Neuroergonomics

THE BRAIN AT WORK

EDITED BY

Raja Parasuraman • Matthew Rizzo

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Neuroergonomics

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Preface

There is a growing body of research and development work in the emerging field of neuroergonomics. For the first time, this book brings together this body of knowledge in a single volume. In composing this book, we sought to show how an understanding of brain function can inform the design of work that is safe, efficient, and pleasant. *Neuroergonomics: The Brain at Work* shows how neuroergonomics builds upon modern neuroscience and human factors psychology and engineering to enhance our understanding of brain function and behavior in the complex tasks of everyday life, assessed outside the confines of the standard research laboratory, in natural and naturalistic settings.

The book begins with an overview of key issues in neuroergonomics and ends with a view toward the future of this new interdisciplinary field. Specific topics are covered in 22 intervening chapters. The subject matter is wide ranging and addresses scientific and clinical approaches to difficult questions about brain and behavior that continue to drive our investigations and the search for solutions. This composition required the input of specialists with a variety of insights on medicine, human factors engineering, physiology, psychology, neuroimaging, public health policy, and the law. Effective response to these issues requires coordinated efforts of many relevant specialists, utilizing shared knowledge and cross-fertilization of ideas. We hope this book contributes to these ends.

The breadth and depth of this volume would not have been possible without the steady influence and vision of Series Editor Alex Kirlik and the Oxford University Press. We are also extremely indebted to the authors for their creative contributions and timely responses to our extensive editorial advice. Raja Parasuraman was supported by grants from the National Institutes of Health and DARPA and Matthew Rizzo by the National Institutes of Health and the Centers for Disease Control and Prevention. Raja Parasuraman is grateful to former members of the Cognitive Science Laboratory, especially Francesco DiNocera, Yang Jiang, Bernd Lorenz, Ulla Metzger, and Sangy Panicker, for stimulating debates in the early days of neuroergonomics, many carried out online and to continuing discussions with current members including Daniel Caggiano, Shimin Fu, Pamela Greenwood, Reshma Kumar, Ericka Rovira, Peter Squire, and Marla Zinni, and to the other members of the Arch Lab at George Mason University. Matt Rizzo thanks his colleagues in neurology, engineering, public health, and the Public Policy Center for their open-minded collaboration and is especially obliged to the past and present members of the Division of Neuroergonomics (http://www.uiowa.edu/~neuroerg/) for their good humor, great ideas, and hard work. He is deeply grateful to Michael and Evelyn for nurturing his curiosity, to Annie, Ellie, and Frannie for their enduring support, and to Big Bill and Margie, now at peace. Both of us are also grateful to Constance Kadala and to Cheryl Moores for their editorial assistance.

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Introduction

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Raja Parasuraman and Matthew Rizzo

Introduction to Neuroergonomics

Neuroergonomics is the study of brain and behavior at work (Parasuraman, 2003). This interdisciplinary area of research and practice merges the disciplines of neuroscience and ergonomics (or human factors) in order to maximize the benefits of each. The goal is not just to study brain structure and function, which is the province of neuroscience, but also to do so in the context of human cognition and behavior at work, at home, in transportation, and in other everyday environments. Neuroergonomics focuses on investigations of the neural bases of such perceptual and cognitive functions as seeing, hearing, attending, remembering, deciding, and planning in relation to technologies and settings in the real world. Because the human brain interacts with the world via a physical body, neuroergonomics is also concerned with the neural basis of physical performance—grasping, moving, or lifting objects and one's limbs.

Whenever a new interdisciplinary venture is proposed, it is legitimate to ask whether it is necessary. To answer this query, we show how the chapters in this book, as well as other work, demonstrate that neuroergonomics provides added value, beyond that available from "traditional" neuroscience and "conventional" ergonomics, to our understanding of brain function and behavior as it occurs in the real world. The guiding principle of neuroergonomics is that examining how the brain carries out the complex tasks of everyday life—and not just the simple, artificial tasks of the research laboratory—can provide important benefits for both ergonomics research and practice. An understanding of brain function can lead to the development and refinement of theory in ergonomics, which in turn will promote new, far-reaching types of research. For example, knowledge of how the brain processes visual, auditory, and tactile information can provide important guidelines and constraints for theories of information presentation and task design. The basic premise is that the neuroergonomic approach allows the researcher to ask different questions and develop new explanatory frameworks about humans and work than an approach based solely on the measurement of the overt performance or subjective perceptions of the human operator. The added value that neuroergonomics provides is likely to be even greater for work settings such as modern semiautomated systems (Parasuraman & Riley, 1997), where measures of overt user behavior can be difficult to obtain (Kramer & Weber, 2000).

