CHAPTER 2

Electroencephalogram based Brain-Computer Interface: An Introduction

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Abstract Electroencephalogram (EEG) signals are useful for diagnosing various mental conditions such as epilepsy, memory impairments and sleep disorders. Brain-Computer Interface (BCI) is a revolutionary new area using EEG that is most useful for the severely disabled individuals for hands-off device control and communication as they create a direct interface from the brain to the external environment, therefore circumventing the use of peripheral muscles and limbs. However, being non-invasive, BCI designs are not necessarily limited to this user group and other applications for gaming, music, biometrics etc have been developed more recently. This chapter will give an introduction to EEG based BCI and existing methodologies; specifically those based on transient and steady state evoked potentials, mental tasks and motor imagery will be described. Two real-life scenarios of EEG based BCI applications in biometrics and device control will also be briefly explored. Finally, current challenges and future trends of this technology will be summarized.

2.1 Introduction

Brain-computer interface (BCI) is a revolutionary field of science that is rapidly growing due to its usefulness in assisting disabled patients as it provides a direct mechanism of controlling external devices through simple manipulation of brain thoughts (Nicolas-Alonso and Gomez-Gil 2012). Disabled individuals here could be those that have lost most or all motor functions (known as 'locked in' syndrome) due to progressive neuromuscular diseases like amyotrophic lateral sclerosis (ALS) or muscular dystrophy or non-progressive such as stroke, traumatic

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brain injury and spinal cord injury. The BCI approaches for such individuals could be used in control of wheelchair, prosthesis, basic communication etc. as shown in Figure 2.1. These users could use BCI to communicate with others to express their needs, feelings, etc. A simple example could be of a communication BCI system such as brain controlled word processing software.

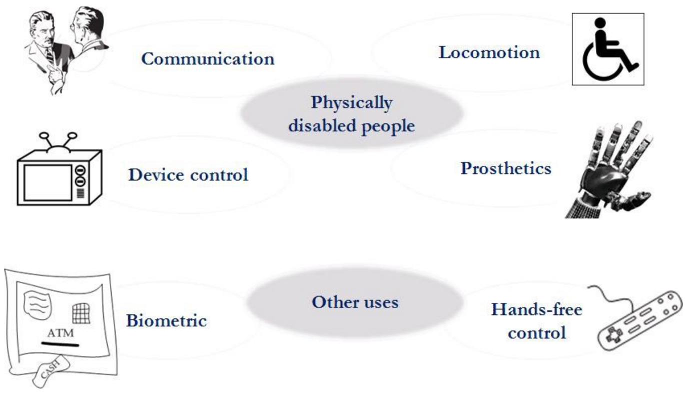


Figure 2.1 Brain-computer interface applications.

However, in recent years, other industries have taken interest in this field where applications related to biometrics (Palaniappan 2008), games (Hasan and Gan 2012), cursor control (Wilson and Palaniappan 2011) etc. have emerged. Table 2.1 gives a non-exhaustive list of possible applications of BCI for both disabled and healthy individuals.

Table 2.1 Examples of possible BCI applications for disabled and healthy individuals

Disabled individuals	Healthy individuals
Restoring mobility – eg. to control wheelchair movement	*(mainly control of external devices)*
Environmental control – eg. to control TV, power beds, thermostats, etc.	Mouse control in PC when fingers are on the keyboard
Prosthetics control (motor control replacement) – to control artificial limbs	Playing musical instruments by thoughts
Rehabilitative (assistive) control – to restore motor control (eg: strengthen/improve weak muscle)	Virtual reality
	Computer games (eg Mind Pacman)
	Flight/space control (pilots, astronauts)
	Biometrics

In general, there are two categories of BCI: invasive and non-invasive methods. Invasive BCI methods such as electrocorticogram (ECoG) have shown excellent performance in human (Langhenhove et al. 2008) and monkey (Borton et al. 2013). Nevertheless, non-invasive approaches based on electroencephalogram (EEG), magnetoencephalogram (MEG), positron emission topography (PET), functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (NIRs) are more popular as it is safer (minimal risk of infection etc).

