Current Practices in Electroencephalogram-Based Brain–Computer Interfaces

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**INTRODUCTION**

Electroencephalogram (EEG) is the electrical activity of the brain recorded by electrodes placed on the scalp. EEG signals are generally investigated for the diagnosis of mental conditions such as epilepsy, memory impairments, and sleep disorders. In recent years there has been another application using EEG: for brain-computer interface (BCI) designs (Vaughan & Wolpaw, 2006).

EEG-based BCI designs are very useful for hands-off device control and communication as they use the electrical activity of the brain to interface with the external environment, therefore circumventing the use of peripheral muscles and limbs. Some current applications of BCIs in communication systems are for paralyzed individuals to communicate with their surroundings through character/menu selection and in device control such as wheelchair movement, prosthetics control, and flight and rehabilitative (assistive) technologies. For the general public, some of the possible applications are hands-off menu selection, flight/space control, and virtual reality (entertainment). BCI has also been applied in biometrics (Palaniappan & Mandic, 2007).

*Figure 1. Main elements of general BCI system*
This research area is extremely exciting, and in recent times, there has been an explosive growth of interest in this revolutionary new area of science which would enable computers (and therefore any other reactive device) to be controlled by thought alone—the benefits for the severely disabled would be truly astonishing. For example, in 1990, there were less than 10 groups (mostly in the U.S.) with research interests in BCI; but this has grown to more than 130 groups worldwide in 2004 (Vaughan & Wolpaw, 2006). It is a multidisciplinary field comprising areas such as computer and information sciences, engineering (electrical, mechanical, and biomedical), neuroscience, and psychology. State-of-the-art BCI designs are still very primitive, but because of their potential to assist the disabled, there is an increasing amount of investment in their development.

This article will give an overview of the general elements in a BCI system and existing BCI methodologies, state the current applications of BCI devices in communication system and device control, and describe the current challenges and future trends in BCI technology.

BACKGROUND

In general, a BCI system comprises five stages: data collection, pre-processing, feature extraction, decision making (which includes translation algorithm1), and device command. Normally, the pre-processing, feature extraction, and decision-making stages are done using a computer, though a dedicated hardware could be designed for this purpose. Sometimes, these five stages can be simplified to just three: sensor, decoder, and actuator (Hochberg & Donoghue, 2006).

Data Collection Through Electrodes

Subjects will generate brain activity through an experimental paradigm that would depend on the particular BCI approach. The protocol to be followed by the subjects could be thinking about making imaginary movements, focusing on flashing characters on a screen, and so forth. This brain activity will be picked by electrodes (normally Ag/AgCl) placed on the scalp. The placement of electrodes commonly follows the 10-20 system (19 electrodes) or extensions of this system (32, 64, 128, or 256 electrodes). The recordings are normally referenced to the left and/or right mastoids. An example of the 10-20 electrode placement system is shown in Figure 2.

As the recorded signals are in the range of microVolts, amplifiers will be needed to amplify the multi-channel signals. These signals will then be sampled at a suitable frequency (a typical sampling frequency is 256 Hz) using an analogue-to-digital conversion device (nowadays with precision of 16-24 bits per channel). Currently, there are electrodes available that do the first-stage amplification in the electrode itself (which minimizes preparation time). In general, a single portable EEG signal acquisition unit is capable of amplification, sampling, and data transfer to the computer. Figure 3 shows an example of a subject using a BCI device.

Pre-Processing

These digital EEG data normally contain a lot of noise (artifacts). Some examples of noise sources are 50/60 Hz power line interference, fluorescent lighting, baseline drift (low frequency noise), electrocardiogram (ECG), electromyogram (EMG), and random noise. Simple frequency-specific filtering is normally sufficient to reduce the narrow band noises such as the power line interference, baseline drift, and fluorescent lighting. However, more sophisticated methods such as principal component analysis (PCA) and independent component analysis (ICA) are popular to reduce ECG and EMG noises that have overlapping spectral information with EEG. Another common artifact that corrupts EEG signals is eye blinks; many techniques have been proposed to solve this problem (Thulasidas et al., 2004).