Some Examples of Neuroergonomics Research

Aviation

The following examples illustrate the value of the neuroergonomic approach. Historically, the greatest influence of human factors on technological design has been in the domain of aviation, specifically in the design of displays and controls in the aircraft cockpit (Fitts, Jones, & Milton, 1950; Wiener & Nagel, 1988). With the worldwide growth in airline travel, new proposals for air traffic management have been put forward. Implementing these proposals requires new cockpit technologies. Consider a new traffic-monitoring system that is to be installed in the cockpit to portray to the pilot other aircraft that are in the immediate vicinity, showing their speed, altitude, flight path, and so on, using color-coded symbols on a computer display. Various types of neuroergonomic research, both basic and applied, can inform the design of this system. For example, designers may wish to know what features of the symbols (e.g., shape, intensity, motion, etc.) serve to best attract the pilot's attention to a potential intruder in the immediate airspace. At the same time, there may be a concern that the presentation of traffic information, while helping the pilot monitor the immediate airspace, may increase the pilot's overall mental workload, thereby degrading the performance of the primary flight task. Although subjective or performance measures could be used to evaluate this possibility, a neuroergonomic approach can provide more sensitive evaluation of any impact on flight performance. It may also lead the researcher to ask new and potentially more profitable questions about attention allocation than before. Measures of brain function that reflect visual attention and oculomotor control can help determine the impact of the new display on the pilot's visual scanning and attentional performance (see chapter 7, this volume). Finally, neuroergonomic evaluation of the manual and physical demands involved in interacting with the information panels and controls of the new traffic-monitoring system would also be required for this system to be used effectively and safely by pilots (see chapter 15, this volume).

Driving

Neuroergonomics is also relevant to assessing interactions between the eye, the brain, and the automobile (Rizzo & Kellison, 2004). Functional magnetic resonance imaging (fMRI) permits noninvasive dynamic imaging of the human brain (see chapter 4, this volume). Analytic approaches to fMRI data, such as independent component analysis, can reveal meaningful patterns in data sets collected in subjects performing complex tasks that capture elements of automobile driving. Preliminary application of these approaches suggests that multiple neural regions, including the frontoparietal, cerebellar, and occipital areas, are differentially activated by various aspects of the driving task, such as speed control. It is also possible to relate physiological correlates of impending sleep (microsleeps) derived from electroencephalographic (EEG) activity recordings of brain activity to imminent declines in driver performance (Paul, Boyle, Rizzo, & Tippin, 2005). Finally, naturalistic studies of driver behavior provide unique evidence of long-range human interactions, strategies, and tactics of "the brain in the wild" (see chapter 8, this volume).

Neuroenginering

A third example concerns the use of brain signals as an additional communication channel for human interaction with both the natural and the human-made environment. This area of research and practice, sometimes also called *neuroengineering* or *brain-computer interface* (BCI), has had significant progress in recent years. In this approach, different types of brain signals are used to control external devices without the need for motor output, which would be advantageous for individuals who either have only limited motor control or, as in the case of "locked-in" patients with amyotrophic lateral sclerosis, virtually no motor control. The idea follows naturally from the work on "biocybernetics" in the 1980s pioneered by Donchin and others (Donchin, 1980; Gomer, 1981) but has progressed beyond the earlier achievements with technical developments in recording of brain activity in real time.

BCIs allow a user to interact with the environment without engaging in any muscular activity, for example, without the need for hand, eye, foot, or mouth movement. Instead, the user is trained to engage in a specific type of mental activity that is associated with a unique brain electrical "signature." The resulting brain potentials are recorded, processed, and classified in such a way as to provide a control signal in real time for an external device. Applications have used a variety of different measures of brain electrical activity. Invasive methods include recording of field potentials and multiunit neuronal activity from implanted electrodes; this technique has been reported to be successful in controlling robotic arms (Nicolelis, 2003). Such invasive recording techniques have superior signal-to-noise ratio but are obviously limited in use to animals or to patients with no motor functions in whom electrode implantation is clinically justified. Noninvasive BCIs have used a variety of brain signals derived from scalp EEG recordings. These include quantified EEGs from different frequency bands such as beta and mu waves (Pfurtscheller & Neuper, 2000), event-related potentials (ERPs) such as P300 (Donchin, Spence, & Wijesinghe, 2000), and contingent negative variation (Birbaumer et al., 1999). BCIs based on these signals have been used to operate voice synthesizers, control cursor movements on a computer display, and move robotic arms.

