Neural Engineering

Edited by
Bin He
University of Minnesota
Minneapolis, Minnesota

Kluwer Academic/Plenum Publishers
New York, Boston, Dordrecht, London, Moscow
PREFACE

Beginning centuries ago, early exploration of neural systems focused on understanding how neural systems work at the cellular, tissue, and system levels, and engineering methodologies were developed to detect, process, and model these neural signals. Recently, tremendous progress has been made in the field of neural engineering, not only understanding the mechanisms, detection, and processing of the signals, but also on restoring neural systems functions and interfacing the neural systems with external devices and computers.

The purpose of this book is to provide a state-of-the-art coverage of basic principles, theories, and methods in several important areas in the field of neural engineering. It is aimed at serving as a textbook for undergraduate or graduate level courses in neural engineering within a biomedical engineering or bioengineering curriculum, as well as a reference book for researchers working in the field of neural engineering, and as an introduction to those interested in entering this discipline or acquiring knowledge about the current state of the this rapidly developing field.

Chapter 1 deals with neural prostheses—implantable devices that mimic normal sensory-motor functions through artificial manipulation of the biological neural system using externally induced electrical currents. While these are generally separated into two classes (sensor and motor) the author provides systematic coverage of the state-of-the-art in sensory neural prostheses.

The next three chapters address neural interfacing at different levels and from different perspectives. Chapter 2 introduces the concept of interfacing neural tissues with microsystems. Microsystems technology is a rapidly developing field that integrates devices and systems at the microscopic and submicroscopic scales. Neural interfacing with microsystems provides an important basis of interfacing neural systems with a variety of artificial devices. Chapter 3 addresses another aspect of neural interfacing—brain-computer interface—which serves as a method of communication based on neural activity generated by the brain that is independent of its normal output pathways of peripheral nerves and muscles. Also reviewed are the state-of-the-art developments in this emerging field, integrating neurophysiology, signal detection, signal processing, and pattern recognition. Chapter 4 reviews the recent developments in neurorobotics, which interface directly with the brain to extract the neural signals that code for movement and use these signals to control a robotic device.
Neural stimulation is discussed in Chapter 5. Functional electrical stimulation of neural tissue can provide additional functional restoration to neurologically impaired individuals. Also covered is the fundamentals of electrical excitation introduced by electrical stimulation of neural tissue and some important applications.

Chapters 6 and 7 discuss neural signal processing and imaging. An important aspect of neural engineering is to properly analyze and interpret the neural signals—a step that plays a vital role for sensing and controlling neural prostheses and other neural interfacing devices, as well as understanding the mechanisms of neural systems. Chapter 6 provides a concise but systematic review of neural signal processing in the central nervous system; Chapter 7 teaches the basic principles and applications of electrophysiological neuroimaging. Applying electromagnetic theory and signal processing techniques, electrophysiological neuroimaging provides spatio-temporal mapping of source distributions within the brain from noninvasive electrophysiological measurements. Knowledge of such spatio-temporal dynamics of source distribution associated with neural activity would aid in the understanding of the mechanisms of neural systems and provide a noninvasive probe of the complex central nervous system.

Chapters 8, 9, and 10 focus on neural computation. Chapter 8 discusses the computational principles underlying cortical function. Recent theoretical models, presenting a range of interesting and sometimes conflicting mechanisms, are reviewed and their relationship with the underlying biology is explored. Cortical computation is an important tool for studying and understanding the mechanisms associated with processes ranging from visual, auditory, and olfactory senses to high-level brain functions such as recognition, memory, and categorization. Chapter 9 introduces nonlinear dynamics of neural systems and provides an overview of the framework to study, simulate, design, fabricate, and test biologically plausible information processing paradigms. In addition, the analog VLSI implementations of the nonlinear computational algorithms are described, providing an important link between the computational algorithms and the devices interfacing with neural systems. Chapter 10 reviews some of the important neural circuit models in order to gain a balanced understanding of the interplay between the dynamics and temporal characteristics of action potential trains and their effects on the neural information processing. Emphasis is placed on neural modeling at the cellular level and its applications for understanding the mechanisms of neural information processing.

The following two chapters emphasize neural system identification and prediction. Chapter 11 introduces important perspectives and techniques for system identification, as well as giving concrete examples of system identification strategies to study sensory processing in the central nervous system and neural control in the peripheral nervous system. An important aspect of neural engineering is not only to detect and understand signals from neural systems but to also interface with, and control, the neural systems. Chapter 12 discusses such strategies and provides an example of predicting epileptic seizures and thus allowing for proper intervention and control of the seizure.

Chapter 13 discusses retinal bioengineering. The mathematical modeling of neural responses in the retinal microenvironment as well as restoration of retinal function are reviewed. The retina has long served as a model for understanding complex parts of the nervous system, but is also simpler than other parts of the brain due to the lack of significant feedback from the brain to the retina.
# CONTENTS

1. **SENSORY NEURAL PROSTHESES** ................................................................. 1  
   *Philip R. Troyk and Stuart F. Cogan*  
   1.1. Introduction ................................................................................. 1  
   1.2. Fundamentals of Sensory Neural Prostheses ................................ 2  
   1.3. Electrodes for Neural Stimulation .............................................. 4  
   1.3.1. Charge Injection Processes and Coatings ................................. 6  
   1.3.2. Fabrication of Neural Stimulating Electrodes ......................... 11  
   1.3.3. Reactions of Neural Tissue to Stimulating Electrodes ............. 18  
   1.4. Transcutaneous Coupling of Power and Telemetry .................... 21  
   1.4.1. Inductive Links ...................................................................... 21  
   1.4.2. Generating the Transmitter Coil Current ................................. 24  
   1.4.3. Data Telemetry ...................................................................... 26  
   1.5. Techniques for Driving Electrodes ............................................ 28  
   1.5.1. A Model for a Stimulating Microelectrode ............................... 28  
   1.5.2. Imbalances in Electrode Current Waveforms ......................... 31  
   1.5.3. Constant-Current Electronic Circuits ....................................... 32  
   1.6. Applications ............................................................................. 35  
   1.6.1. Cochlear Implants .................................................................. 35  
   1.6.2. Visual Prostheses ................................................................... 38  

2. **INTERFACING NEURAL TISSUE WITH MICROSYSTEMS** ................. 49  
   *Ph. A. Passeraub and N. V. Thakor*  
   2.1. Introduction ............................................................................... 49  
   2.2. Neural Microsystems ................................................................... 50  
   2.2.1. Background ........................................................................... 50  
   2.2.2. Function Block Diagram ....................................................... 52  
   2.2.3. Neural Microsystems Configurations ..................................... 56  
   2.3. Generic Methods to Interface Microsystem and Neural Tissue ...... 59  
   2.3.1. How to Interface Electrical Signals in Neural Microsystems .... 59  
   2.3.2. How to Interface Chemical Signals in Neural Microsystems .... 63  
   2.3.3. How to Interface Other Types of Signals in Neural Microsystems 66
3. BRAIN–COMPUTER INTERFACE ............................................. 85

