Chapter 6
Neurofeedback:
Refining the Methodology of Brain–Computer Interface Training

David Vernon
Canterbury Christ Church University, UK

Tammy Dempster
Canterbury Christ Church University, UK

ABSTRACT

This chapter explores the use of neurofeedback training as a mechanism for altering human brain functioning and in turn influencing behaviour. It outlines the notion that such training provides a plausible mechanism by which an individual may be able to learn to alter and control specific aspects of his electro-cortical activity. The chapter highlights some of the findings from research, including clinical, peak performance, and functional validation studies. In addition, it delineates some important methodological issues that remain to be addressed. It is hoped that outlining these issues will serve a dual purpose. First, it will assist in the understanding of some of the theoretical and methodological limitations that may be holding the field back. Second, it is hoped that such information will stimulate researchers to work towards designing more efficient and effective research protocols and neurofeedback training paradigms.

INTRODUCTION

This chapter provides an outline of some of the applications for neurofeedback training (NFT) and in doing so highlights some key unresolved methodological issues. The first section describes how your brain produces a constant stream of electrocortical activity which can be recorded and then separated into a range of pre-set frequency components. This is followed by a brief overview of NFT which is based on a standard operant conditioning paradigm and can enable you to learn how to use computer based technology to alter specific aspects of your brain wave activity. The chapter then provides a brief outline of the main rationales that have been put forward for conducting such training. This is followed by a section which focuses on some of the outstanding

DOI: 10.4018/978-1-4666-2077-3.ch006

methodological issues that pertain to NFT. These are: the range of spectral components that may be altered using NFT, how to identify whether someone has learnt to alter their EEG via NFT, what measures should be used when exploring possible changes in the EEG as a result of NFT, how the reward threshold level should be set, whether there is a particularly efficient strategy that has been identified, and what effect the participant's motivation level may have on the outcome of such training. By highlighting these issues, which relate to the methodology of NFT, we hope to stimulate future researchers to address them empirically and in doing so improve the efficiency and effectiveness of the NFT protocol. The final section of the chapter outlines the possible future trend of using full scalp recording along with simultaneous feedback of multiple frequency components across multiple sites to provide a more comprehensive training approach.

THE ELECTROENCEPHALOGRAM

It was Richard Caton who, in the late 19th century, first discovered that it was possible to record the weak electrical signals emanating from the brains of living animals. This work was later extended and developed by Hans Berger to encapsulate the recording of such signals from human participants. Since then the electroencephalogram (EEG) has become an integral part of the modern clinician's battery and provided research scientists with a plethora of intriguing links between your behaviour and the activity of your brain.

The EEG is a non-invasive technique and is invariably recorded by placing sensors across the scalp using an agreed placement system. This is commonly referred to as the montage and follows a preset pattern on the scalp according to an international EEG nomenclature called the 10-20 system and is based on the relationship between the location of an electrode and the underlying area of cerebral cortex (Jasper, 1958). It is called the 10-20 system because the sensors are placed at distances of either 10% or 20% apart from each other or set points across the scalp. In addition to this each site is identified by a letter, which corresponds to the underlying cortical region, and another letter or number to denote the location. For example, the letters F, T, C, P, and O refer to the Frontal, Temporal, Central, Parietal and Occipital regions. In addition to this any accompanying even numbers (2,4,6,8) refer to the right hemisphere and odd numbers (1,3,5,7) refer to the left hemisphere, with the letter z denoting a sensor placed on the midline. Thus, the position Cz refers to the central region of the scalp along the midline whereas C3 refers to the central position of the scalp on the left. See Figure 1 below for an illustration of some the commonly used scalp locations.

Though the EEG may be recorded by a single sensor it is important to realise that such a measure necessarily represents the gross brain activity and function from millions of cells beneath that sensor (see e.g., Davidson, 1988). According to Barlow (1993) the EEG represents the summation of excitatory and inhibitory postsynaptic potentials in the pyramidal cells of the cerebral cortex. As such, the EEG recorded from your scalp represents the current flow associated with summed postsynaptic potentials in synchronously activated, vertically oriented, pyramidal cells. In addition to this, the rapid changes which can be seen in the rhythm of the EEG, from slower to faster and vice versa, are believed to reflect the unique properties of thalamocortical circuits (see Sterman, 1996).

The raw EEG trace recorded from each active sensor can be separated into a range of pre-defined frequency components. Much in the same way as white light can be 'split' by a prism into its spectral components of red, orange, yellow etc, your raw EEG trace can be divided into a range of frequency components using a Fast Fourier Transform (FFT), see Figure 2.

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