Virtual Reality

Virtual reality (VR) is particularly relevant to neuroergonomics because VR can replicate situations with greater control than is possible in the real world, allowing behavioral and neural measures of the mind and brain at work in situations that are impractical or impossible to observe in the real world. In doing so, VR can be used to study the performance of human operators engaged in hazardous tasks without putting them and others at risk for injury (see chapter 17, this volume). For example, VR can be used to study the influence of disease, drugs, fatigue, or in-vehicle technologies (such as cell phones) on aircraft piloting and automobile driving, to study how to reduce the risk of falls in the elderly, and to train students to avoid novice misjudgments and errors in performing critical medical procedures, flying aircraft, and operating heavy machinery. VR is particularly useful in workers whose jobs require spatial awareness, complex motor skills, or decisions that require evaluation of multiple possible responses amid changing contingencies, and is also proving to be useful for therapy and rehabilitation of persons with motor, cognitive, and psychiatric impairments.

Conceptual, Theoretical, and Philosophical Issues

The constituent disciplines of neuroergonomics—neuroscience and ergonomics/human factors research—are both twentieth-century, post–World War II fields. The spectacular rise of neuroscience toward the latter half of that century and the smaller but no less important growth in human factors research can both be linked to technological developments in computer science and engineering. The brain imaging technologies that have revolutionized modern neuroscience (e.g., fMRI) and the sophisticated automated systems that have stimulated much human factors work (e.g., the aircraft flight management system) were both made possible by these engineering developments. Nevertheless, the two fields have developed independently.

Traditionally, ergonomics has not paid much attention to neuroscience or to the results of studies concerning brain mechanisms underlying human perceptual, cognitive, affective, and motor processes. At the same time, neuroscience and its more recent offshoot, cognitive neuroscience, has only been recently been concerned with whether its findings bear any relation to human functioning in real (as opposed to laboratory) settings. Recent calls to move neuroscience "beyond the bench" ("Taking Neuroscience beyond the Bench," 2002) include studies of group social behavior (Cacciopo, 2002) and the development of neural prosthetics for control of robots, home automation, and other technologies for physically disabled people (see chapter 19, this volume).

The relative neglect by ergonomics of human brain function is understandable given that this discipline had its roots in a psychology of the 1940s that was firmly in the behaviorist camp. More recently, the rise of cognitive psychology in the 1960s influenced human factors, but for the most part neuroscience continued to be ignored by cognitive theorists, a state of affairs consistent with a functionalist approach to the philosophy of mind (Dennett, 1991). Such an approach implies that the characteristics of neural structure and functioning are largely irrelevant to the development of theories of mental functioning. Cognitive psychology (and cognitive science) also went through a functionalist period in the 1970s and 1980s, mainly due to the influence of researchers from artificial intelligence and computer science. However, the recent influence of cognitive neuroscience has led to a retreat from this position. Cognitive neuroscience proposes that neural structure and function constrain and in some cases determine theories of human mental processes (Gazzaniga, 2000).

If neuroscience has freed cognitive science from rigid functionalism, then ergonomics may serve to liberate it from a disembodied existence devoid of context and provide it an anchor in the real world. Even though researchers are aware of the importance of ecological validity, modern cognitive psychology (with a few exceptions) tends to study mental processes in isolation, apart from the artifacts and technologies of the world that require the use of those processes. Technology, particularly computers, can be viewed as an extension of human cognitive capability. Related to this view is the framework of cognitive engineering, in which humans and intelligent computer systems constitute "joint cognitive systems" (Hutchins, 1995; Roth, Bennett, & Woods, 1987). Furthermore, much human behavior is situated and context dependent. Context is often defined by and even driven by technological change. How humans design, interact with, and use technology—the essence of ergonomics—should therefore also be central to cognitive science.

The idea that cognition should be considered in relation to action in the world has many antecedents. Piaget's (1952) work on cognitive development in the infant and its dependence on exploration of the environment anticipated the concept of situated or embodied cognition. Clark (1997) also examined the characteristics of an embodied mind that is shaped by and helps shape action in a physical world. If cognitive science should therefore study the mind not in isolation but in interaction with the physical world, then it is a natural second step to ask how to design artifacts in the world that best facilitate that interaction. This is the domain of ergonomics or human factors. Neuroergonomics goes one critical step further. It postulates that the human brain, which implements cognition and is itself shaped by the physical environment, must also be examined in interaction with the environment in order to understand fully the interrelationships of cognition, action, and the world of artifacts.

Currently, a coherent body of concepts and empirical evidence that constitutes neuroergonomics theory does not exist. Of course, broad theories in the human sciences are also sparse, whether in ergonomics (Hancock & Chignell, 1995) or in neuroscience (Albright, Jessell, Kandel, & Posner, 2001). Sarter & Sarter (2003) proposed that neuroergonomics must follow the same reductionist approach of cognitive neuroscience in order to develop viable theories. There are small-scale theories that could be integrated into a macrotheory, but which would still pertain only to a specific domain of human functioning. For example, neural theories of attention are becoming increasingly well specified, both at the macroscopic level of large-scale neural networks (Parasuraman, 1998; Posner, 2004) and at the level of neuronal function and gene expression (Parasuraman, Greenwood, Kumar, & Fossella, 2005; Sarter, Givens, & Bruno, 2001). At the same time, psychological theories of attention have informed human factors research and design (Wickens & Hollands, 2000). Difficult though the task may be, one can envisage amalgamation of these respective theories into a neuroergonomic theory of attention. Integration across a broader range of functional domains, however, is as yet premature.