Anirudh Vallabhaneni, Tao Wang, and Bin He

3.1. Introduction ................................................................. 85

3.1.1. What is BCI ................................................................. 85

3.1.2. History of BCI ............................................................... 86

3.2. Components of a BCI System ........................................ 86

3.2.1. Functional Components ............................................. 87

3.2.2. Feedback ................................................................. 88

3.3. Signal Acquisition ....................................................... 89

3.3.1. Invasive Techniques ................................................ 89

3.3.2. Noninvasive Techniques ............................................ 93

3.4. Feature Extraction and Translation ................................ 93

3.4.1. Types of Signals ...................................................... 95

3.4.2. Training ................................................................. 100

3.4.3. Signal Processing and Feature Extraction Techniques .... 102

3.4.4. Translation Techniques ............................................. 106

3.4.5. Extraction and Translation in Action: A Case Study on Classification of Motor Imagery Tasks ...................................... 107

3.5. Typical BCI Systems .................................................. 113

3.6. BCI Development ..................................................... 116

4. NEUROBOTICS .............................................................. 123

Karen A. Moxon

4.1. Introduction ............................................................... 123

4.2. Directly Interfacing with the Brain ................................ 126

4.2.1. Representation of Information in the Brain .................. 126

4.2.2. Coding Strategies of Ensembles of Single Neurons ........ 128

4.2.3. Decoding the Neural Signal ...................................... 129

4.3. Neurobotic Control .................................................... 130

4.3.1. Feasibility of Neurobotic Control ................................ 130

4.3.2. Neurobotic Control as Tool for Investigating Neural Coding Strategies ......................................................... 136

4.3.3. Neurobotic Control as a Therapeutic Device ............... 138

4.4. Hardware Requirements for Neurobotic Control ............ 140

4.4.1. The Neural Interface ............................................... 142

4.4.2. Signal Conditioning ................................................ 144

4.4.3. Neurobotic Control Algorithms .................................. 146

4.4.4. Packaging and Telemetry ......................................... 148

4.5. New Directions for a Neurobotic Control ....................... 149
## 5. ELECTRICAL STIMULATION OF THE NEUROMUSCULAR SYSTEM

*Dominique M. Durand, Warren M. Grill, and Robert Kirsch*

<table>
<thead>
<tr>
<th>Section</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1. Introduction</td>
<td>157</td>
</tr>
<tr>
<td>5.2. Mechanisms of Excitation of Applied Electrical Fields</td>
<td>158</td>
</tr>
<tr>
<td>5.2.1. Anatomy and Physiology</td>
<td>158</td>
</tr>
<tr>
<td>5.2.2. Electric Fields in Volume Conductors</td>
<td>159</td>
</tr>
<tr>
<td>5.2.3. Effects of Applied Electric Fields on Transmembrane Potentials</td>
<td>164</td>
</tr>
<tr>
<td>5.3. Electrode–Tissue Interface</td>
<td>168</td>
</tr>
<tr>
<td>5.3.1. Regulated Voltage and Regulated Current Stimulation</td>
<td>169</td>
</tr>
<tr>
<td>5.3.2. Tissue Damage</td>
<td>170</td>
</tr>
<tr>
<td>5.3.3. Effect of Waveform</td>
<td>172</td>
</tr>
<tr>
<td>5.4. Neuromuscular Prostheses</td>
<td>174</td>
</tr>
<tr>
<td>5.4.1. Recruitment Properties</td>
<td>175</td>
</tr>
<tr>
<td>5.4.2. Electrodes for Muscle Stimulation</td>
<td>177</td>
</tr>
<tr>
<td>5.4.3. Upper Extremity Applications</td>
<td>179</td>
</tr>
<tr>
<td>5.4.4. Lower Extremity Applications</td>
<td>180</td>
</tr>
<tr>
<td>5.4.5. Bladder Prostheses</td>
<td>183</td>
</tr>
<tr>
<td>5.5. Conclusions</td>
<td>185</td>
</tr>
</tbody>
</table>

## 6. NEURAL SIGNAL PROCESSING

*Donna L. Hudson and Maurice E. Cohen*

<table>
<thead>
<tr>
<th>Section</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.1. Overview</td>
<td>193</td>
</tr>
<tr>
<td>6.2. Biological Foundations and History</td>
<td>193</td>
</tr>
<tr>
<td>6.2.1. Biological Foundations</td>
<td>193</td>
</tr>
<tr>
<td>6.2.2. Central Nervous System</td>
<td>194</td>
</tr>
<tr>
<td>6.3. Analysis of Signals from Single Neurons</td>
<td>194</td>
</tr>
<tr>
<td>6.3.1. Neuron Models</td>
<td>196</td>
</tr>
<tr>
<td>6.3.2. Neurotransmitters</td>
<td>197</td>
</tr>
<tr>
<td>6.3.3. Action Potential Detection</td>
<td>197</td>
</tr>
<tr>
<td>6.3.4. Implanted Electrodes</td>
<td>197</td>
</tr>
<tr>
<td>6.4. Time Series Analysis</td>
<td>198</td>
</tr>
<tr>
<td>6.4.1. Properties of Time Series</td>
<td>198</td>
</tr>
<tr>
<td>6.4.2. Correlation and Covariance Functions for Stationary Processes</td>
<td>198</td>
</tr>
<tr>
<td>6.4.3. Correlation and Covariance Functions for Nonstationary Processes</td>
<td>199</td>
</tr>
<tr>
<td>6.4.4. Fourier Analysis</td>
<td>199</td>
</tr>
<tr>
<td>6.4.5. Power Spectral Density Functions</td>
<td>200</td>
</tr>
<tr>
<td>6.4.6. Wavelet Analysis</td>
<td>200</td>
</tr>
<tr>
<td>6.4.7. Chaotic Analysis</td>
<td>204</td>
</tr>
<tr>
<td>6.4.8. Linear versus Nonlinear Analysis</td>
<td>205</td>
</tr>
<tr>
<td>6.4.9. Biomedical Signals</td>
<td>205</td>
</tr>
<tr>
<td>6.5. Peripheral Neural Signals</td>
<td>206</td>
</tr>
<tr>
<td>6.6. Signal Processing in the CNS</td>
<td>207</td>
</tr>
<tr>
<td>6.6.1. EEG Analysis</td>
<td>207</td>
</tr>
<tr>
<td>6.6.2. Preprocessing</td>
<td>209</td>
</tr>
</tbody>
</table>
# Contents

