Reading the Mind: the Potential of Electroencephalography in Brain Computer Interfaces

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***Abstract*—Over the past 15 years the field of brain computer interfaces (BCI) has truly emerged. An increased understanding of the brain has combined with advances in hardware and software to allow us to decode brain activity in real time. This *mind reading* can be used to provide assistive technologies to restore motor function that has been lost, or even to augment the healthy.**

There are many different techniques to read brain activity, and this article will discuss the potential of electroencephalography (EEG) BCIs to move out of the lab and into the real world. The EEG signal is very noisy and difficult to analyse but many advances have recently been made in this area. Before the first devices can enter the homes of the disabled, many hardware and software limitations must be overcome via interdisciplinary collaboration.

At the University of Auckland, EEG based BCIs have been under development for the past few years. Our laboratory has produced excellent results including an EEG controlled video game, and an EEG phone dialling system. Research is ongoing in this area, with new projects starting for control of prostheses or rehabilitation robots.

I. Introduction

Although the prospect of capturing signals from the brain has captivated the interest of both scientists and the public, it is only in the last 5 – 15 years that the field of brain computer interfaces (BCI) has truly emerged [1]. An increased understanding of the function of the brain, an appreciation of its incredible adaptability, access to powerful inexpensive computer hardware, and intelligent software, allows us to decode brain activity in real time. "A BCI is a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment" [1]. As far as we currently understand the only natural way the brain can interact with the rest of the body and the world is via hormonal and muscular outputs; a BCI provides a third electronic output.

Recent developments hint at the significant future role BCIs could play as the control system for devices that can restore function to the disabled or augment the healthy. To create effective and commercially viable BCI devices, engineers must combine knowledge from the fields of neuroscience, biocompatibility, signal processing, robotics, behavioural science, artificial intelligence and more.

A. Applications

BCIs have a wide range of possible practical applications, from very simple binary controls to extremely complex systems that emulate existing systems in the body.

Simple BCI applications have already been demonstrated in the laboratory. They include systems for answering yes/no questions, controlling lights and televisions, modifying the temperature level of air conditioning, moving a cursor on a computer screen up and down, typing messages into a computer, controlling electric wheelchairs, or opening and closing a hand/leg prosthetic.

These devices can provide significant benefits to people who are totally paralysed and thus cannot use conventional assistive communication devices. Although still needing care, they can increase their independence — improving their overall quality of life and reducing healthcare costs. Simple BCIs could also supplement existing assistive devices by allowing finer control where needed, or an extra channel of control so more things can be done at once (for example using a hand to control a wheelchair while using a BCI for typing into a speech synthesiser).

More complex BCI applications might support control of a high resolution cursor or a prosthesis that enables the multidimensional movements of a paralysed or amputated limb. While most present efforts are focused on invasive implants to support such applications, non-invasive BCIs also appear to offer the possibility of such control. Even if implanted devices that interface directly with the brain are likely to be the future of BCIs, they are a long way off for the disabled, and even further away from being worth the risk for the able-bodied.

II. Why Electroencephalography

To non-invasively measure brain activity for use in a BCI there are essentially three signals that can currently be detected. These are changes in blood flow (as more active areas use up oxygen and require more blood), and changes in the electric and magnetic fields produced by the firing of large numbers of neurons.

Measuring changes in blood flow has limited use in BCIs for two reasons. Firstly, it generally requires large immobile equipment such as positron emission tomography (PET), or magnetic resonance imaging (MRI) machines. An exception is functional near-infrared spectroscopy (fNIRS) which detects changes in blood flow on the surface of the brain by shining light through the scalp and detecting changes in the amount reflected. Secondly, these methods have excellent spatial resolution, but have poor temporal resolution. The response in blood flow lags the activity by one or two seconds, and takes a few seconds longer to peak and then return to normal — limiting the reaction time, as well as the total information transfer rate.

Measuring the magnetic fields produced by the brain currently requires a magnetoencephalograph (MEG), which is very large, and requires a magnetically shielded room.