Feature Extraction

Though the raw EEG signal could be used by the next decision-making stage, very often features are extracted from these EEG signals. Depending on the EEG approach used in the BCI, the feature extraction approach would vary. For example, for the mental-activity-based BCI, autoregressive (AR) features have been used (Anderson, Stolz, & Sham-sunder, 1998), where Burg’s method (Shiavi, 1999) is the common procedure used to estimate the AR coefficients with
the model order chosen by Akaike Information Criterion (AIC) (Akaike, 1974). When there are inter-hemispheric differences, asymmetry ratio (Keirn & Aunon, 1990) provides to be a good feature extraction method. Some of the other common feature extraction methods are spectral analyses, voltage amplitude measurements, spatial filtering, and single neuron-separation (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). The features could be in the time domain, such as the P300-evoked potential amplitude (Farwell & Donchin, 1988), or they could be in the frequency domain, using classical or modern spectral analyses—for example, mu or beta rhythm amplitudes (Pfurtscheller & Da Silva, 1999). Joint time-frequency features could also be used (Schalk, Wolpaw, McFarland, & Pfurtscheller, 2000).

### Decision Making

This stage normally classifies the features from the previous stage into different categories based on the required device output. For example, for the P300 speller matrix paradigm (Donchin, Spencer, & Wijesinghe, 2000), this stage would classify the features into one of the categories representing the alphanumeric characters. There are several popular classification methodologies that have been explored in BCI: linear classifiers, non-linear classifiers, and Bayesian classifiers.

The most popular linear classifier in BCI design is the linear discriminant analysis (LDA), sometimes known as Fisher’s LDA. This classifier uses hyperplanes to separate the
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features into different classes (Duda, Hart, & Stork, 2001). For a two-class problem with two features, the boundary is simply a straight line (as shown in Figure 4). It should be noted that a simple binary switch (‘YES’, ‘NO’) such as the one shown is capable of generating more complex responses through, say, nested menu icon selection or by using some translation algorithm (such as Morse code).

For classifying several classes, the general strategy is multi-levels of ‘one vs. the rest’ classification, though one level of multi-class classification is also possible with the generation of several hyperplanes.

LDA is simple to use and in general gives acceptable levels of performance (Lotte, Congedo, Lecuyer, Lamarche, & Arnaldi, 2007), though EEG data is generally non-linear, but its low complexity makes it particularly suitable for online BCI systems. It has been used successfully in motor imagery-based BCI (Pfurtscheller & da Silva, 1999; Tsui, Vuckovic, Palaniappan, Sepulveda, & Gan, 2006), P300 speller matrix (Donchin et al., 2000), mental activity BCI (Huan & Palaniappan, 2004), and asynchronous BCI (Leeb et al., 2007).

The artificial neural network (ANN), typically the multilayer perceptron (MLP) architecture, is one of the most common non-linear classifiers employed in BCI designs (Garret et al., 2003). With enough neurons in the single hidden layer, MLP could approximate any continuous function, thereby being suitable for BCI designs. Typically, the back propagation and its modern variants have been used to train the MLP ANN (Palaniappan, 2004). Some of the other ANNs that have been used in BCI studies are Fuzzy ARTMAP (Palaniappan, Rapeendran, Nishida, & Saiwaki, 2002) and learning vector quantization (Pfurtscheller, Flotzinger, & Kalcher, 1993).

A support vector machine (SVM) could be either a linear or non-linear classifier depending on which kernel function is used. SVMs have also been used successfully in several BCI designs: linear SVMs use linear decision boundaries (Rakotomamonjy, Guigue, Mallet, & Alvarado, 2005), while the non-linear ones use Gaussian or radial basis function kernels (Garret et al., 2003).