## 7. Electrophysiological Neuroimaging

*Bin He and Jie Lian*

- Introduction .................................................. 221
- The Generation and Measurement of the EEG .............. 221
- Spatial and Temporal Resolution of the EEG .............. 222
- EEG Forward Problem and Inverse Problem .................. 223
- Head Volume Conductor Models and Source Models ......... 223
- Electrical Potentials in a Concentric Three-Sphere Volume Conductor Model ....................................... 225
- Dipole Source Localization .................................... 226
- Equivalent Current Dipole Models ........................... 226
- EEG-based Dipole Source Localization ....................... 227
- Constrained Dipole Source Localization ..................... 229
- Distributed Source Imaging ................................... 230
- Distributed Source Models .................................... 232
- Linear Inverse Filters ......................................... 233
- Regularization Parameters .................................... 236
- Two-Dimensional Cortical Imaging Technique ............. 239
- Concept of Cortical Imaging Technique ....................... 239
- Cortical Current Imaging ...................................... 240
- Cortical Potential Imaging .................................... 243
- Multimodal Integration ........................................ 246
- Surface Laplacian .............................................. 249
- Three-Dimensional Brain Electric Source Imaging ........ 249
- Challenges of 3D Neuroimaging ............................... 249
- Inverse Problem of the 3D Neuroimaging ..................... 250
- 3D Brain Electric Source Models ............................... 251
- Nonlinear Inverse Problem .................................... 252
- Discussion ...................................................... 254

## 8. Mechanisms of Cortical Computation

*Leif H. Finkel and Diego Contreras*

- Introduction ..................................................... 263
- Learning and Synaptic Plasticity ............................ 267

## 9. Computational Models

*Dongming J. Mark Skowri and Jose C.*

- Introduction ..................................................... 268
- Review of E ..................................................... 269
- Linear Time ...................................................... 270
- Nonlinear S ...................................................... 271
- Bifurcations ..................................................... 272
- Poincare–Birkhoff .............................................. 273
- The Olfactory of Coupled Oscillators ...................... 274
- The Hierarchical ................................................. 275
- Dynamic Architecture ......................................... 276
- Digital Simulation .............................................. 277
- Digital Implementation ........................................ 278
- Quantitative ...................................................... 279
- The Reduction .................................................... 280
- Designing it ...................................................... 281
- Training the ...................................................... 282
- Examples ......................................................... 283
- Hardware In ....................................................... 284
- Input Stage ....................................................... 285
- Nonlinear Fit ..................................................... 286
- Second-order ..................................................... 287
- Chip Measure ..................................................... 288
- Comparison ....................................................... 289
- Conclusions ...................................................... 290

## 10. Circuit Models

*Yin Ma, Yin*

- Introduction ..................................................... 291
- Circuit Models ................................................... 292
- A Simple Circuit ............................................... 293
- Equivalent Circuit .............................................. 294
- Computational .................................................... 295
- Models for ....................................................... 296
- An Integrate ...................................................... 297
CONTENTS

8.3. Spike-Based Computation .................................. 270
8.4. Spatiotemporal Pattern Recognition ...................... 273
8.5. Neuronal Firing Characteristics .......................... 278
8.6. Time Constraints on Cortical Computation .............. 280
8.7. Putting It All Together .............................. 281
8.8. Conclusions ...................................... 285

9. COMPUTATIONAL NEURAL NETWORKS .................. 289

Dongming Xu, Bryan Davis, Mustafa Ozturk, Liping Deng,
Mark Skowronska, John G. Harris, Walter J. Freeman,
and Jose C. Principe

9.1. Introduction ....................................... 289
9.2. Review of Dynamical Systems Analysis .................. 290
9.2.1. Linear Time-Invariant Systems and Their Qualitative Behavior ............ 290
9.2.2. Nonlinear Systems ............................ 291
9.2.3. Bifurcations ................................... 291
9.2.4. Poincaré–Bendixson Theorem ...................... 292
9.3. The Olfactory System as a Distributed Neural Network
     of Coupled Oscillators ................................ 292
9.3.1. The Hierarchy Structure of Freeman’s Model .............. 292
9.3.2. Dynamic Analysis of a Reduced KII Set .............. 294
9.4. Digital Simulation of the Freeman Model ................. 309
9.4.1. Digital Implementation Approaches .................. 309
9.4.2. Quantitative Performance Analysis .................. 313
9.5. The Reduced KII Network as an Associative Memory .... 317
9.5.1. Designing the Excitatory Interconnections of the KII Network .......... 319
9.5.2. Training the KII Interconnection Weights with Oja’s Rule .............. 319
9.5.3. Examples ....................................... 320
9.6. Hardware Implementation in Analog VLSI ............... 322
9.6.1. The Input Stage ................................ 323
9.6.2. Nonlinear Function ................................ 323
9.6.3. Second-order Dynamics .......................... 325
9.6.4. Chip Measurement Results ......................... 325
9.6.5. Comparison of Digital Simulation and Hardware Design .............. 326
9.7. Conclusions ...................................... 327