This leaves the electrical fields generated by the brain. There are three scales of electric fields that are usually discussed in the context of BCI research. Microscale fields are recorded inside brain tissue and reflect activity in a volume of neurons around an implanted electrode of 10^{-3} to $1\ \mathrm{mm}^3$. Mesoscale fields are usually recorded from the surface of the brain (called an electrocorticogram ECoG), and record tissue volumes of $1 - 20\ \mathrm{mm}^3$ [1]. Macroscale fields are obtained from the scalp, called an electroencepholagram (EEG), and record volumes of 10^3 to $10^4\ \mathrm{mm}^3$ range — containing 100 million to a billion neurons [1].

EEG detects the electrical fields generated by the brain by measuring the voltages at electrodes placed on the scalp. Unlike other devices for recording brain activity (excluding fNIRS), portable EEG devices are available. As the voltages measured are extremely small (μV to nV range) interference can be a significant issue — however with proper design they can operate in many different environments. This leaves EEG as not the ideal choice for creating a BCI system (future invasive systems in direct contact with the brain may take that position) but the only currently available system which can operate in the real world.

III. Why Steady State Visual Evoked Potentials

A. Other Common EEG BCI Methods

1) P300 Potentials: A P300 evoked potential is a positive potential generated about 300 ms after a the user's desired choice is flashed on a screen, Fig. 1 (b) [4], [5]. Typically a matrix of possible selections (letters or symbols) is shown on a screen. Scalp EEG is then recorded over the centroparietal cortex while these selections flash in rapid succession. Only the flashing of the letter or symbol that the user wants to select produces a P300 potential. By detecting this P300 potential, the BCI system can determine the user's choice.

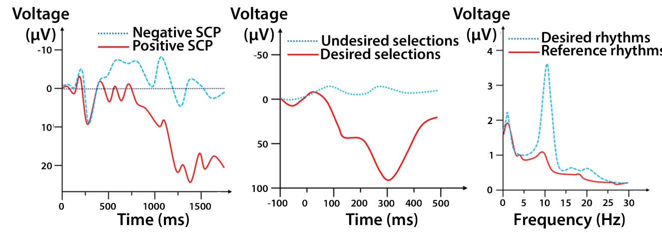

Fig. 1. Three kinds of non-invasive EEG-based BCI methods (modified from Kbler, et al. [2]). These methods all use EEG recorded from the scalp. (a) Slow Cortical Potential (SCP) BCI, negative SCPs reflect movement or imagined movement, while positive ones reflect relaxation or inhibition [2], [3]. (b) P300 evoked potential BCI, a positive potential about 300ms after the desired selection flashes on a screen [4], [5]. (c) Sensorimotor rhythm BCI, different frequency spectra reflect different cortical activities [6], [7].

This BCI method can support a simple word processing program that enables users to write words at a rate of a few letters per minute.

2) Slow Cortical Potentials: Slow cortical potentials (SCP), and neural oscillations (alpha, beta, mu, and gamma rhythms) are what are commonly referred to as *brain-waves*. These rhythms involve the synchronisation of the firing of large numbers of neurons, and are associated with changes in state of consciousness such as attention and sleep.

Fig. 1 (a) illustrates a SCP signal, which lasts from 300 ms to several seconds, as used by a BCI . With appropriate training, people can learn to control SCPs to move a cursor to a target at the bottom (more positive SCP) or top (more negative SCP) of a computer screen [2], [3].

Detecting and classifying these signals is comparatively easy as they are strong and consistent. However, generating these signals generally requires concentration from the user, the degrees of freedom is limited to the number of rhythms the user can be trained to control, and the response is often slow.

3) Sensorimotor Rhythms: Sensorimotor rhythms (SMR) are 8 – 12 Hz (μ) and 18 – 26 Hz (β) oscillations in the EEG recorded over the sensorimotor cortices. The sensorimotor cortices are an area of the cerebral cortex (the outermost layer of the brain, or *grey matter*) which is involved in the processing of sensory information, planning, control, and execution of voluntary movements.