Among these non-invasive methods, EEG based BCI is preferred due to it being practical (i.e. cheap and portable). We'll focus on EEG based BCI techniques here, specifically on transient visual evoked potential (better known as P300), motor imagery, steady state visual evoked potential (SSVEP), mental tasks and briefly on slow cortical potential (SCP). Figure 2.2 shows a block diagram of the components involved in the processing of EEG data to implement a BCI.

Figure 2.2 EEG data processing for a BCI.

2.2 Electroencephalogram

Acquiring electroencephalogram (EEG) is the first step in the BCI design. EEG is a type of oscillating electrical potential recorded from the scalp surface. It is generated by neuronal activations in the brain (as shown in Figure 2.3) and is very small in amplitude (in the μV range) due to the attenuation caused by the skull and scalp. Evoked potentials is a specific type of EEG evoked during a stimulus like visual, auditory, etc.

EEG is usually recorded from a number of electrodes on the scalp. A standard electrode (channel) configuration is the 10-20 electrode system (Jasper 1958) of 19 active electrodes and two mastoids (reference) as shown in Figure 2.4. However, it is common to extend this configuration and use higher number of channels such as 32, 64, 128 and even 256. The electrode locations are prefixed by a letter denoting the cortical area followed by a number (even for the right hemispshere and odd for the left). The prefix letter F stands for frontal, similarly C for central, P for parietal and O for occipital. The electrodes (normally made with Ag/AgCl) are used with gel to increase the conductance between scalp and electrodes but there are more recent advances in using dry electrodes made from gold. It is also common to re-reference the EEG using methods such as common averaging and Laplacian (Neuper and Klimesch 2006).

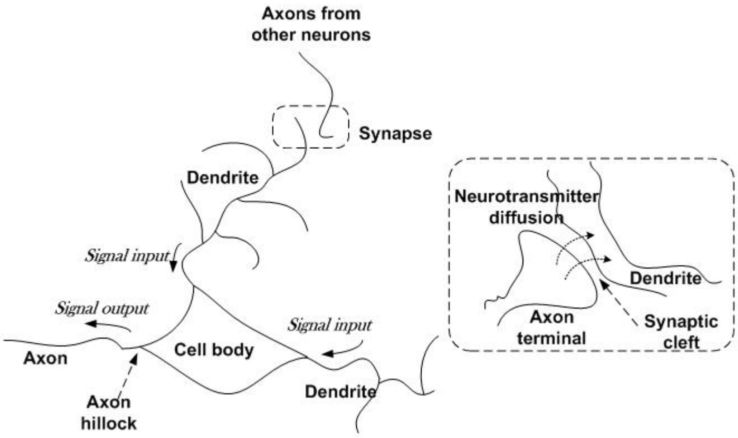


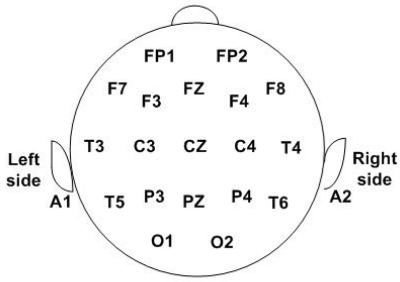
Figure 2.3 Neuronal connections resulting in the generation of EEG. The recorded EEG is normally the cumulative effect of thousands of such neurons (Palaniappan 2010).

As the EEG is of very small amplitude, it is normaly amplified and converted to digital using an analog-to-digital converter. The digital conversion using sampling rates such as 256 Hz[1] is necessary to process the EEG signal using digital devices (like computers).

The EEG is normally obtained using certain BCI paradigms (to be discussed later) and the first processing step is to reduce noise such as muscle artifacts, powerline interference and other random noises from the EEG signals. Frequency specific filtering using digital filters is commonly employed to filter the noise from the EEG; recently more sophisticated methods such as principal component analysis (PCA) and independent component analysis (ICA) have been employed. Figure 2.5(a) shows an example of the recorded EEG (using the SSVEP BCI paradigm) corrupted with powerline intereference. It can be seen the occurence of this 50 Hz noise along with the signal frequency in the power spectral density plot of the EEG in Figure 2.5(b). The objective of noise reduction would be to reduce the noise as much as possible without distorting the signal contents.