The nearest neighbor classifier is one of the simplest classifiers, but due to its computational complexity (as the distance of every test data from every training data must be computed), it has not seen much use in BCI except in a few studies (Palaniappan & Danilo, 2007; Ravi & Palaniappan, 2005).

Similarly, Bayesian classifiers are also not popular, though they were used successfully in motor imagery (Lemm, Schafer, & Curio, 2004) and mental activity BCI (Keirn & Aunon, 1990). Bayesian classifiers (typically the naïve version that assumes independence of features) use the prior class probability and conditional probability of the training data to estimate the maximum posterior hypothesis (i.e., class) of the test data.

Translation Algorithms

The translation algorithm translates the output of the classifier into meaningful information or command controls. For example, a sequence of mental activity denotes a particular command to move a wheelchair or some code to translate a sequence of imagined movements into English alphabets.

Figure 5. Example of a recorded EEG signal
However, this element is not present nor required for all BCI designs.

Sometimes, there is feedback from the device output to the subject. This will allow the subject to enhance its EEG output to increase the accuracy; this sort of feedback is common during the design of some BCIs like those using slow cortical potential (SCP).

OVERVIEW OF NON-INVASIVE BCI METHODOLOGIES

Basically, the BCI approaches could be either invasive or non-invasive. The non-invasive BCI methods using EEG, magnetoencephalogram (MEG), positron emission topography (PET), functional magnetic resonance imaging (fMRI), and optimal imaging (near-infrared spectroscopy (NIRS)) are more popular than the invasive one based on electrocorticogram (ECoG), though effective due to health hazards posed by the latter (as the electrodes are surgically implanted).

EEG-Based BCI

EEG is the brain’s electrical activity recorded using electrodes attached to the scalp; it is the cumulative effect of thousands or more neurons (in the cortex) that are activated during mental processes. It is in the microVolts range due to high attenuation by skull and scalp (so for proper analysis, they have to be amplified). Figure 5 shows an example of a recorded EEG signal.

There are several methodologies for implementing EEG-based BCI: evoked potentials (typically from visual stimulus, though not always), better known as visual evoked potential (VEP) (Donchin et al., 2000; Wang, Wang, Gao, Hong, & Gao, 2006), mental activity (Palaniappan, 2006b), motor imagery (Wolpaw et al., 2002), and SCP (Mensh, Werfel, & Seung, 2002). The VEP approach could be further divided into P300-based VEP (Donchin et al., 2000) and steady state VEP (SSVEP) (Wang et al., 2006).

P300-Based VEP

VEP is a component in EEG that is evoked in response to an external visual stimulus like visualizing a picture or flash of light. The recorded signal consists of spontaneous EEG and VEP, where the spontaneous EEG is many times higher in amplitude as compared to VEP. Hence, measures like averaging from many trials are needed to obtain a reliable enough VEP. In recent years, principal component analysis (Palaniappan & Ravi, 2006) and independent component analysis (Palaniappan, 2006a) have been suggested for separating VEP from EEG in single trials.

P300 (or P3) is the third positive component in VEP (see Figure 6), and it is maximal in midline (like locations Cz, Pz, Fz, etc). It is evoked in a variety of decision-making tasks and, in particular, when a target stimulus is recognized. It is evoked around 300 ms after stimulus onset, and in general, P300 components encountered for BCI purposes are limited to 8 Hz.

Typically, the oddball paradigm is used to evoke P300 (Polich, 1991). In this paradigm, a target stimulus that oc-
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curs infrequently compared to a non-target stimulus will evoke P300. In P300-VEP BCI designs (Donchin et al., 2000), a variation of this paradigm is used: spelling matrix or Donchin paradigm. In this paradigm, the screen consists of alphabetic characters. Spontaneous EEG plus VEP is recorded when rows and columns flash, where each trial consists of 12 flashes and trials are repeated, typically 15, 20, or 40 times. Averaging from trials is performed to reduce unrelated spontaneous EEG from VEP. Normally, a low-pass filter (LPF) with cut-off at 8 Hz is used, and P300 peak detected around 300-400 ms (sometimes, other ranges like 300-500 or 400-600 ms are also used) and amplitude of P300 peak stored for analysis. The row and column containing the target (focused) character will have a higher P300 amplitude compared to the row or column that does not contain the target character. Figure 7 shows the onscreen display in this paradigm, while Figure 8 shows an example of real averaged VEP signals from 12 flashes obtained from a subject, where the focused target character is N (row 3, column 2). The abscissa is the amplitude of the VEP (in microVolts) and ordinate is the time (in seconds) after stimulus onset.