Changes in μ or β rhythm amplitudes are associated with movement, sensation, and motor imagery (imagined movement such as thinking about performing a golf swing). Several research groups have shown that people can learn to control μ or β rhythm amplitudes in the absence of movement or sensation [8]–[11], as can be seen in Fig. 1 (c) where a BCI based on SMR is illustrated. Like the P300 and SCP-based BCIs, SMR BCIs can support basic word processing or other simple functions. Trained users can also achieve multi-dimensional control of a robotic arm or wheelchair [7].

B. Steady State Visual Evoked Potentials

An EEG evoked potential (EP) is a distinctive EEG signal that is produced a consistent time after a specific sensory stimulus or event. Visual evoked potentials (VEP) are therefore those signals which are evoked by a visual stimulus such as a flash of light, change in colour, or appearance of an image. The most prominent signals are the N70 and P100 [12], so named because they are generated in the primary visual cortex approximately 70 and 100 ms after the visual stimulus.

Steady state VEP (SSVEP) are the stable oscillations generated when the visual stimulus is applied rapidly and repetitively such as by a strobe light, flashing LED, or reversing checker board pattern on a monitor. Frequency analysis shows peaks at the stimulation frequency as well as higher harmonics [1].

To create a BCI, the user is usually presented with several stimuli flashing rapidly at different frequencies. To select an option the user focuses their gaze on the stimulus that represents the desired option. The resulting EEG signal is then time averaged to reduce noise and non-CNS artefacts, and the strongest signal that matches a stimulus frequency is used as the output. This is the standard and easiest method to implement a SSVEP BCI, but there are alternatives such as flashing each stimulus one-by-one, or flashing in a pseudo-random pattern [13] (although these are not strictly SSVEPs as they do not generate steady state outputs [1]).

These SSVEP systems can be used to control a variety of devices, with 64 or more simultaneous stimuli to control a complex menu [14], four stimuli to control the movement of a computer avatar in 2D [15]–[17], or twelve stimuli to select numbers to dial a telephone [18].

Although this could be interpreted as simply functioning as an eye tracking system, it has become clear that SSVEPs are not entirely dependent on the what the eye is pointing at. Indeed even without directly pointing the eye at the stimulus an SSVEP BCI can function based on what the user is *focusing* on, or *attending* to, on a conscious level [19], [20]. There are also advantages over eye tracking methods in that the constant rapid eye movements that occur even when a user has their gaze fixed do not influence the SSVEP, and multiple stimuli can be closely spaced in the visual field [1].

IV. Improving the Signal to Noise Ratio

A. Electrodes

To decrease the signal to noise ratio (SNR) of EEG BCIs selecting the right electrodes is very important, especially with older EEG systems which require low impedances of less than 10 kΩ. To achieve impedances this low the scalp must usually be abraded and a conductive gel or paste used between the scalp and electrode. More modern EEG systems can tolerate impedances of 30 – 50 kΩ without degrading performance, with the main negative effect being higher amplitude power-line artefacts.

This means that sponge-saline electrodes can be used instead of conductive gel (which have the advantage of being faster and less messy to apply but being limited in recording time as they dry out). Due to these problems a great deal of work is being done to create dry electrodes which could be applied much more easily, be more robust in day to day use, and work all day — obviously a huge advantage for BCI systems. However the technology is not quite there yet [1].

B. Removing non Central Nervous System Artefacts

EEG artefacts are noise from any source not originating in the brain and spinal cord (the central nervous system, CNS). Since artefacts are generally several orders of magnitude larger than actual EEG signal, one of the main problems in EEG analysis is the detection and removal of them so the classifying algorithms can function correctly. There are five main sources of such artefacts: EEG equipment (e.g., amplifier drift, moving cables), changes in skin resistance (e.g., sweating, variation in electrode pressure), displacement of the electrodes relative to the brain, external electromagnetic fields (e.g., power-line noise), and largest of all — muscle activities (eye blinks, eye movements, facial or limb movements, and the beating of the heart) [21].

Although muscle movements may be useful for certain communication or control systems, in EEG BCI research they can mislead investigators by mimicking actual EEG-based control (for example a user might inadvertently control BCI output by raising their eyebrows or blinking). Alternatively they may impede measurement of the EEG features used for control. Thus in most cases muscle movements are simply noise that must be detected and reduced as much as possible.