[1] With 256 Hz sampling rate, one second EEG will have 256 data points, other sampling rate up to 2048 Hz is common.

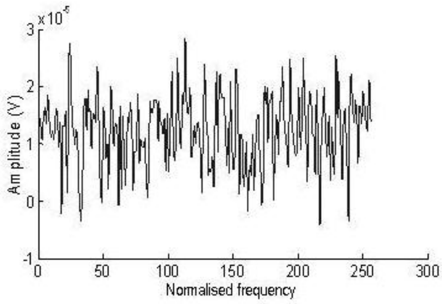
(a)



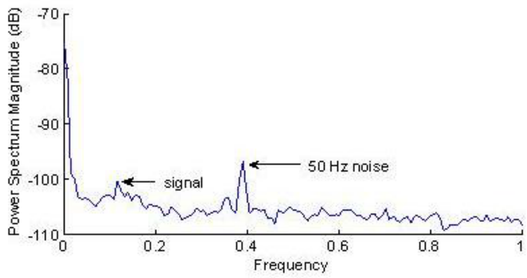
(b)

Figure 2.4 BCI system (a) a user using BCI and (b) 10-20 electrode configuration.

The signals with noise reduced are then sent to the feature extraction stage, where mathematical models such as autoregressive (Huan and Palaniappan 2004) are used to extract parameters representative of the signal. Nowadays, nonlinear methods such as Lypunov and approximate entropy coefficients (Balli and Palaniappan 2013) are also being used to obtain more accurate representation due to EEG signals being nonlinear. Nevertheless, linear methods are still popular due to their simplicity and ease of computation.



(a)



(b)

Figure 2.5 (a) example of recorded EEG and (b) power spectral density of EEG showing signal and noise frequencies.

The extracted features are then classified into respective categories depending on the application. In some BCI paradigms (such as the SSVEP (Miranda et al. 2011)), the classifier is relatively simple but in others, classifiers such as neural network (Huan and Palaniappan 2004) and linear discriminant analysis (LDA) (Asensio et al. 2011) are used. The final stage is the device control stage where the BCI output is used to control an external device (for example to select on-screen menus or move a wheelchair). Certain BCIs employ feedback of the output to improve the reliability of the system.

2.3 EEG based BCI paradigm 1 – motor imagery

Voluntary movement is composed of three phases: planning, execution and recovery. Even during imaginary movement (known as motor imagery), there is the planning stage that causes a change in EEG. For example, imagined movements of left hand causes a change known as event related desynchronisation (ERD) in the right motor cortex area, i.e. contralaterally to the imagined movement side and event related synchronisation (ERS) in the left motor cortex area. Discrimination of these ERD/ERS can be used to design a BCI.

2.3.1 ERD/ERS

ERD and ERS generally occur in mu (~8-12 Hz) and beta (~13-20 Hz) frequency ranges. ERD is the EEG attenuation in primary and secondary motor cortices during preparatory stage which peaks at movement onset in the contralateral hemisphere while ERS is EEG amplification in ipsilateral hemisphere occurring during the same time. ERS appears to be an evolutionary built-in inhibitory mechanism, which explains why it is difficult to execute dissimilar tasks on both sides of the body simultaneously[2].

In addition to mu and beta frequency ranges, sometimes there is also an increase in EEG energy in gamma (> 30 Hz) frequency range. A simple electrode setup for motor imagery will consist of two active channels in location C3 and C4 (i.e. motor cortex area) and EEG is obtained during an imagined movement (say either left or right hand). The EEG is filtered in mu and beta bands and the energy of EEG from channels C3 and C4 are computed to decide on the movement class:

- if energy of $C3_{EEG}$ > energy of $C4_{EEG}$: left hand motor imagery
- if energy of $C4_{EEG}$ > energy of $C3_{EEG}$: right hand motor imagery
- if energy of $C3_{EEG} \approx$ energy of $C4_{EEG}$: no motor imagery

But this is a crude example and the actual EEG analysis involves several stages such as determining the appropriate electrode locations, spectral range and use of features such as band powers and classifiers to obtain accurate detection of the class of motor imagery.