Mental-Activity-Based BCI

In this BCI design (Keirn & Aunon, 1990; Palaniappan et al., 2002; Palaniappan, 2006b), EEG signals are recorded when users think of different mental tasks covering a wide range of cognitive abilities (without any vocalizing or physical movements). Some examples of used mental tasks include:

- **Baseline**—Subjects relax and think of nothing in particular.
- **Letter Composing**—Subjects mentally compose a letter to someone.
- **Math**—Subjects do nontrivial multiplication problems, such as $42 \times 18$.
- **Visual Counting**—Subjects visually imagined sequential numbers being written on a blackboard with the previous number being erased before the next number is written.
- **Geometric Figure Rotation**—Subjects imagine a figure being rotated around an axis.

These four active mental tasks (i.e., excluding baseline tasks) exhibit inter-hemispheric differences. For example: math tasks utilize more processes in the left hemisphere as compared to visual tasks that utilize more processes in the right hemisphere.

One useful measure to detect the activated hemisphere is through asymmetry ratio (AS) (Keirn & Aunon, 1990):

![Figure 7. Onscreen display for speller matrix paradigm (Donchin et al., 2000)](image)

![Figure 8. An example of real averaged VEP signals from 12 flashes (the focused target character is from row 3, column 2: N)](image)
where $E_1$ is the energy in one EEG channel in the left hemisphere and $E_2$ is the energy of EEG in another channel but in the right hemisphere. For example, for the electrodes shown in Figure 10, $AS$ using channels (electrodes) O1 and O2 will be positive for maths activity as compared to object rotation (visual) activity. $AS$ for baseline tasks will be near zero. So we can use baseline (B) and two tasks—maths (M) and object rotation (O)—to construct a communication method using a translation algorithm.

Here, translation algorithm translates the sequence of detected mental tasks into a command/output. For example, for wheelchair movement: task sequence MBO could denote ‘turn left’, while task sequence OBM could denote ‘turn right’. For communication purposes, Morse code could be used to translate the sequence of mental tasks into alphabets. For example, letter I in Morse code is ‘dot dot’, so the sequence of mental tasks: OBOB or (MBMB) could denote letter I, where the baseline denotes the end and start of a new mental task (except for the first mental task). Figures 11 and 12 illustrate the use of this translation algorithm.

### SSVEP BCI

SSVEP is the response due to a visual stimulus modulated at a frequency higher than 6 Hz. It is maximum in the visual cortex, specifically in the occipital region. In this design, each onscreen target flickers with a specific frequency, and a photic driving response in the brain causes the frequency (and its harmonics) to appear in SSVEP. In other words, the onscreen “flickers” drive a photic response (with corresponding frequencies) in the optical regions of the brain. So, determination of SSVEP frequency (through spectral analysis like Fourier methods) is enough to decide on the focused target. An example of the onscreen display for dialing telephone numbers is shown in Figure 13.

The flicker frequency selection can be up to 45 Hz; in general the higher frequency is better as this causes less strain on the eyes of the user (Wang et al., 2006). For example, for the onscreen telephone keypad as in Figure 13, the flicker frequencies could be in 1 Hz intervals: 1 (9 Hz), 2 (10 Hz), 3 (11 Hz), ……0 (16 Hz), # (17 Hz). In the work by Wang et al (2006), normalized fast Fourier transform (FFT) magnitude is computed from four seconds of SSVEP. Peak detection (above a certain threshold) is used to determine the frequency. Once detected, the number appears onscreen and the subject moves on to look at another number.