1) Artefact Removal Methods: The simplest method for removing eye blink artefacts is simply remove the peak if the energy of the signals surpasses an established blink threshold. Although it is simple, the results are satisfactory enough to consider it as an option for a real-time BCI. Nevertheless, this method rejects some non-corrupted data in other scalp channels, as well as in the frontal channels (where the blink artefact is strongest).

Another technique is training an artificial neural network to recognise artefacts in EEG signals. In one study [22], a large training set including coefficients for over 27,000 windows was used, containing many different kinds of artefact. The best algorithm had a classification error of only 1.40%, with a classification time of the test set (6,227 windows) of 2 seconds.

There many other techniques, such as: a fixed bandpass finite impulse response (FIR) filter, or independent component analysis (ICA).

C. Statistical Methods

After removing artefacts as much as possible the EEG signal can then be processed to improve the resolution of the resulting data, or to isolate particular signals of interest.

There are many different methods, but the easiest, and most relevant to SSVEP BCI (also P300, or other VEP) is signal averaging. This is because the amplitude of the evoked signals are often much smaller than the background EEG, so they cannot be recognized from raw EEG data.

To extract these components, recordings of the EEG time-locked to repeated applications of the stimuli can be averaged. The random spontaneous EEG components will be averaged out, leaving the time-locked evoked potential. This slows down the BCI response, but the loss in communication rate can be minimized by overlapping the trials [5]. Also, non-periodic signals (like the SCP and sensorimotor rhythms) cannot be enhanced by an averaging algorithm.

V. Signal Translation / Classification

In order to produce a useful output the BCI system must convert signal features in the EEG into device control commands. These commands may be discrete (e.g., icon selection) or continuous (e.g., cursor movements, control of a prosthetic). The success of a translation algorithm is determined by the appropriateness of its selection of signal features and by how effectively it translates this into device commands. As the ultimate function of almost all of the various translation algorithms is to classify signal features into various categories, they can be called classifiers.

A. Linear Classifiers

Linear classifiers are generally more robust than nonlinear ones, because linear classifiers have fewer parameters to tune, and are thus less prone to over-fitting. The most commonly used techniques are linear discriminant analysis (LDA), and threshold detection.

B. Non-linear Classifiers

When there are large amounts of data and complex relationships between the variables, non-linear methods are better suited. However there are a large number of parameters to tune, which is difficult if the relationships are poorly understood as in the case of EEG. This means that typically methods that are good at tuning the parameters when there is a large search space are used — such as neural-networks.

C. Mixed Classifiers

Kernel-based classifiers maintain all the benefits of linear classification while the overall classification is non-linear. Examples of such kernel-based classification methods are support vector machines (SVMs) and Kernel Fisher Discriminant (KFD).

These systems do not take into account the temporal information in the input data. Classification rates can be improved with algorithms such as Finite Impulse Response & Multi-Layer Perceptron neural networks (FIR-MLP) and Tree Based Neural Networks (TBNN) that do [23]–[25].

VI. Improving Classifier Accuracy

A. Committee of Classifiers

A group (committee) of classifiers usually yields better classification accuracy than any individual classifier could provide, and can be used to combine information from several channels, i.e., from different spatial regions [26].

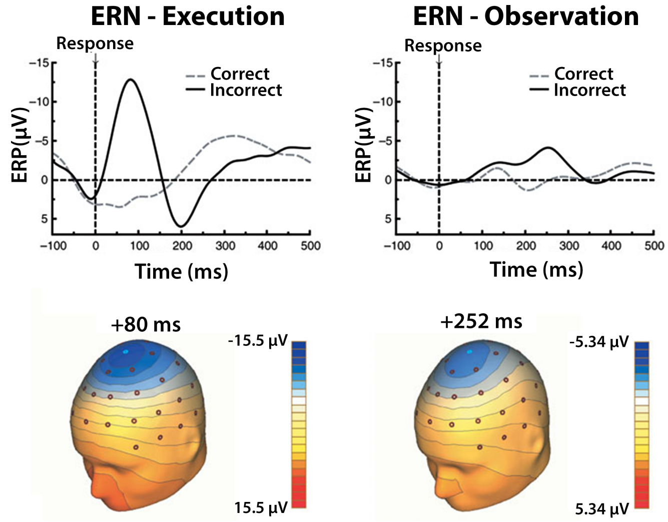

Fig. 2. Error-related potentials (ErRP). Top, response-locked averages for correct and incorrect responses in the execution condition (left) and the observation condition (right). Bottom, spline maps showing the topography ErRP signal the execution condition and the observation condition (image from [27]).

