

Current Practices in Electroencephalogram–Based Brain–Computer Interfaces

Ramaswamy Palaniappan
University of Essex, UK

Chanan S. Syan
University of the West Indies, West Indies

Raveendran Paramesran
University of Malaya, Malaysia

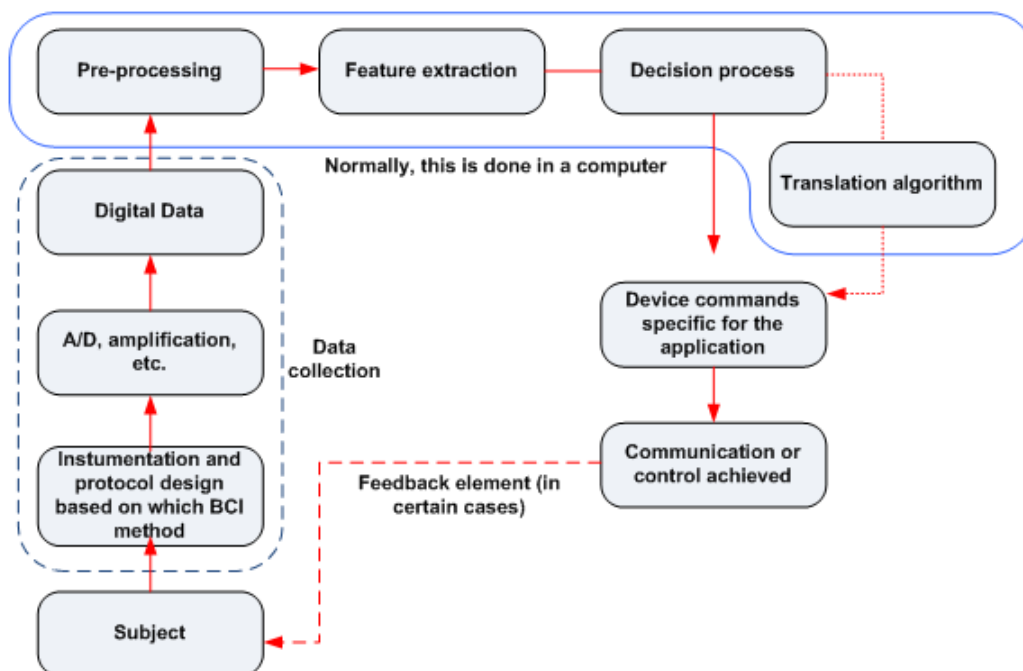
INTRODUCTION

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



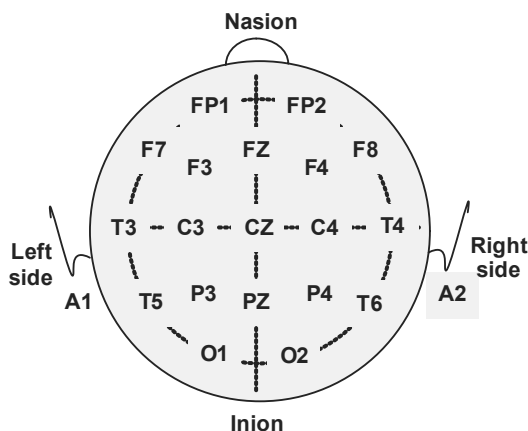
This research area is extremely exciting, and in recent times, there has been an explosive growth of interest in this revolutionary new area of science which would enable computers (and therefore any other reactive device) to be controlled by thought alone—the benefits for the severely disabled would 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).

Figure 2. 10-20 electrode placement system



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, & Shamsunder, 1998), where Burg's method (Shiavi, 1999) is the common procedure used to estimate the AR coefficients with

12 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-global.com/chapter/current-practices-electroencephalogram-based-brain/13681

Related Content

Using Incoming Traffic for Energy-Efficient Routing in Cognitive Radio Networks

Constandinos X. Mavromoustakis, Athina Bourdena, George Mastorakis and Evangelos Pallis (2015). *Journal of Information Technology Research* (pp. 1-24).

www.irma-international.org/article/using-incoming-traffic-for-energy-efficient-routing-in-cognitive-radio-networks/127047

Investigating Web 2.0 Application Impacts on Knowledge Workers' Decisions and Performance

Haya Ajjan, Richard Hartshorne and Scott Buechler (2012). *Information Resources Management Journal* (pp. 65-83).

www.irma-international.org/article/investigating-web-application-impacts-knowledge/70600

Product Evaluation Services for E-Commerce

Sheng-Uei Guan (2009). *Encyclopedia of Information Communication Technology* (pp. 683-690).

www.irma-international.org/chapter/product-evaluation-services-commerce/13422

New Technologies in Hospital Information Systems

Dimitra Petroudi and Nikolaos Giannakakis (2009). *Encyclopedia of Information Science and Technology, Second Edition* (pp. 2817-2820).

www.irma-international.org/chapter/new-technologies-hospital-information-systems/13988

The Importance of a Comprehensive Adoption Decision in the Presence of Perceived Opportunities - The Test Results Case

Pankaj Bagri, L. S. Murty, T. R. Madanmohan and Rajendra K. Bandi (2004). *Annals of Cases on Information Technology: Volume 6* (pp. 195-207).

www.irma-international.org/chapter/importance-comprehensive-adoption-decision-presence/44577