10. CIRCUIT MODELS FOR NEURAL INFORMATION
     PROCESSING ........................................ 333

Ting Ma, Ying-Ying Gu, and Yuan-Ting Zhang

10.1. Introduction ....................................... 333
10.2.1. A Simple Circuit Model for Passive Neuronal Membranes .............. 334
10.2.2. Equivalent Circuit Model for Active Neurons .................. 336
10.2.3. Compartment Model ................................ 340
10.3. Models for Neuronal Rate Coding ....................... 344
10.3.1. An Integrate-and-Fire Circuit Model .................. 344
| CONTENTS |
|------------------|------------------|
| 10.3.2. Integral Pulse Frequency Modulation (IPFM) Model | 347 |
| 10.4. Modeling Rate–Intensity Function in an Auditory Periphery | 354 |
| 10.4.1. Biophysics of Auditory Periphery | 355 |
| 10.4.2. IHC Model and Rate–Intensity Function | 356 |
| 10.5. Conclusion | 361 |
| **11. NEURAL SYSTEM IDENTIFICATION** | **367** |
| **Garrett B. Stanley** |
| 11.1. Introduction | 367 |
| 11.2. System Identification | 368 |
| 11.2.1. Dynamical Systems | 368 |
| 11.2.2. Estimation | 369 |
| 11.3. Representations of Neuronal Activity | 373 |
| 11.3.1. Spike Times | 373 |
| 11.3.2. Firing Rate | 375 |
| 11.3.3. Neuronal Variability | 375 |
| 11.4. Neuronal Encoding in the Visual Pathway | 376 |
| 11.4.1. Estimation of the STRF | 377 |
| 11.4.2. Adaptive Estimation | 378 |
| 11.5. Nonlinear Encoding in the Somatosensory Pathway | 380 |
| 11.5.1. The Impulse Response and Nonlinear Encoding | 381 |
| 11.6. Neural Control of Cardiac Function | 383 |
| 11.6.1. Input-Driven Threshold Model | 384 |
| 11.7. Summary | 385 |
| **12. SEIZURE PREDICTION IN EPILEPSY** | **389** |
| **Wim van Drongelen, Hyong C. Lee, and Kurt E Hecox** |
| 12.1. Introduction | 389 |
| 12.2. Processes Underlying the Electroencephalogram | 392 |
| 12.3. Electrographic Seizure Activity | 393 |
| 12.4. Time Series Analysis and Application in Eeg | 397 |
| 12.4.1. Linear Methods | 398 |
| 12.4.2. Nonlinear Methods | 398 |
| 12.4.3. Multichannel-Based Methods | 406 |
| 12.4.4. Surrogate Time Series | 406 |
| 12.5. Evaluation and Future Directions | 407 |
| 12.6. Appendix 1: C Function to Calculate Maximum Likelihood Kolmogorov Entropy | 412 |
| 12.7. Appendix 2: Matlab Scripts to Create Figures 12.2 and 12.5 | 415 |
| **13. RETINAL BIOENGINEERING** | **421** |
| **Robert A. Linsenmeier** |
| 13.1. Introduction | 421 |
| 13.2. The Neural Structure and Function of the Retina | 422 |
| 13.2.1. Photoreceptors | 422 |
| 13.2.2. Retinal Circuits | 425 |

INDEX ...
3

BRAIN–COMPUTER INTERFACE

Anirudh Vallabhaneni,1 Tao Wang,1 and Bin He2∗

1University of Illinois at Chicago, Illinois
2Department of Biomedical Engineering, University of Minnesota, Minneapolis, Minnesota

3.1. INTRODUCTION

Human–computer interfaces (HCIs) have become ubiquitous. Interfaces such as keyboards and mice are used daily while interacting with computing devices (Ebrahimi et al., 2003). There is a developing need, however, for HCIs that can be used in situations where these typical interfaces are not viable. Direct brain–computer interfaces (BCI) is a developing field that has been adding this new dimension of functionality to HCI. BCI has created a novel communication channel, especially for those users who are unable to generate necessary muscular movements to use typical HCI devices.

3.1.1. WHAT IS BCI

Brain–computer interface is a method of communication based on neural activity generated by the brain and is independent of its normal output pathways of peripheral nerves and muscles. The neural activity used in BCI can be recorded using invasive or noninvasive techniques. The goal of BCI is not to determine a person’s intent by eavesdropping on brain activity, but rather to provide a new channel of output for the brain that requires voluntary adaptive control by the user (Wolpaw et al., 2000b).

The potential of BCI systems for helping handicapped people is obvious. There are several computer interfaces designed for disabled people (Wickelgren, 2003). Most of these systems, however, require some sort of reliable muscular control such as neck, head, eyes, or other facial muscles. It is important to note that although requiring only neural activity, BCI utilizes neural activity generated voluntarily by the user. Interfaces based on involuntary neural activity, such as those generated during an epileptic seizure, utilize many of the same components and principles as BCI, but are not included in this field. BCI systems, therefore, are especially useful for severely disabled, or locked-in, individuals with no

∗ Address for correspondence: Department of Biomedical Engineering, University of Minnesota, 7-105 BSBE, 312 Church Street, Minneapolis, Minnesota 55455; e-mail: binhe@umn.edu.
reliable muscular control to interact with their surroundings. The focus of this chapter is on the basics of the technology involved and the methods used in BCI.

### 3.1.2. HISTORY OF BCI

Following the work of Hans Berger in 1929 on a device that later came to be known as electroencephalogram (EEG), which could record electrical potentials generated by brain activity, there was speculation that perhaps devices could be controlled by using these signals. For a long time, however, this remained a speculation.

As reviewed by Wolpaw and colleagues (2000b), 40 years later, in the 1970s, researchers were able to develop primitive control systems based on electrical activity recorded from the head. The Pentagon's Advanced Research Projects Agency (DARPA), the same agency involved in developing the first versions of the Internet, funded research focused on developing bionic devices that would aid soldiers. Early research, conducted by George Lawrence and coworkers, focused on developing techniques to improve the performance of soldiers in tasks that had high mental loads. His research produced a lot of insight on methods of autoregulation and cognitive biofeedback, but did not produce any usable devices.

DARPA expanded its focus toward a more general field of biocybernetics. The goal was to explore the possibility of controlling devices through the real-time computerized processing of any biological signal. Jacques Vidal from UCLA's Brain–Computer Interface Laboratory provided evidence that single-trial visual-evoked potentials could be used as a communication channel effective enough to control a cursor through a two-dimensional maze (Vidal, 1977).

Work by Vidal and other groups proved that signals from brain activity could be used to effectively communicate a user's intent. It also created a clear-cut separation between those systems utilizing EEG activity and those that used EMG (electromyogram) activity generated from scalp or facial muscular movements. Future work expanded BCI systems to use neural activity signals recorded not only by EEG but also by other imaging techniques.

Current BCI-based tools can aid users in communication, daily living activities, environmental control, movement, and exercise, with limited success and mostly in research settings. A more detailed evolution of BCI systems is detailed later in this chapter. The primary users of BCI systems are individuals with mild to severe muscular handicaps. BCI systems have also been developed for users with certain mental handicaps such as autism. Basic and applied research is being conducted with humans and animals for using BCIs in numerous clinical and other applications for handicapped and nonhandicapped users.

### 3.2. COMPONENTS OF A BCI SYSTEM

To understand the requirements of basic research in BCI, it is important to put it in the context of the entire BCI system. The recent work of Mason and Birch (2003), which is adapted in this section, presented a general functional model for BCI systems upon which a universal vocabulary could be developed and different BCI systems could be compared in a unified framework.
3.2.1. FUNCTIONAL COMPONENTS

Any BCI system is subject to the conditions in which it operates. The operating environment is the physical location and the surrounding objects at the location(s) in which the system is being used. This includes physical boundaries, temperature, terrain conditions, external noise, etc. Other components in the system must be able to adapt to the changing conditions in the operating environment.

A user is any entity that can relay its intent by intentionally altering its brain state to generate the control signals that are the input for the BCI system. The user's brain state...
is captured by electrodes, or any device that captures and converts the neural activity into detectable signals. The signal is then processed by the Amp, which amplifies, bandpass filters, and digitizes the signal. User control on the BCI Control is exerted through this signal.