Generally, harmonics should be avoided (e.g., if 9 Hz is used for a block, integer multiples of this such as 18, 27, 36, or 45 Hz should not be used). However, recently Muller-Putz, Scherer, Brauneis, and Pfurtscheller (2005) showed that using harmonics could improve the detection of the focused target.

### Motor Imagery BCI

In this approach, BCI is designed using imaginary movements, that is, when the subject imagine is moving a limb (could be arm, leg, tongue, etc). An actual voluntary movement is composed of three phases: planning, execution, and recovery. But it is known that even during imaginary movement (motor imagery), there is the planning stage.

During planning, event-related desynchronization (ERD) and event-related synchronization (ERS) occur in \( \mu \)meter (alpha, 10-12 Hz) and beta (12-14 Hz) frequency ranges. ERD is the attenuation in EEG in primary and secondary
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motor cortices during the preparatory stage which peaks at movement onset in contralateral hemisphere (e.g., left-hand motor imagery, ERD in the right side of the brain), while ERS is the corresponding EEG amplification but in an ipsilateral hemisphere. The ERD/ERS can be computed using power values by squaring the samples in the frequency ranges or using some power spectral density (PSD) measure (Pfurtscheller & Da Silva, 1999). In addition to these changes in alpha and beta frequency ranges, there is also the gamma burst, which is a sharp increase in EEG in the gamma (36-40 Hz) frequency range. Figure 15 shows an example of these ERD/ERS and gamma bursts.

One simple method to implement this paradigm is shown in Figure 16. Here, the subject imagines moving his or her left or right hand. Discrimination of these imagined movements can be used for a BCI design. This could be done by computing the PSD of EEG in C3, C4, and CZ. Next, the sum of PSD (SPSD) is computed. If $C3_{SPSD} - CZ_{SPSD} > C4_{SPSD} - CZ_{SPSD}$, then it is a left-hand motor imagery; if $C4_{SPSD} - CZ_{SPSD}$
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Figure 14. Normalized amplitude spectra corresponding to different data lengths. The 'number' focused here is '#', as there is a clearly defined peak at 17 Hz (Wang et al., 2006).

SCP BCI

SCP is the potential shift in EEG (around 1-2 Hz) which can last several seconds. Humans can control SCP using feedback and a positive reinforcement mechanism, where the negativity SCP can be generated with tasks such as readiness to move or mobilization of resources for cognitive tasks, and the positivity SCP can be generated during execution of cognitive tasks or simply in inactive states. Self-regulation of SCP can be used to generate a binary signal or even menu/letter selection on screen for use in BCI designs. But the main problem with this approach is that it requires extensive training, typically a few months (Hinterberger et al., 2004).

Other Non-Invasive BCIs

Though the focus of this article is not on non-EEG-based BCIs, a short discussion on other current non-invasive BCIs would be useful and is given here.

PET-based BCI is where a tracer medium (radioactive isotope with short half life) is injected in blood. This tracer medium moves in blood and decays by emitting a positron, and gamma photons are generated when the positron annihilates with an electron. A special scanner measures these gamma photons. So, changes in blood flow due to specific
brain activity could be detected. For example, in a subject thinking of moving his or her right hand, brain activity will be detected in the left hemisphere, and vice versa. This detected brain activity could be translated for BCI applications. It is not popular as the equipment is too expensive and bulky where a cyclotron is needed for generation of tracer medium. It is also partially invasive (as it requires radioactive injection), though no surgery is involved. Furthermore, the waiting period is typically an hour before the system can be used and not suitable for continuous usage.

fMRI-based BCI detects oxygen-level changes in blood hemoglobin which generates magnetic resonance. The resulting image intensity variations show the brain activation areas, and this could be translated for BCI application. This is also not popular as it requires a bulky scanner (hence no mobility for subjects) and the vascular response is too slow—local response to this oxygen utilization occurs after a delay of approximately 1-5 seconds, with peaks at 4-5 seconds; in addition there is the possible detrimental effects due to prolonged exposure.