Methods

A number of methods have been developed for use in neuroergonomic research and practice. Among these are brain imaging techniques, which have been influential in the development of the field of cognitive neuroscience. Brain imaging techniques can be roughly divided into two classes. The first group of techniques is based on measurement of cerebral hemodynamics (blood flow), such as positron emission tomography (PET), fMRI, and transcranial Doppler sonography (TCD). The second group of methods involves measurement of the electromagnetic activity of the brain, including EEG, ERPs, and magnetoencephalography (MEG). For a review of brain imaging techniques for use in studies of cognition and human performance, see Cabeza and Kingstone (2001).

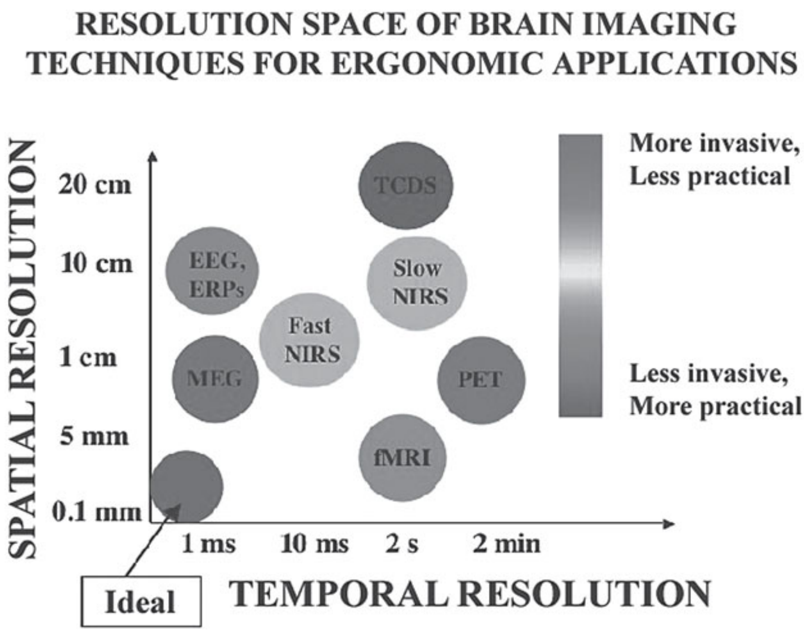

Figure 1.1. Resolution space of brain imaging techniques for ergonomic applications. Trade-offs between the criteria of the spatial resolution (*y*-axis) and temporal resolution (*x*-axis) of neuroimaging methods in measuring neuronal activity, as well as the relative noninvasiveness and ease of use of these methods in ergonomic applications (color code). EEG = electronencephalography; ERPs = event-related potentials; fMRI = functional magnetic resonance imaging; MEG = magnetoencephalography; NIRS = near-infrared spectroscopy; PET = positron emission tomography; TCDS = transcranial doppler sonography. See also color insert.

PET and fMRI currently provide the best noninvasive imaging techniques for the evaluation and localization of neural activity. However, these methods suffer from two drawbacks. First, their temporal resolution is poor compared to electrophysiological techniques such as ERPs. Second, their use is restricted to highly controlled lab environments in which participants must not move. This limits their use for examining the neural basis of performance in more complex tasks with a view to ergonomic applications, as in flight, driving simulation, or the use of virtual reality systems, although components of complex task performance are being studied (Peres, Van de Moortele, & Pierard, 2000; Calhoun et al., 2002; see also chapter 4, this volume). Optical imaging techniques such as fast near-infrared spectroscopy (NIRS) may provide both spatial and temporal resolution and the ability to be used in neuroergonomic applications (see chapter 5, this volume).

An overview of the relative merits and disadvantages of these various techniques is shown in figure 1.1. This illustration is a variant of a representation of the spatiotemporal resolution of brain imaging methods first described by Churchland and Sejnowski (1988). The ease of ergonomic application (color code) has been added to the trade-off between the criteria of spatial resolution and temporal resolution in measuring neuronal activity. Currently, there is no one technique that reaches the ideal (blue circle) of 0.1 mm spatial resolution, 1 ms temporal resolution, and ease of use in ergonomics.

In addition to brain imaging methods, oculomotor techniques can provide additional tools for neuroergonomics researchers. With the advent of low-cost, high-speed systems for measuring different types of eye movements and increasing knowledge of the underlying neural systems, oculomotor measures can provide important information not available from traditional measurement of response accuracy and speed (see chapter 7, this volume).