The brains of the BCI system are part of the BCI control, which is responsible for processing and understanding the signal. The first part of the BCI control is the feature extractor. This component can handle one or more types of signals and transform the amplified signal into relevant feature values with a goal of maximizing the signal-to-noise ratio. The second part of the BCI control is the feature translator, which classifies the feature vectors into two or more classes. This generates a continuous logical control signal that is exerted on the control interface. A majority of basic BCI research is focused on creating new BCI control components and improving on existing techniques.

The control interface converts the logical control signal into device-dependent semantic controls. Control interfaces are typically context- and menu-driven so that a maximum number of semantic controls are produced utilizing a minimum number of logical controls. The control display (visual, aural, etc.) attached to the control interface is used to display the interpretation of the user’s control signals within the device-dependent context. Some BCI systems have an external stimulator attached to the control interface and emits visual and/or aural stimuli for externally paced events. The release of the stimulus is controlled by the control interface and synchronized with the feature extractor for an accurate extraction of time- or phase-locked brain responses.

The device controller changes the semantic control signals from the control interface to physical control signals that are used to manipulate the device. Finally, the device itself can be any target physical object such as a wheelchair or virtual device such as a keyboard on a display screen.

3.2.2. FEEDBACK

Similar to other forms of human–computer interaction, proper use of BCI systems is extremely dependent on the adaptation of brain activity based on the feedback or response the user receives from the system. Therefore, it is critical that any BCI system provides the appropriate amount of feedback, as detailed in Figure 3.1, and adapts to the changes made by the user in response to the feedback provided by the components of the system.

From a neuroscience perspective, real-time feedback facilitates two types of corrective mechanisms. First, continuous feedback allows the user to control and correct errors during the execution of an action in real-time. This is in contrast to discrete or delayed feedback, which is intermittent and does not allow for real-time adaptivity. Second, the feedback that occurs after the successful completion of a command aids in gradually learning that command (Curran and Stokes, 2003).

Device state feedback is the status of the target device and is reported to the user through his or her sensory channels. It is also reported to the device controller to ensure it is synchronized with the status of the device. Device controller state feedback is the status of the device controller and is reported to the control interface to ensure synchronization of the semantic mapping.

The control display state feedback can be used to report to the user the status of the control interface and information of the status of the entire system through one or more sensory channels. This feedback loop is fed back from the control interface.

3.3. SIGNAL

As discussed, expressed in the proper form of the voluntary act, each method of acquisition. The approach of acquiring the translation.

3.3.1. INVASIVE

Invasive surgical implanting electrodes has large pyramidal nerve cells from the thalamus and the thalamus can help improve the process (Bakay, 1998). Nerve cells grow into the electrode, the velocity of which is converted to a second pulse when a mouse click or row of icons req
The user-reported error feedback is extremely important in making use of the adaptiveness of the feature extractor and translator. Through the use of a bidirectional control display, the user can report situations where intent was misclassified so that the system can adapt to the user’s signal by adjusting its performance parameters or eliminating the trial from its training data.

The user state feedback reports the user’s mental and physical state and is fed into the control interface to synchronize the system with the capabilities of the user at any particular point in time. Similarly, the environment state feedback is fed into the control interface to adjust system performance and functions to any changing environmental conditions.

3.3. SIGNAL ACQUISITION

As discussed before, translation of intent to action is dependent on the intent being expressed in the form of a measurable signal. Proper acquisition of this signal is important for the proper functioning of any BCI. The goal of signal acquisition methods is to detect the voluntary neural activity generated by the user through invasive or noninvasive methods. Each method of signal acquisition can be measured in terms of spatial and temporal resolution. The appropriate method to use depends on striking a balance between the feasibility of acquiring the signal in the operating environment and the resolution required for proper translation.

3.3.1. INVASIVE TECHNIQUES

Invasive signal acquisition primarily relies on electrophysiologic recordings made by neurosurgically implanting micro-electrodes inside the user’s brain. The preferred site for implanting electrodes is the motor cortex. This area of the brain is more easily accessible and has large pyramidal cells, which are easier to record from. In addition, signals in this area can be generated through simple tasks such as actual or imaginary motor movements (Wolpaw et al., 2000b). Other areas such as the supplementary motor cortex, subcortical motor areas, and the thalamus could also serve as potential sites for electrode implantation. Information from complementary imaging techniques such as functional magnetic resonance imaging (fMRI) can help determine potential target areas for a specific subject (Wolpaw et al., 2000b). Recent developments with fMRI have allowed not only finding cortical areas of activity, but also reliable control of BCI based on fMRI imaging of changing blood oxygen levels across several cortical areas with different cognitive tasks (Weiskopf et al., 2003).

Several types of electrodes have been tested on animals, but the neurotrophic cone electrode has been able to achieve a limited success in human subjects (Kennedy and Bakay, 1998). As shown in Figure 3.2, the cone contains a neurotrophic factor that causes neurites to grow into the cone and contact one of the gold wires inside the electrode which transmits the electrical signal out of the brain (Musso-Ivaldi and Miller, 2003). Intentions are conveyed, for example, by training the patients to control a cursor with their implant, and the velocity of the cursor is determined by the rate of neural firing. The neural waveshapes are converted to pulses, and three pulses are fed as input into the BCI Control. The first and second pulses control the X and the Y position of the cursor and the third pulse serves as a mouse click or an enter command. The patients are trained using software that contains a row of icons representing common phrases (Kenney and Bakay, 1998).
A notable experiment has been conducted by Nicolelis and Chapin (2002) on monkeys to control a robot arm in real time by electrical discharge recorded by microwires that lay beside a single motor neuron. Various motor-control parameters, including the direction of hand movement, gripping force, hand velocity, acceleration, three-dimensional position, etc., were derived from the parallel streams of neuronal activity by mathematic models. In this system, monkeys learn to produce complex hand movements in response to arbitrary sensory cues. The monkeys could exploit visual feedback to judge for themselves how well the robot could mimic their hand movements. Refer to Figure 3.3 for a detailed description (Nicolelis, 2003).

A less invasive approach that has been well applied to epileptic patients for surgical planning is patching subdural electrode array over cortex to record electrocorticogram (ECoG) signals. Subdural electrodes are closer to neuronal structures in superficial cortical layers than electroencephalogram (EEG) electrodes placed on the scalp. It is estimated that scalp electrodes represent the spatially averaged electrical activity over a cortical area of at least several square centimeters. Several closely spaced subdural electrodes can be placed over an area of this size such that each of these electrodes measures the spatially averaged bioelectrical activity of an area very likely much smaller than several square centimeters. The advantages of subdural recordings include recording from smaller sources of "synchronized activity," higher signal-to-noise ratio than that of scalp recordings, and increased ability to record and study gamma activity above 30 Hz. Gamma activity is generated by rapidly oscillating cell assemblies composed of a small number of neurons. Consequently, gamma activity is characterized by small amplitude fluctuations that are not easily recorded with scalp electrodes (Pfurtscheller et al., 2003).