NIR-based BCI is a relatively new method that uses the near infra-red region of the electromagnetic spectrum (from about 800 nm to 2500 nm). The penetration is deeper into the skull as it uses NIR; NIR light is emitted and the reflection from the blood cells (specifically, oxygen level in hemoglobin) is used as a measure of blood flow. This blood flow denotes activation of brain areas (activation deduced from images with higher reflectance intensity). This procedure is sometimes known as an optical method, as NIR produces intensity images. Mobility is not limited (unlike fMRI) as the sensor-detector can be fixed on the skull, but its main hindrance is the slow vascular response (on the order of a few seconds). Also, though most NIR energy is reflected, a small portion of NIR energy might be absorbed by the brain cells and potentially be damaging in the long run.

MEG-based BCI is similar to EEG but uses measurements of magnetic fields rather than electric fields. The magnetic field generated by the brain is measured outside the scalp. The temporal resolution is better than EEG, but not popular due to high cost and difficulty in obtaining proper MEG readings as ultra-sensitive magnetic field detectors are needed. Mobility is also restricted, and shielding from other magnetic sources is also necessary which inhibits usage outside the lab environment.

**BCI APPLICATIONS**

One of the most important BCI applications is restoring control functions to those with motor impairments caused by progressive disorders such as amyotrophic lateral disorder (ALS), muscular dystrophy, and multiple sclerosis,
and non-progressive disorders such as brainstem stroke, traumatic brain injury, spinal cord injury, and numerous orders that impair the neural pathways preventing proper muscle control. But BCI devices can also be developed for everyday use by the healthy population, though this is not its main use.

**Individuals with Motor Disabilities**

Severely affected individuals may lose all forms of voluntary muscle control. However, these individuals are able to survive with modern life technology support, but are completely ‘locked-in’ without any ability to communicate at all. The use of EEG-based BCI technologies can offer these individuals an alternative mode of communication. A typical example of a communication BCI system would be brain-controlled word processing software.

These technologies could also aid the disabled in restoring mobility (controlling wheelchair movement); environmental control (controlling TV, power beds, thermostats, etc); prosthetics control (motor control replacement, controlling artificial limbs); and rehabilitative (assistive) control—to restore motor control (strengthen or improve weak muscles).

**Other Applications**

The general population might also benefit from BCI devices. A simple example is environmental control (hands-off control), for example, control of external devices without using the external limbs (hand/legs). Other examples are in areas such as virtual reality (entertainment), for example, computer games like Mind Pacman (Krepki, Blankertz, Curio, & Müller, 2007). Recently, BCI has also been studied for use by astronauts in space, for example when they become temporarily paralyzed or to control devices in severely restricted extra terrestrial environments (Menon et al., 2007).

Biometrics is yet another recent application of BCI where BCI devices are used to identify an individual (Palaniappan, 2004) or authenticate an individual using thoughts alone (Palaniappan & Danilo, 2007). It is very useful for high-security individual identification applications, as EEG-based biometrics is more fraud resistant compared to other biometrics like fingerprints, iris scans, retina, ear shape, odor, and so forth (since thoughts cannot be forged!). EEG-based biometric verification is also more secure than personal identification numbers (PINs) and passwords, which can be easily compromised through shoulder surfing or other means. For example, the BCI device used to spell alphabets (Donchin et al., 2000) can actually be adapted to generate passwords that are based on thoughts alone.

**CURRENT CHALLENGES**

There are numerous current challenges for BCI designs. The following descriptions are not exhaustive but serve to illustrate some of the issues facing this research field that is still very much in its infancy.