It should be noted that the use of brain imaging or oculomotor measures need not be a defining characteristic of neuroergonomic research. A neuroergonomic study may use behavioral measures or a computational analysis; however, in each case the performance measure or the computational model is related to a theory of brain function.

Consider the following example. Suppose that as a result of the manipulation of some factor, performance on a target discrimination task (e.g., detection of an intruder aircraft in the cockpit traffic-monitoring example discussed previously) in which location cues are provided prior to the target yields the following results: reaction time (RT) to the target when preceded by an invalid location cue is disproportionately increased, while that to a valid cue is not. This might happen, for example, if the cue is derived from the output of an automated detection system that is not perfectly reliable (Hitchcock et al., 2003). In simple laboratory tasks using such a cueing procedure, there is good evidence linking this performance pattern to a basic attentional operation and to activation of a specific distributed network of cortical and subcortical regions on the basis of previous research using noninvasive brain imaging in humans, invasive recordings in animals, and performance data from individuals who have suffered damage to these brain regions (Posner & Dehaene, 1994). One could then conduct a study using the same cueing procedure and performance measures as a behavioral assay of the activation of the neural network in relation to performance of a more complex task in which the same basic cognitive operation is used. If the characteristic performance pattern was observed—a disproportionate increase in RT following an invalid location cue, with a normal decrease in RT following a valid cue—then one could argue that the distributed cortical/subcortical network of brain regions is likely to have been involved in task performance. This would then enable the researcher to link the full body of neuroscience work on this aspect of attentional function to performance on the complex intruder-detection task. Thus, even though no physiological index was used, and although the same performance measure (RT) was used as in a traditional ergonomic analysis, the type of question asked and the explanatory framework can be quite different in the neuroergonomic approach.

Finally, a neuroergonomic study could also involve a computational analysis of brain or cognitive function underlying performance of a complex task. So long as the analysis was theoretically driven and linked to brain function, the study would qualify as neuroergonomic even though no physiological index was used. Several computational models of human performance have been developed for use in human factors (Pew & Mavor, 1998). Of these, models that can be linked, in principle, to brain function—such as neural network (connectionist) models (O'Reilly & Munakata, 2000)—would be of relevance to neuroergonomics.

Neuroergonomics and Neuropsychology

Neuropsychology and related fields (e.g., behavioral neurology, clinical and health psychology, neuropsychiatry, and neurorehabilitation) have also helped pave the way for neuroergonomics. Hebb (1949) used the term *neuropsychology* in his classic book *The Organization of Behavior: A Neuropsychological Theory*. The field broadly aims to understand how brain structure and function are related to specific psychological processes. The neuropsychological approach uses statistical techniques for standardizing psychological tests and scales to provide clinical diagnostic and assessment tools in normal and impaired individuals (de Oliveira Souza, Moll, & Eslinger, 2004).

Like neuroergonomics, neuropsychology is dedicated to a psychometric approach, holding that human behavior can be quantified with objective tests of verbal and nonverbal behavior, including neural states, and that these data reflect a person's states of mind and information processing. These processes can be divided into different domains, such as perception, attention, memory, language, executive functions (decision making and implementation), and motor abilities, and they can be assessed using a wide variety of techniques.

Both neuropsychology and neuroergonomics rely on principles of reliability (how repeatable a behavioral measure is) and validity (what a measure really shows about human brain and behavior). Neuropsychology has traditionally relied on paper-and-pencil tests, many of which are standardized and well understood (e.g., Lezak, 1995). The neuroergonomics approach is more rooted in technology, as indicated in this book. Novel techniques and tests are developing at a rapid pace, and guidelines and standards are going to be needed.

Contributions to Neuroergonomics from Other Fields: Genetics, Biotechnology, and Nanotechnology

While we have emphasized the contribution of neuroscience to neuroergonomics in this chapter, developments in other fields are also affecting the study of human brain function at work. Three such fields are molecular genetics, biotechnology, and nanotechnology, and we briefly consider their relevance here.

As discussed previously, cognitive psychology has increasingly capitalized on findings from neuroscience. More recently, the study of individual differences in cognitive function is being influenced by developments in molecular genetics and, in particular, the impressive results of the Human Genome Project. Much of what we know about the genetics of cognition has come from twin studies in which identical and fraternal twins are compared to assess the heritability of a trait. This paradigm has been widely used in behavioral genetics research for over a century. For example, the method has been used to show that general intelligence, or *g*, is highly heritable (Plomin & Crabbe, 2000). However, this approach cannot identify the particular genes involved in intelligence or the cognitive components of *g*. Recent advances in molecular genetics now allow a different, complementary approach to behavioral genetics, called *allelic association*. This method has been applied to the study of individual differences in cognition in healthy individuals, revealing evidence of modulation of cognitive task performance by specific neurotransmitter genes (Fan, Fossella, Sommer, Wu, & Posner, 2003; Greenwood, Sunderland, Friz, & Parasuraman, 2000; Parasuraman et al., 2005). This work is likely to provide the basis not only for improved understanding of the neural basis of cognition, but also for better characterization of individual differences in cognition. That, in turn, can have an impact on important human factors issues such as selection and training.