Levine and coworkers (2000) have implemented a "direct brain interface" that accepts voluntary commands directly from recording ECoG signal in epileptic patients. The subjects...
FIGURE 3.3. Experimental design used to test a closed-loop control brain-machine interface for motor control in macaque monkeys. Chronically implanted microwire arrays are used to sample the extracellular activity of populations of neurons in several cortical motor regions. Linear and nonlinear real-time models are used to extract various motor-control signals from raw brain activity. The outputs of these models are used to control the movements of a robot arm. For instance, while one model might provide a velocity signal to move the robot arm, another model, running in parallel, might extract a force signal that can be used to allow a robot gripper to hold an object during an arm movement. Artificial visual and tactile feedback signals are used to inform the animal about the performance of a robot arm controlled by brain-derived signals. Visual feedback is provided by using a moving cursor on a video screen to inform the animal about the position of the robot arm in space. Artificial tactile and proprioceptive feedback is delivered by a series of small vibromechanical elements attached to the animal's arm. This haptic display is used to inform the animal about the performance of the robot arm gripper (whether the gripper has encountered an object in space, or whether the gripper is applying enough force to hold a particular object). ANN, artificial neural network; LAN, local area network. (From Nicolelis, 2003, with permission, © 2003, Nature)

were instructed to make different movements of the face, tongue, hand, and foot in either a prompt-paced or a self-paced manner. Half of the ECoG recoding was used to produce an averaged ECoG segment (as "ERP templates") and the cross-correlation of templates with the continuous ECoG was used to detect ERPs that correspond to specific movements. The cortical locations of the subdural electrodes were based solely on clinical considerations relating to epilepsy surgery (as opposed to research needs). The accuracy of ERP detection for the five best subjects has hit more than 90%. In another experiment of self-paced movement study using ECoG (Pfurtscheller et al., 2003), it was concluded that self-paced movement is accompanied not only by a relatively widespread mu and beta ERD, but also by a more focused gamma ERS in the 60–90 Hz frequency band.
In a different system, individual electrodes in the Utah electrode (Maynard et al., 1997) are tapered to a tip, with diameters <90 μm at their base, and they penetrate only 1–2 mm into the brain. Invasive techniques cause significant amount of discomfort and risk to the patient. Researchers use them in human subjects only if it will provide considerable improvement in functionality over available noninvasive methods. A majority of the initial research, therefore, is conducted in animals, especially monkeys and rats, and is also called the brain–machine interface (BMI) (Nicoletis, 2001). Research in these animals has led to the rapid development of microelectronics that enables recording electrophysiological activities from a small group of neurons or even a single neuron. Present technology allows reliable simultaneous sampling of 50–200 neurons, distributed across multiple cortical areas of small primates, for a period of a few years (Wessberg et al., 2000).

The advantage of these types of invasive techniques is the high spatial and temporal resolution that can be achieved, as recordings can be made from individual neurons at very high sampling rates. Intracranially recorded signals could obtain more information and allow quicker responses, which might lead to decreased requirements of training and attention (Sanchez et al., 2004). Several issues, however, have to be considered (Lauer et al., 2000). First, the long-term stability of the signal over days and years is hard to achieve. The user should be able to consistently generate the control signal reliably without the need for frequent retuning. Second is the issue of cortical plasticity following a spinal cord injury. It has been hypothesized that the motor cortex undergoes reorganization after a spinal cord injury, but the degree is unknown (Brouwer and Hopkins-Rosseel, 1997). Finally, if a neuroprosthesis that requires a stimulus to the disabled limb is used, this stimulus would also produce a significant artifact on the scalp that might interfere with the signal of interest. In such cases, BMI systems must be able to accurately detect and remove this artifact.

It is also necessary to develop a better understanding of the principles by which neural ensembles encode sensory, motor, and cognitive information (Isaacs et al., 2000; Nicoletis, 2001; Serruya et al., 2002). In the case of motor control, for instance, the areas of the primate brain that are involved are well known and even the physiological properties of individual neurons located in these areas have been studied well (Nicoletis, 2001). Little is known, however, about how the brain makes use of this information from neurons to generate the movements. In the movement control design, therefore, further work is needed to develop a method that can efficiently sample and accurately decode the motor signals generated by neurons so an artificial device can mimic the intended movement.

Classic experiments in primates, for example, have demonstrated that fundamental parameters of motor control emerge by the collective activation of large distributed populations of neurons in the primary motor cortex (M1). To compute a precise direction of arm movement, the brain may have to perform the equivalent of a neuronal “vote” or, in mathematical terms, a vector summation of the activity of these broadly tuned neurons. This implies that to obtain the motor signals required to control an artificial device it is necessary to sample the activity of many neurons simultaneously as well as to design algorithms that are capable of extracting motor control signals from these ensembles. Several well-established models such as linear regression, population vector, and neural network have been successfully applied to deal with large neural data to estimate the hand movement trajectory from the firing rate of motor cortex populations (Wessberg et al., 2000, Taylor et al., 2002, Serruya et al., 2003). But these signals and models are far from providing the full range of motion that the arm can produce (Donoghue, 2002).

3.3.2. NG

There is an invasive technique using a device to control a robotic arm. The device is a high-temp device that is applied to the brain in order to control the movement of the arm.

3.4. FE:

Basic features of the system have been developed, including activation of motor signals from the brain.
As mentioned earlier, experiments with humans thus far have been limited. Currently, only a few severely disabled patients have been implanted with electrodes. In some cases, success has been limited, with some patients able to communicate at a rate of only three letters per minute (Mussa-Ivaldi and Miller, 2003). Further advancements in microelectrodes, however, are required to obtain stable recordings over a long term (i.e., more than 1 year). In addition to the areas mentioned above, additional research focusing on minimizing the number of cells required for simultaneous recordings to obtain a useful signal as well as on providing feedback to the nervous system via electrical stimulation through electrodes is also essential for a potential widespread use of invasive techniques in humans. For a comprehensive review of the BMI and neurorobotic research, see Chapter 4 in this book.

3.3.2. NONINVASIVE TECHNIQUES

There are many methods of measuring brain activity through noninvasive means. Noninvasive techniques reduce risk for users since they do not require surgery or permanent attachment to the device. Techniques such as computerized tomography (CT), positron electron tomography (PET), single-photon emission computed tomography (SPECT), magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and electroencephalography (EEG) have all been used to measure brain activity noninvasively.