It is not clear how the BCI designs will require adaptation for real users (like disabled people) and in real noisy environments. Most of the BCI research studies are conducted in laboratory environments where the condition is ideal. For example, the BCI experiments at the University of Essex are conducted in the BCI laboratory where there is special lighting with an electromagnetic radiation shield and under noise-free conditions. However, it should be remembered that the main BCI users will be disabled individuals, who will use the devices in a not ideal environment. So, it is important to realize that the high performances obtained in the laboratory are unlikely to be repeated in the real world. Another similar issue is that a large number of BCI studies are tested using healthy subjects (typically university students), and BCI systems may not perform up to expectation when used by disabled individuals and will require special adaptations.

A BCI system cannot be ‘on’ all the time. So we will need to separate algorithms to turn on or off the devices. In recent years, studies that combine the required BCI output and this on/off state recognition have been explored. These systems are known as asynchronous or self-paced BCI.

The current maximum information transfer rate for BCI systems is about 25 bits per second (Wolpaw et al., 2002), and even this—‘still slow’ for practical performance—is normally achieved only after extensive training or fine tuning. Improved systems are needed so that they are more accurate and give faster response. It may not be possible to train a disabled individual, and so systems that do not require any prior training and ease of use will be needed as well.

In general, most of the BCI systems are fine tuned for specific subjects. This results in individual BCI and not universal BCI, which is a problem as it may not be possible for fine tuning in disabled individuals. Therefore, universal BCIs should be explored more extensively.

Since BCI research is relatively new, it is not evident on the long-term effects of these systems on the user’s health and if the performance would be stable across time.

Ethics is especially an issue of using (or testing) BCI with those already paralyzed. For example, it is difficult to decide if the permission from a responsible nearest relative of a completely disabled subject is sufficient or even appropriate to conduct experiments with the disabled subject.
FUTURE TRENDS

The solutions for all the issues discussed in the previous section will need to be explored—of course, some of these are already under consideration. For example, the use of active electrodes\(^1\) simplifies the set-up and minimizes the preparation time. Also, dry electrodes (which do not require any wet gel to achieve the necessary impedance) are being investigated, as this will allow 24/7 use by subjects (especially the disabled).

Advancement in BCI algorithms related to signal preprocessing, feature extraction, and classification will need to be explored to maximize the accuracy while achieving a quicker response. Further, other more suitable paradigms should be explored for BCI designs.

END NOTES

1. This algorithm translates the decision system output into usable information or action.
2. A frequency range that is similar to alpha but occurs during actual movement/motor imagery.
3. Active electrodes have miniscule chips that are able to reduce noise caused by poor skin contact, thereby circumventing the necessity to clean the scalp prior to electrode attachment.

ACKNOWLEDGMENTS

The support of the following organizations in different parts of the work are acknowledged: University Malaya (Malaysia), Multimedia University (Malaysia), Ministry of Science (IRPA Grant, Malaysia), Nanyang Technological University (Singapore), Singapore–University of Washington Alliance, Essex University (UK), and European Space Agency.

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**KEY TERMS**

**Biometrics**: Identification or authentication of the individuality of a person using the behavioral or physiological characteristics of the person.

**Brain-Computer Interface/Brain-Machine Interface (BCI/BMI)**: Devices that use electroencephalogram signals to perform a communication or control action.

**Electrodes (channels)**: Sensors normally made of Ag/AgCl that are used to record electroencephalogram.

**Electroencephalogram (EEG)**: Brain activity obtained as recorded signals from the scalp using electrodes.

**Mental Activity/Task**: Any task that generates EEG for use in BCI designs.

**Motor Imagery**: Used in BCI designs where subjects imagine moving a limb.

**P300 Component**: The third positive component in visual evoked potential; normally evoked around 300 ms after stimulus onset.

**Slow Cortical Potentials**: The potential shifts in EEG (around 1-2 Hz), which can last several seconds.

**Steady State VEP**: A type of VEP caused by photic response (frequency following effect).

**Visual Evoked Potential (VEP)**: An EEG component that is in response (i.e., evoked) by a visual stimulus modality.