Reliable quantification of individual differences in cognitive function will have obvious implications for selection of operators for occupations that demand a high workload. While it would be premature to state that the molecular genetic approach to cognition has immediate applications to selection, further programmatic research on more complex cognitive tasks will undoubtedly lead to progress in such an endeavor. The postgenomic era has clearly demonstrated that inheritance of a particular genotype only sets a range for the phenotypic expression of that genotype, with the exact point within that range being determined by other genetic and environmental factors. Genomic analysis allows for a much more precise specification of that range for any phenotype, and for linking phenotypic variation to specific genetic polymorphisms. Selection and training have traditionally been considered together in human factors research and practice (e.g., Sanders & McCormick, 1983) but rarely in terms of a common biological framework. Examining the effects of normal genetic variation and of various training regimens on brain function may provide such a common framework.

The goal of neuroergonomics is to better understand the brain's functional structures and activities in relation to work and technology. In addition to molecular genetics, biotechnology can contribute to this effort by providing a means to study neuronal activities down to the molecular level. Biomimetic studies also allow for precise modeling of the human brain's activities. If the validity of such models can be established in the near future, then researchers could examine various manipulations of brain function that are not ethically possible with human participants.

The currently available measures of brain function are limited by sensor size and the inability to monitor brain function and influence function simultaneously. Nanotechnology provides the measurement tools that can achieve such dual-purpose needs. It can also provide new sensors for monitoring changes in neuronal function in otherwise undetectable brain structures. In addition, nanotechnology has the appropriate scale of operations necessary to deliver chemicals needed to precisely monitor and modify effects of neurotransmitters or encourage targeted neurogenesis, with the objective of improving human performance in certain work environments.

Although there are few current examples of the influence of biotechnology and nanotechnology on neuroergonomics, these fields are likely to have greater impact in the near future. De Pontbriand (2005) provided a cogent discussion of the potential benefits that biotechnology and nanotechnology can bring to neuroergonomics.

Overview of *Neuroergonomics: The Brain at Work*

This book represents a collective examination of the major theoretical, empirical, and practical issues raised by neuroergonomics. In this opening chapter, which forms part I, we have provided an overview of the field, covering theoretical and conceptual issues involved in the merging of cognitive neuroscience and human factors research. We have also briefly described neuroergonomic methods, but these are covered in more detail in part II, which consists of seven chapters describing different cognitive neuroscience methods: fMRI, EEG, ERPs, NIRS, TCD, and oculomotor measures. In addition, measures to track behavior and brain function in naturalistic environments are also described. Each chapter outlines the major features of each method, describes its principal merits and limitations, and gives illustrative examples of its use to address issues in neuroergonomics. We understand that readers will bring a variety of technical backgrounds to the examination of these methodological issues. Accordingly, key readings provided at the end of each chapter provide additional background for understanding some of the more technical details of each method, as needed.

Part III examines basic research in a number of different domains of cognition that have particular relevance for the understanding of human performance at work. We did not attempt to be comprehensive. Rather, we chose areas of cognition in which significant progress has been made in identifying the underlying neural mechanisms, thereby allowing for theory-driven application to human factors issues. The cognitive domains discussed are spatial cognition, vigilance, executive functions, and emotion and decision making. In addition, working memory, planning, and prospective memory are variously described in some of these chapters as well as in other sections of the book.

As the study of the brain at work, neuroergonomics must also examine the work environment. It is an undeniable fact that many work settings are stressful, induce fatigue, and are poorly designed in terms of workspace layout. Accordingly, part IV examines issues of stress, sleep loss, and fatigue, as well as the effects of the physical work environment.

Part V consists of four chapters that discuss several different domains of application of neuroergonomics. Again, we did not attempt to cover all of the application areas that are emerging as a result of the use of neuroergonomic research. We chose four: adaptive automation, virtual reality, robotics, and neuroengineering.

Neuroengineering applications are designed in part to help individuals with different disabilities that make it difficult for them to communicate effectively with the world. This area of work is covered in more detail in part VI. Four chapters describe neuroergonomic technologies that can be used to help the paralyzed, individuals with low or no vision, and those who require prostheses. A final chapter in this section is concerned with the evaluation of medical safety in health care settings.

Finally, in part VII, we close the volume by surveying prospects for the future of neuroergonomics.