2.4 EEG based BCI paradigm 2 – SSVEP

SSVEP is a type of EEG that occurs when the visual stimulus flashes at a frequency higher than 6 Hz. It is maximal at the visual cortex, specifically in the occipital region. In this paradigm, a target block flickers with a certain frequency on screen (the flicker can also be achieved using LEDs) and the user looks at the flashes. The frequency following effect (sometimes known as photic response) of the brain causes EEG to oscillate in the frequency of the flickering object. The response is spontaneous and does not require any physical effort other than to gaze at the stimulus as required. In a similar manner, audio based methods are explored but

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[2]This can be demonstrated using an old trick. While sitting comfortably, lift right leg off the ground and rotate the right foot clockwise. Now, with right hand, draw number six in the air – what happens to the foot direction?

the results are not as accurate as the visual based methods. The detection of the frequency of the EEG is sufficient to detect the focused object, though there is a recent study that showed the possibility of using SSVEP with eyes closed (Lim et al. 2013).

2.5 EEG based BCI paradigm 3 – P300 VEP

P300 visual evoked potential (VEP) is another type of EEG that is evoked around 300-600 ms after visual stimulus onset (hence the term P300) and is maximal is midline locations (such as Fz, Cz and Pz). The potential is limited to 8 Hz and hence a low pass filter is normally used to filter VEP prior to analysis. It is evoked in a variety of decision-making tasks and in particular, when a target stimulus is identified, for example when a picture is recognised. A popular paradigm is the Donchin’s speller matrix paradigm (Donchin et al. 2000) shown in Figure 2.6. It consists of alphanumeric characters on screen and the rows and columns flash randomly. The row and column containing the target (focused) character will have a higher P300 amplitude compared to row or column that contains the unfocused character. However, this P300 amplitude is not normally detectable in a single trial due to contamination from higher background EEG and hence require averaging (or other forms of processing such as PCA and ICA) from a number of trials.

The principle is based on the oddball paradigm where the frequency of the target stimulus is lower than the non-target stimulus. In this case, the target frequency is one sixth since only either one row or one column flashes at a time. A variation of this paradigm is where each alphanumeric character flashes thereby decreasing the frequency to one thirty-sixth – the lower this frequency, the higher is the P300 amplitude response, which allows easier detection, however resulting in slower response overall as it takes longer to complete the cycle.

2.6 EEG based BCI paradigm 4 - Mental Task BCI

In this paradigm, users think of different mental tasks and since different tasks activate different areas of the brain, a set of multi-channel EEG recordings will have distinct EEG patterns to differentiate the tasks, which could be used to design a BCI.

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

Figure 2.6 Example of P300 VEP paradigm - Donchin's speller matrix.

Examples of mental tasks used are (Keirn and Aunon 1990, Palaniappan 2006):

- Baseline task where users are asked to relax and think of nothing in particular;
- Computation task where users do nontrivial multiplication problems;
- Mental letter task composing where users mentally compose a letter to someone;
- Visual counting task where users visually imagine numbers written on a board with the previous number being erased before the next number is written;
- Geometric figure rotation task where users imagine a figure being rotated about an axis.

These mental tasks exhibit inter-hemispheric differences and hence the EEG pattern will be distinct (Keirn and Aunon 1990). For example, computation task involves the left hemisphere more while the visual task exhibits more activity in the right hemisphere. The detection of the inter-hemispheric activity can be done using asymmetry ratio where the powers of EEG channels in the left and right hemispheres are compared to decide the activated hemisphere, which can then be used to design a control interface.