B. Machine Learning

A learning process is usually incorporated into BCI to adapt the system to different users, as well as to maintain or improve performance over time. The human brain is highly adaptable (or *plastic*) so at the same time the BCI system is adapting to the user, the users brain will be adapting to the new output to the world provided to the BCI.

This means that ideally the system must have some way to identify errors, and the desired outcome so it can use this information to improve future accuracy.

At the same time the function of the BCI needs to be consistent enough that the brain can adapt its own output to reduce errors, and consideration needs to be made of the fact that something a user initially finds difficult may eventually become second nature.

C. Error Related Potentials

One useful way to improve the accuracy of a classifier over time is the error related potential (ErRP). This is a signal visible in the EEG after the user perceives an error has been made (in this case by the BCI). The ErRP most likely originates in a brain area called the pre-Supplementary Motor Area (pre-SMA) and Anterior Cingulate Cortex (ACC) which are areas that are involved in regulating emotional responses.

When the subject is asked to respond as quickly as possible to a stimulus, execution ErRP arise if the subject makes an incorrect motor action (e.g., the subject presses a key with the left hand when they should have responded with the right hand). When the subject is asked to observe someone else performing a reaction task, observation ErRP arise when the subject observes and error being made. Usefully these two types of ErRP can be distinguished in the EEG signal [27], as can be seen in Fig. 2.

VII. Current Limitations

In the past several decades, there have been many acheivements in the area of EEG based BCI, such as control of a visual keyboard, cursor, wheelchair, smart home, and robotic arms. Nevertheless, few of them can be used in a practical environment outside the laboratory, because of following limitations.

A. Limited Information Transfer Rate

Limitations in information transfer rate from the user through the BCI to the outside world is not only limited by immaturity of the technologies, it can also be limited by the inherent characteristics of the EEG signal being observed (e.g. changes in SCP take 1 – 2 seconds).

B. Limited Accuracy

The second obstacle for practical BCIs is the relatively low accuracy. This is not only due to the low identification rate of signal features. It is also because of fluctuations in the users state of mind, such as fatigue, illness, and attention which can greatly affect the EEG signal. To improve overall accuracy therefore not only requires improvement of the classification accuracy in ideal circumstances — the complete BCI system must also be less fatiguing to use (hopefully by emulating things a healthy user would have done naturally).

C. Tedious Preparation and Cleaning

Practical factors will also play significant a significant role in the actual uptake and ultimate success of a BCI. Issues such as the steps involved in donning and doffing electrodes, accessing a BCI application, or a person's appearance while using it may greatly affect the extent to which they are actually used.

This will likely involve development of EEG systems specifically designed for BCI use, as unlike research where signal accuracy takes top priority, EEG systems for a commercial BCI must be a compromise between many different factors. The development of new dry electrode technologies will be a huge step in this direction.

D. Lack of a User Initiated Switch

Present day (research) BCI system all rely on protocols that begin at fixed times set by the system. However, in real life applications BCIs in which the start and stop of operation is determined by the user will be preferable.

Without a safety cutoff (difficult if the user cannot operate a mechanical switch), operation in daily life could even be dangerous. Efforts to develop such a user initiated switch, based on detection of certain features in the ongoing EEG have begun (Mason & Birch, 2003). But there may be many other options as yet unexplored, and are likely to be very influenced by the individual abilities of the user.

E. Different EEG patterns in different users

There are very significant differences in the EEG between different users — especially when neurological disorders, psychological issues, and damage to the brain are considered. To create a universal classification algorithm that suits every user may in some cases be impossible. Therefore highly effective training methods that can match a new user after a short training session will be important.