Conclusion

Neuroergonomics represents a deliberate merger of neuroscience and ergonomics with the goal of advancing understanding of brain function underlying human performance of complex, real-world tasks. A second major goal is to use existing and emerging knowledge of human performance and brain function to design technologies and work environments for safer and more efficient operation. More progress has been made on the first goal than on the second, but both neuroergonomic research and practice should flourish in the future, as the value of the approach is appreciated. The basic enterprise of ergonomics—how humans design, interact with and use technology—can be considerably enriched if we also consider the human brain that makes such activities possible.

Main Points

1. Neuroergonomics is the study of brain and behavior at work.
2. Neuroergonomics attempts to go beyond its constituent disciplines of neuroscience and ergonomics by examining brain function and cognitive processes not in isolation but in relation to the technologies and artifacts of everyday life.
3. Some examples of neuroergonomics include research in the areas of aviation, driving,

brain-computer interfaces, and virtual reality.

4. Neuroergonomics is inconsistent with a purely functional philosophy of mind, in which brain structure and function are deemed irrelevant. In addition, neuroergonomics views brain and mind as influenced by context and technology.
5. Neuroergonomic methods include behavioral and performance studies, brain imaging, oculomotor measures, and computational techniques. These methods have different relative merits and disadvantages.

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II

Neuroergonomics Methods

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2

Alan Gevins and Michael E. Smith

Electroencephalography (EEG) in Neuroergonomics

This chapter considers the utility of the ongoing, scalp-recorded, human electroencephalogram (EEG) as a tool in neuroergonomics research and practice. The EEG has been extensively documented to be a sensitive index of changes in neuronal activity due to variations in the amount or type of mental activity an individual engages in, or to changes in his or her overall state of alertness and arousal. The EEG is recorded as a time-varying difference in voltage between an active electrode attached to the scalp and a reference electrode placed elsewhere on the scalp or body. In the healthy waking brain, the peak-to-peak amplitude of this scalp-recorded signal is usually well under 100 microvolts, and most of the signal power comes from rhythmic oscillations below a frequency of about 30 Hz. In many situations, the EEG is recorded simultaneously from multiple electrodes at different positions on the scalp, often placed over frontal, parietal, occipital, and temporal lobes of the brain according to a conventional placement scheme.

The scalp-recorded EEG signal reflects postsynaptic (dendritic) potentials rather than action (axonal) potentials. Since the laminar structure of the cerebral cortex facilitates a large degree of electrical summation (rather than mutual cancellation) of these postsynaptic potentials, the extracellular EEG recorded from a distance represents the passive conduction of currents produced by summating synchronous activity over large neuronal populations. Several factors determine the degree to which potentials arising in the cortex will be recordable at the scalp, including the amplitude of the signal at the cortex, the size of a region over which postsynaptic potentials are occurring in a synchronous fashion, the proportion of cells in that region that are in synchrony, the location and orientation of the activated cortical regions in relation to the scalp surface, and the amount of signal attenuation and spatial smearing produced by conduction through the highly resistive skull and other intervening tissue layers. While most of the scalp-recordable signal in the ongoing EEG presumably originates in cortical regions near the recording electrode, large signals originating at more distal cortical locations can also make a significant contribution to the activity observed at a given scalp recording site. For example, because of the orientation of the primary auditory cortices, some EEG signals generated in them project more toward the top of the head than to the geometrically closer lateral scalp surfaces.

The decomposition of an instantaneous scalp-recorded voltage measure into the constituent set of neuronal events throughout the brain that contributed to it is a mathematically ill-conditioned inverse problem that has no unique solution. Because of this indeterminacy, the EEG has significant limitations with respect to its use as a method for three-dimensional anatomical localization of neural activity in the same sense in which functional magnetic resonance imagining (fMRI) or positron emission tomography (PET) are used. However, the EEG has obvious advantages relative to other functional neuroimaging techniques as a method for continuous monitoring of brain function, either over long periods of time or in environments such as a hospital bed. Indeed, it is often the method of choice for some clinical monitoring tasks. For example, continuous EEG monitoring is an essential tool in the diagnostic evaluation of epilepsy and in the evaluation and treatment of sleep disorders. It is also coming to play an increasingly important role in neurointensive care unit monitoring and in gauging level of awareness during anesthesia.

For many years, efforts have also been under way to evaluate the extent to which the EEG might be useful as a monitoring modality in the context of human factors research. To be most useful in such settings, a monitoring method should be robust enough to be reliably measured under relatively unstructured task conditions, sensitive enough to consistently vary with some dimension of interest, unobtrusive enough to not interfere with operator performance, and inexpensive enough to eventually be deployable outside of specialized laboratory environments. It should also have reasonably good time resolution to allow tracking of changes in mental status as complex behaviors unfold. The EEG appears to meet such requirements. Furthermore, the compactness of EEG technology also means that, unlike other functional neuroimaging modalities (which typically require large expensive measuring instruments and complete immobilization of the subject), EEGs can even be collected from an ambulatory subject wearing a lightweight and nonencumbering headset.