2.7 EEG Based BCI 5 - SCP BCI

Slow cortical potential (SCP) are low frequency potential shifts in EEG (around 1-2 Hz) and can last several seconds. It is possible to control SCP using feedback and reinforcement mechanism. Different tasks can be used to control either the positivity or negativity SCP. For example, cognitive tasks (or even inactive relaxed states) can generate positivity SCP while negativity SCP can be generated with tasks such as readiness/planning to move. Hence, it can be used to generate a binary signal, which can be used as a control mechanism. It is not as popular as the other EEG based BCIs as it requires extensive training in order to give good performance.

2.8 EEG based BCI – a brief comparison of the paradigms

Comparing the different EEG based BCIs, it can be seen that each method has its strengths and weaknesses. For example, motor imagery requires user training and also the response time is slower (the imaginary movement causes changes in EEG to show up typically after a few seconds) but this paradigm circumvents a visual interface and also be can run in the asynchronous mode, thereby allowing the user to turn the system ON/OFF and also use the control mechanism. Mental thoughts are similar in this regard but with the brain rapidly changing over time, such EEG based BCIs will require frequent retraining.

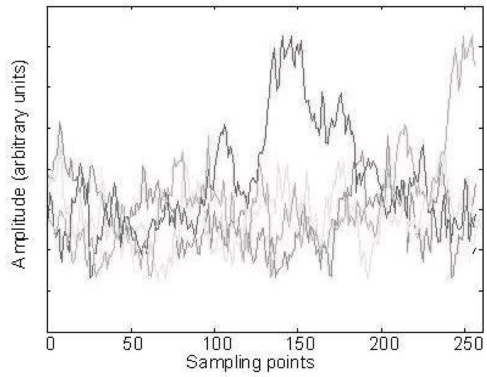
SSVEP is very robust and requires only a single active channel but require users to gaze at flashing blocks, which is only practical for short periods of time (typically a few minutes). There is also the risk of triggering epilepsy if the flashing frequency is set to be too low. P300 VEP also suffers from this risk, though of a lesser degree. Of all the EEG based BCIs, SCP requires the most extensive training and is less appealing for this reason but gives good performance.

2.9 Application 1 - Biometrics (password, PIN generation)

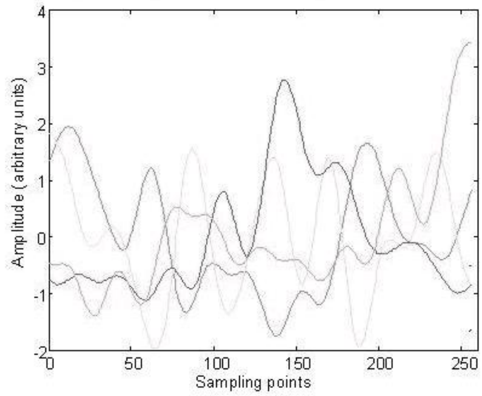
The common biometric is fingerprint but in recent years, others such as DNA, hand geometry, palm print, face (optical and infrared), iris, retina, signature, ear shape, odor, keystroke entry pattern, gait, voice, etc have been proposed. But all these biometrics can be compromised at some stage but biometrics based on BCI is more fraud resistant as thoughts can't be forged!

The P300 BCI paradigm can be used to generate a sequence of passwords (or personal identification number, PIN) that can be used in ATM machines and computer logins (Gupta et al. 2012). Instead of entering the password using a keypad, the alphanumeric characters will pop on the screen and when the character in the password appears on screen, this evokes the P300 potential which is not evoked when non-password characters appear. Similarly, colours can be used instead of alphanumeric characters (having the advantage of being language independent) to code a password (Gupta and Palaniappan 2013). For example, red-green-blue-red-yellow could be the 'pass-colour' for someone.

Figure 2.7(a) shows raw EEG signal and Figure 2.7(b) shows the filtered P300 signal from channel Cz where the bolder line shows the focused or target colour and the higher amplitude can be seen for the focused colour compared to the non-focused colours. The detection of the colours/characters through this mechanism overcomes problems like shoulder surfing[3].



(a)



(b)

Figure 2.7. Pass-colour biometric based on P300 VEP BCI (a) raw EEG (b) filtered EEG.