EEG, however, is the most prevalent method of signal acquisition for BCI. EEG has a high temporal resolution capable of measuring every thousandth of a second. Modern EEG also has a reasonable spatial resolution as signals from up to 256 electrode sites can be measured at the same time.

Practicality of EEG in a laboratory and in a real-world setting is unsurpassed. The device is portable, and the electrodes can be easily placed on the subject’s scalp by simply donning a cap. In addition, EEG systems have seen widespread use in numerous fields since its inception. Therefore, the techniques and technology of signal acquisition through this method have been standardized. Finally, and most important, the method is noninvasive (Wolpaw et al., 2000a).

Many EEG-based BCI systems use an electrode placement strategy suggested by the International 10/20 system as detailed in Figure 3.4. For better spatial resolution, it is also common to use a variant of the 10/20 system that fills in the spaces between the electrodes of the 10/20 system with additional electrodes (Malmivuo and Plonsey, 1995).

3.4. FEATURE EXTRACTION AND TRANSLATION

Basic research in BCI is focused on improving methods of feature extraction from the acquired signals and translating them into logical control commands for single-trial and averaged trials. A feature in a signal can be viewed as a reflection of a specific aspect of the physiology and anatomy of the nervous system (Wolpaw et al., 2000b). The goal of feature extraction methods, based on this definition, would be to obtain the specific physiological aspect of the nervous system across a specific time series. The steps involved in feature extraction and translation are detailed in Figure 3.5.
FIGURE 3.4. Placement of electrodes for noninvasive signal acquisition using an electroencephalogram (EEG). This standardized arrangement of electrodes over the scalp is known as the International 10/20 system and ensures ample coverage of all parts of the head. The exact positions for each electrode are at the intersection of the lines calculated from measurements between standard skull landmarks. The letter at each electrode identifies the particular subcortical lobe (FP, frontal lobe; T, temporal lobe; C, central lobe; P, parietal lobe; O, occipital lobe). The number or the second letter identifies its hemispherical location (Z, denoting line zero refers to an electrode placed along the cerebrum's midline; even numbers represent the right hemisphere; odd numbers represent the left hemisphere). The numbers are in ascending order with increasing distance from the midline. (From Malmivuo and Plonsey, 1995 [web edition at http://butler.cc.tut.fi/~malmivuo/bem/bembook/in/in.html], with permission)

FIGURE 3.6. Theta band range BCI resean band is sor band indic
3.4.1. TYPES OF SIGNALS

3.4.1.1. Spikes and Field Potentials

The brain generates a tremendous amount of neural activity. There are a plethora of signals, also referred to as components, which can be used for BCI. These signals fall into two major classes: spikes and field potentials (Wolpaw, 2003). Spikes reflect the action potentials of individual neurons and thus acquired primarily through microelectrodes implanted by invasive techniques. Field potentials, however, are measures of combined synaptic, neuronal, and axonal activity of groups of neurons and can be measured by EEG or implanted electrodes depending on the spatial resolution required. As previously mentioned, most of the BCI research is focused on using signals from EEG, and thus the most commonly used components are derived from EEG recordings.

3.4.1.2. EEG Frequency Bands

Signals recorded from EEG are split into several bands as shown in Figure 3.6. Delta band ranges from 0.5 to 3 Hz and the theta band covers the 4–7 Hz range. A majority of BCI research focuses on the alpha band (8–13 Hz) and the beta band (14–30 Hz). The beta band is sometimes considered to have an extended range of up to 60 Hz with the gamma band indicating all signals greater than 30 Hz.

3.4.1.3. Components of Interest

Components of particular interest to BCI can be divided into four categories: oscillatory EEG activity, event-related potentials (ERP), slow cortical potentials (SCP), and neuronal potentials.
3.4.1.4. Oscillatory EEG Activity

Oscillatory EEG activity is caused by a complex network of neurons that create feedback loops. The synchronized firing of the neurons in these feedback loops generates observable oscillations. The frequency of oscillations decreases as the number of synchronized neuronal bodies increases. The underlying membrane properties of neurons and dynamics of synaptic processes, the strength and complexity of connections in the neuronal network, and the influences from other neurotransmitter systems also play a role in determining the oscillations.

Two distinct oscillations of interest are the Rolandic mu-rhythm, occurring in the 10–12 Hz range, and the central beta rhythm, occurring in the 14–18 Hz range. Both originate in the sensorimotor cortex region of the brain. These oscillations occur continuously during “idling” or rest. During nonidling periods, however, these oscillations are temporarily modified and the change in frequency and amplitude are evident on the EEG. The amplitude of oscillations decreases as the frequency increases because the frequency of the oscillations is negatively correlated with their amplitude (Pfurtscheller and Neuper, 2001).

3.4.1.5. Event-Related Potentials

Event-related potentials (ERPs) are time-locked responses by the brain that occur at a fixed time after a particular external or internal event. These potentials usually occur when subjected to sensory or aural stimulus, mental event, or the omission of a constantly occurring stimulus.

Exogenous ERP components are obligatory responses to physical stimuli and occur due to processing of the external event but independent of the role of the stimuli in the processing of information. The random flash of a bulb, for example, will generate an exogenous component as the brain responds to the sudden flash of light regardless of the context.

Endogenous ERP components occur when an internal event is processed. It is dependent on the role of the stimulus in the task and the relationship between the stimulus and the context in which it occurred. A user trying to spell the letter R in a word, for example, will generate an endogenous ERP component if the letter R is presented since it is the event he or she is looking for. If the user is trying to spell the letter S, however, he or she will not generate an endogenous ERP component if the same letter R is presented since the relationship between the stimulus and the context in which it occurred is no longer valid.

3.4.1.6. Event-Related Synchronization/(De)synchronization

A particular type of ERP is characterized by the occurrence of an event-related desynchronization (ERD) and an event-related synchronization (ERS). Changes in the factors that control the oscillation of neuronal networks, such as sensory stimulation or mental imagery, are responsible for the generation of these event-related potentials. A decrease in the synchronization of neurons causes a decrease of power in specific frequency bands and this phenomenon is defined as an ERD and can be identified by a decrease in signal amplitude. Presence of ERD is very widespread in the alpha band, especially during tasks involving perception, memory, and judgment. Increasing task complexity or attention amplifies the magnitude of the ERD.

