tests the influence of the vertical transmitter position on the data.

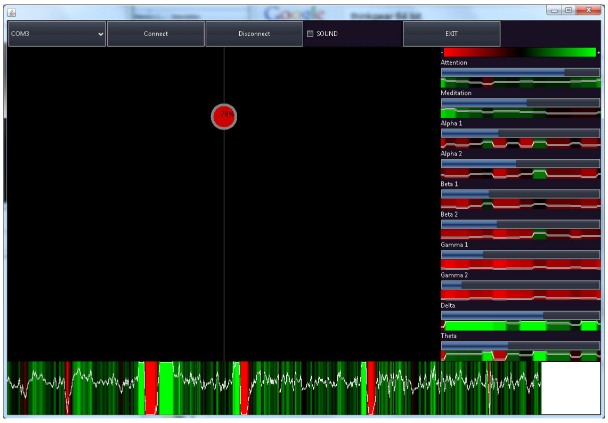

Figure 2: A Screenshot of the Neuro Training Program. This training program taught each participant how to control a virtual ball with concentration. The balls position is related to concentration level

The experiments were carried out on the real time interactive BCI MCSEM modeling program utilising the Neurosky Mindwave EEG device. All users successfully raised and lowered the virtual ball within the training program. We found that the optimal approach to control the position of the ball was to imagine the ball rising to increase its height and lowering it by relaxing and de-focusing. For our experiment we used transmitter height above sea floor as our parameter. It was chosen to best replicate the training exercise. All users were able to control the vertical position of the transmitter location with varying degrees of accuracy in all eight cases. The positioning of the transmitter was highly granular, with it being located within ±5 to 30% of the desired vertical location. The transmitter position ranged from -1500m to 1500m height above sea floor, which correlated with an error of between 150 to 750m.The participants observed the effect of transmitter height on the modelled CSEM data for 5 to 10 minutes. They were then asked to describe the influence of the changing transmitter height on the 1D MCSEM data. All participants were expected to describe the flattening of the profile and reduction of peak amplitude with increased distance from the seafloor. All participants could describe this effect accurately. However, most found it difficult to fully control the ball's position and interpret data concurrently. This effect had been described by various participants as a "vicious cycle", "highly dynamic" and "overwhelming". Users could not easily examine data associated with a low transmitter positions (i.e. low attention level) because attention increased the moment they begin to examine the data. This compounding effect was not considered to be an effective learning experience despite the all participants describing the effect of changing parameters on the data. The users were also asked to perform the same experiments with frequency and transmitter inline offset. This was found not be as successful due to the dissimilarity to the ball training exercise.

This study was designed to prove that BCI systems can be successfully applied to geophysical modelling and learning. Despite the successful implementation, we found there were more pitfalls than benefits in using BCI systems for operant conditioning. Firstly participants required 10 minutes or more to learn how to operate the device before using the system. At the start of training many users felt that the virtual ball was in fact"controlling itself", but could control it with varying degrees of success after several more minutes. The training period varied widely due to different testing environments, participant rest levels and characteristics individual to the participant. A rested participant in quiet room with no distractions produced the best results. The experiment was only designed as a proof of concept and was made simple to match the EEG apparatus limitations. Typically subjects found the learning experience too dynamic since modelling results changed with varying attention levels. Overall the BCI program could be controlled by using only brain signal, but with varying success. That being said, using traditional user input such as the keyboard and mouse would still be considerably superior to BCI systems.

CONCLUSIONS

The results show that it is possible to control geophysical software using a BCI system. The training phase was considered to be most crucial for achieving this. The ability to control the BCI linked software was linked to both individual and environmental conditions. All participants were successful in describing the effect of parameter variation on marine controlled source electromagnetic data. However, the level of success was limited due to what was described by participants as strong cyclical and compounding thought levels. Despite this setback the experiment did show some level of connection between thought level and the effect on parameter variation. The emerging field of BCI systems has many hurdles to clear before reaching functionality but we hope this pioneering proof of concept experiment demonstrates the feasibility of future brain computing applications in geophysics.

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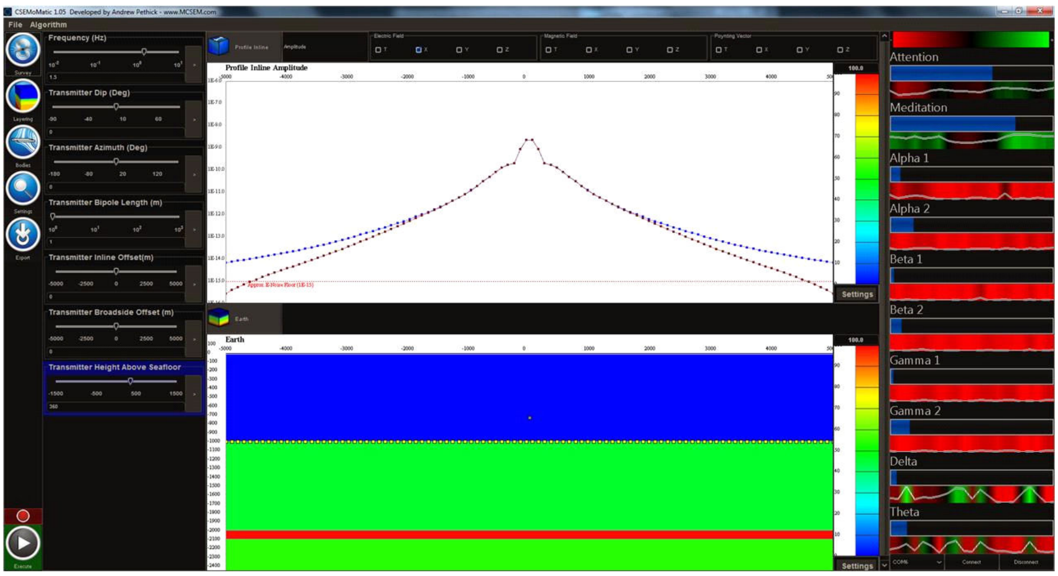

Figure 3: Screenshot of the BCI connected CSEMoMatic forward modelling engine. The BCI System parameters can be seen on the right of the screenshot. The main component is the attention bar. This attention level is connected to the transmitter height above sea floor survey parameter highlighted in blue on the left side of the screenshot. The data is interactively modeled and the resulting dataset is visualised (center-top) along with the corresponding survey geometry (center-bottom).