[3]Peeking over the shoulder to steal another person's password.

2.10 Application 2 – Cursor control

Most of the SSVEP based BCIs focus on discrete control, for example selecting a menu on screen. In Wilson and Palaniappan (2011), an analogue pointer was developed where instead of discrete control, the cursor on screen moved analogously based on the phase locking index (PLI) of the SSVEP frequency. The cursor was designed as shown in Figure 2.8, where each edge flickers with either 15Hz, 12Hz, 10Hz or 8.57Hz (the frequencies were chosen based on the refresh rate of the LCD screen of 60 Hz). The EEG was recorded from channel Oz in the visual cortex referenced to channel PO3. Depending on which block the user was looking at, the SSVEP will contain the respective frequency and its harmonics which can be detected using Discrete Fourier Transform (DFT) and other spectral analysis methods. Using this frequency measure, the cursor moved accordingly – the stronger the SSVEP response (measured by the PLI measure from DFT), the further the cursor moved on screen.

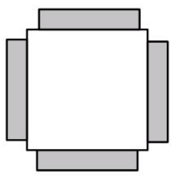


Figure 2.8 SSVEP based cursor – each shaded edge flickers with a certain distinct frequency.

2.11 Challenges in BCI

The most difficult challenge at the moment for general BCI use is on the requirement of using gel to improve the conductance though the advances in electrode design (such as active electrodes) have reduced the set-up time considerably. Dry capacitive electrodes have been invented but the quality of the EEG signals is still poor. When it comes to patient usage, most of the advances are being tested on healthy abled bodied subjects and the required adaptation for disabled people and in real noisy environments are not being studied extensively. Asynchronous (or self-paced) BCIs are more suitable for the disabled as these give additional ON/OFF control to the users but proving to be difficult to obtain reliable accuracies as compared to synchronous systems. The response time of BCI systems need to be improved for practical applications – SSVEP BCI is relatively fast (with high bit rates of 100 bits/min (Nicolas-Alonso and Gomez-Gil 2012)) but not without issues especially as it can’t be used for long periods of time.

2.12 Conclusion

BCI systems are certainly useful for the disabled. However, in recent years, the focus has shifted from this original objective to other application areas like biometrics, games, virtual reality etc. EEG based BCI still proves to be the most practical, portable, and cheap enough (with some systems such as NeuroSky available for less than USD$100). The current many advances in BCI technology (such as the advent of non-contact electrodes) will allow mind-controlled devices to become a reality in a decade if not sooner. Imagine a thought based speed dial: selecting a phone number to dial just by thinking/looking at photo of the person using EEG from headphones – it could become a reality before we know it!

2.13 Questions

1. BCI approaches could be categorized as invasive or non-invasive. Discuss the advantages and disadvantages of each approach and list examples of approaches in each case.

2. Describe the different EEG based BCI methods and comment on the practicality of each method.

3. Explore the appropriateness of other biological signals such as those based on electrocardiography, plethysmography, imagined speech etc. for use in non-muscular based control systems.

4. Figure 2.6 shows a VEP paradigm based on P300 potential. It is based on oddball paradigm where the probability of target occurrence is lower than non-targets. Describe other ways where the characters can be flashed that will still evoke P300 potential in an appropriate manner for use as BCI-speller.

5. Assuming the refresh rate of LCD screen of 60 Hz, list all the different possibilities of flicker frequencies for a SSVEP based BCI system?

6. Two applications using EEG based BCI have been discussed in this chapter. Describe other applications that might be appropriate using an EEG based BCI.

7. What are the hurdles in the implementation of current BCI systems? Suggest possible solutions.

8. BCI system has been used in US judicial courts in place of polygraph (i.e. as a lie detector) and there is a common fear among the public that BCI technology can

be exploited to read the mind. Based on the current level of technology, discuss if this is possible or just a sci-fi scenario.

9. An electroencephalophone (or sometimes known as encephalophone) uses BCI technology to generate or modulate sounds. Suggest how such as device could work using EEG signals.

10. What are the ethical, legal and societal issues surrounding BCI technology?

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