ERS, on the other hand, is characterized by an increase of power in specific frequency bands that is generated by an increase in the synchronization of neurons and can be identified
Brain–Computer Interface

FIGURE 3.7. Evidence of event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena before and after movement onset. ERD is the result of a decrease in the synchronization of neurons, which causes a decrease in power in specific frequency bands, and can be identified by a decrease in signal amplitude. ERS is the result of an increase in the synchronization of neurons, which causes an increase in power in specific frequency bands, and can be identified by the increase in signal amplitude. (From Pfurtscheller and Neuper, 2001, with permission, © 2001, IEEE)

by an increase in signal amplitude. ERD and ERS are measured relative to a baseline or reference interval, so the strength of an ERD/ERS is affected by the variance of the rhythms in this interval.

The time-locked property of ERPs is particularly evident for ERD/ERS during imagined or actual motor tasks as shown in Figure 3.7. An ERD in the mu rhythm starts 2.5 s prior to movement onset and peaks after onset of movement before recovering to baseline. A short-lived ERD in the central beta rhythm occurs prior to movement onset and is immediately followed by an ERS that peaks after movement onset. Oscillations and ERS are also found around the 40-Hz gamma band when subjected to visual stimulation owing to binding of sensory information and in motor tasks owing to sensorimotor integration. The high frequency of the gamma band works well to set up rapid coupling or synchronization between spatially separated groups of neurons (Pfurtscheller and Lopes da Silva, 1999).

3.4.1.7. Visual-Evoked Potentials

Another type of ERP commonly used in BCI is the visual-evoked potential (VEP), an EEG component that occurs in response to a visual stimulus. VEPs are dependent on the
user's control of their gaze and thus require coherent muscular control. One frequently used VEP is the steady-state visual evoked potential (SSVEP).

SSVEP is an exogenous ERP component. The user visually focuses on one of two objects on a screen that flicker at different frequencies in the alpha and beta bands. The SSVEP component is amplified when the user shifts focus to the other object and then returns to baseline. The user can continue to switch focus between the two objects on the screen to generate changes in the signal (Middendorf et al., 2000).

3.4.1.8. P300

The P300 is an endogenous ERP component and occurs as part of the “oddball paradigm” (Donchin and Coles, 1988; Donchin et al., 2000). In this phenomenon, users are subject to events that can be categorized into two distinct categories. Events in one of the two categories, however, are rarely displayed. The user is presented with a task that cannot be accomplished without categorization into both categories. When an event from the rare category is displayed, it elicits a P300 component, which is a large positive wave that occurs approximately 300 ms after event onset as shown in Figure 3.8. The amplitude of the P300 component is inversely proportional to the rate at which the rare event is presented. This ERP component is a natural response and thus especially useful in cases where either sufficient training time is not available or the user cannot be easily trained (Spencer et al., 2001).

![FIGURE 3.8. P300 ERP component. When the user is randomly flashed objects on a screen, the P300 component occurs when the object the user is looking for is flashed, while any of the other objects do not elicit a similar change in voltage. The amplitude of the P300 component is inversely proportional to the rate at which the object of interest is presented and occurs approximately 300 ms after the object is displayed. It is a natural response and requires no user training. (From Kubler et al., 2001, with permission)
frequently used on one of two beta bands. The object and then objects on the

of the “oddball” xenon, users are ts in one of the task that cannot at from the rare wave that oc-

plitude of the nt is presented. ses where either (Spencer et al.,

FIGURE 3.9. Different slow cortical potential (SCP) signals conveying different intents. SCPs are caused by shifts in the depolarization level of certain dendrites. It occurs from 0.5 to 10 s after the onset of an internal event and thus considered a slow cortical potential. (From Kubler et al., 2001, with permission)

3.4.1.9. Slow Cortical Potential

A completely different type of signal is the slow cortical potential, which is caused by shifts in the depolarization levels of certain dendrites. Negative SCP indicates the sum of synchronized potentials, whereas positive SCP indicates reduction of synchronized potentials from the dendrites. As behavioral and cognitive performance of the user improves, so do the synchronized potentials, resulting in an increase of negativity of SCP. Since this cortical potential occurs anywhere from a 0.5 to 10 s after the onset of an internal event, as shown in Figure 3.9, it is referred to as the slow cortical potential (Birbaumer et al., 1999, 2000; Wolpaw et al., 2000b).

3.4.1.10. Neuronal Potential

Neuronal potential is a voltage spike from individual neurons as shown in Figure 3.10. This potential can be measured for a particular neuron or a group of neurons. The signal is a measure of the average rate, correlation, and temporal pattern of the neuronal firing. The central nervous system presents information on the firing rate of each neuron. Therefore, learning can be measured through changes in the average firing rate of neurons located in the cortical areas associated with the task.

Neuronal potential is extremely useful since it can achieve two-dimensional controls for the BCI by identifying the location of the neurons which are firing and also their rate of firing (Wolpaw, 2003). Research in neuronal potentials has been limited to animals until very recently because of the invasive procedures required to implant the electrodes as well as a lack of electrodes that generate stable recordings over a long period of time. The limited work, however, helps prove that better machine control is achievable by isolating signals with better spatial resolution (Wolpaw et al., 2002; Moxon, 2005).
3.4.2. TRAINING

According to the review by Curran and Stokes (2003) and other research (Kostov and Polak, 2000; Laubach et al., 2000), which is adapted here, the effectiveness of BCI is dependent on the capacity of the user to willingly and consistently control their EEG activity. Unlike motor tasks, control of brain activity is harder to achieve since the user cannot identify nor discern the activity. The user can only comprehend their EEG activity through the feedback received from the components in the BCI system.

The goal of training, therefore, is to have users voluntarily produce detectable EEG signals that can be altered to achieve a specific result. From the definition of BCI, it should be evident that the components produced by the user must be voluntary. Although the user might not be aware of how and when the signals are generated, the signal generation process can only be activated by voluntary actions from the user. BCI systems, however, differ in whether these voluntary signals must be produced through conscious mental activity (e.g., adding numbers) (Birbaumer, 1999) or as an automatic response to the situation that requires minimal conscious effort (e.g., riding a bicycle).

3.4.2.1. Cognitive Tasks

Most training methods require the user to perform specific cognitive tasks. These methods focus on developing the user’s ability to generate EEG components through voluntary and conscious mental activity. Motor imagery (MI) tasks have been among the most widely used cognitive tasks. In each trial the user imagines or plans one of several motor movements (i.e., left or right hand movement) based on visual or aural cues. Research has shown that this generates signals from the sensorimotor cortex of the brain and can be detected by EEG (Annett, 1995; Jeannerod, 1995). After several training sessions, the user is able to control the amplitude and frequency of the required component (Babiloni et al., 2000).

Other commonly used cognitive tasks do not involve motor imagery. Rather, they require the user to perform actions such as arithmetic (addition of a series of numbers), visual counting (sequential visualization of numbers), geometric figure rotation (visualization of rotation of a 3D object around an axis), letter composition (nonvocal letter composition), and