VIII. Future Trends

Briefly, the development of BCI in the near future can be concluded as: cheaper, easier, faster, and more accurate.

Future BCIs will benefit from improvements in technology, and novel theories that will come from interdisciplinary collaboration. Such as: novel sensors, more powerful computers, signal refinement, electrode improvements, optimised algorithms, understanding of neuro-mechanisms, and advanced artificial intelligence.

A. Research Funding

Fortunately, many grant giving organisations all over the world have rapidly growing interests in BCI. Such as, the US National Institute of Health (interested in rehabilitation medicine), private research foundations, and of course — the military.

The US Defense Advanced Research Programs Agency (DARPA) in particular is interested in both rehabilitation for injured soldiers, sensory substitution for orientation and guidance of troops, and control of machines and vehicles by thought.

B. Research at the University of Auckland

A video game controlled by an EEG-based BCI was demonstrated by the Medical and Rehabilitation Robotics Research group (MR3) [18]. Participants learned to control their δ and μ rhythms by expressing specific emotions, and imagining arm movements.

They were able to master the basic operation of the BCI after only a few short training sessions, and maintain this level of control in later tests. The results of this experiment showed that a combination of detecting changes in motor imagery and emotional state could allow BCI users control with more degrees of freedom.

Recently, the MR3 group developed a phone dialling system for those with mobility impairments named Mind-Angel. This uses only three EEG electrodes to record SSVEP signals, as shown in Fig. 3. The stimulation source consists of a grid of 12 flickering lights that flash at evenly spaced frequencies between 5.5 and 19 Hz — representing the phone digits 0 – 9, backspace, and dial.

When the subject gazes at the 19 Hz visual stimulus (representing dial the call) an SSVEP with a fundamental frequency of 19 Hz is detected in the EEG, and can be identified by the BCI as the dominating frequency component. Results from nine healthy participants show that an accuracy

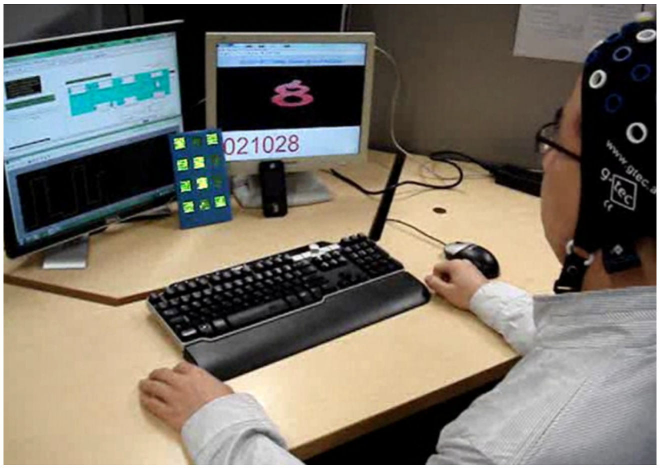

Fig. 3. Dialling a phone number via an SSVEP-based BCI developed by the Medical and Rehabilitation Robotics Research group, University of Auckland

of 97.3 $\pm$ 1.5 % can be achieved in this 12-stimulus SSVEP-based BCI with two-channel recording.

Research has also been started in the area of SMR, with the intention of correlating motion capture of arm movements, with EEG recordings for control of prostheses.

IX. Conclusion

Over the past 25 years, and especially in the recent 15 years, many productive BCI research programs have arisen. Because of its relatively low cost, high temporal resolution, and low clinic risk, EEG based BCIs are probably the best choice for a practical BCI. So far, many EEG-based prototypes have been demonstrated in laboratories such as: cursor control, visual keyboards, and mind controlled wheelchairs and prosthetics.

These new innovations in neuroscience will be a milestone in human history. While we have only made a baby step into the world of bio-mechatronics, through this field we can slowly enter a world where there are no longer physically handicapped people other than the most severely brain damaged. At the same time, the possibilities for use for augmentation of our abilities are also endless, as the barrier between our minds and our computers is weakened and finally broken.

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