A monitoring capability with such characteristics could provide unique value in the context of neuroergonomics research that seeks to better understand the neurobiological impact of task conditions that impose excessive cognitive workload or that result in significant mental fatigue. The need for expansion of knowledge in this area is evidenced by the extensive literature indicating that task conditions that impose cognitive overload often lead to performance errors even in alert individuals working under routine conditions. The potential for compromised performance in such circumstances can be exacerbated in individuals who are debilitated because of fatigue or sleep loss, illness or medication, or intoxication or hangover. In fact, even modest amounts of sleep loss can degrade performance on tests that require contributions from prefrontal cortical regions that control attention functions (Harrison & Horne, 1998, 1999; Harrison, Horne, & Rothwell, 2000; Linde & Bergstrom, 1992; Smith, McEvoy, & Gevins, 2002; see also chapter 14, this volume) and the magnitude of the behavioral impairment observed on such tasks can exceed that observed following a legally intoxicating dose of alcohol (Arendt, Wilde, Munt, & MacLean, 2001; Krull, Smith, Kalbfleisch, & Parsons, 1992; Williamson & Feyer, 2000).

While most often just a barrier to productivity, some critical jobs are particularly demanding in terms of the fatigue and cognitive workload they impose, and are particularly unforgiving in terms of the severe negative consequences that can be incurred when individuals performing those jobs make mistakes. For instance, in medical triage and crowded emergency room contexts the patient's life often hinges on a physician's ability to manage complex, competing demands, often after long hours on the job (Chisholm, Collison, Nelson, & Cordell, 2000). Similarly, the sleep deprivation and circadian desynchronization imposed by shift work scheduling has been noted to be a source of severe performance decrements (Scott, 1994) and has been implicated as a probable cause in a number of aviation (Price & Holley, 1990) and locomotive (Tepas, 1994) accidents. The high personal and societal costs associated with such performance failures motivate efforts to develop advanced methods for detecting states of cognitive overload or mental fatigue.

In this chapter, we review progress in developing EEG methods for such purposes. We first describe how the spectral composition of the EEG changes in response to variations in task difficulty or level of alertness during highly controlled cognitive tasks. We also consider methods for analysis of such signals that might be suitable for use in a continuous monitoring context. Finally, we review generalizations of those methods to assess complex, computer-based tasks that are more representative of real-world tasks.

EEG Signals Sensitive to Variations in Task Difficulty and Mental Effort

A significant body of literature exists concerning the EEG changes that accompany increases in cognitive workload and the allocation of mental effort. One approach to this topic has focused on EEG changes in response to varying working memory (WM) demands. WM can be construed as an outcome of the ability to control attention and sustain its focus on a particular active mental representation (or set of representations) in the face of distracting influences (Engle, Tuholski, & Kane, 1999). In many ways, this notion is nearly synonymous with what we commonly understand as effortful concentration on task performance. WM plays an important role in comprehension, reasoning, planning, and learning (Baddeley, 1992). Indeed, the effortful use of active mental representations to guide performance appears critical to behavioral flexibility (Goldman-Rakic, 1987, 1988), and measures of it tend to be positively correlated with performance on psychometric tests of cognitive ability and other indices of scholastic aptitude (Carpenter, Just, & Shell, 1990; Gevins & Smith, 2000; Kyllonen & Christal, 1990).

Many EEG studies of WM have required subjects to perform controlled *n*-back-style tasks (Gevins & Cutillo, 1993; Gevins et al., 1990, 1996) that demand sustained attention to a train of stimuli. In these tasks, the load imposed on WM varies while perceptual and motor demands are kept relatively constant. For example, in a spatial variant of the *n*-back task, stimuli are presented at different spatial positions on a computer monitor once every 4 or 5 seconds while the subject maintains a central fixation. Subjects must compare the spatial location of each stimulus with that of a previous stimulus, indicating whether a match criterion is met by making a key press response on a computer mouse or other device. In an easy, low-load version of the task, subjects compare each stimulus to the first stimulus presented in each block of trials (0-back task). In more difficult, higher-load versions, subjects compare the position of the current stimulus with that presented one, two, or even three trials previously (1-, 2-, or 3-back tasks). These require constant updating of the information stored in WM on each trial, as well as constant attention to new stimuli and maintenance of previously presented information. To be successful in such tasks when WM demands are high, subjects typically must exert significant and continuous mental effort. Similar *n*-back tasks have been used to activate WM networks in a controlled fashion in the context of functional neuroimaging studies employing PET or fMRI methods (Braver et al., 1997; Cohen et al., 1994; Jansma, Ramsey, Coppola, & Kahn, 2000).

The spectral composition of the ongoing EEG displays regular patterns of load-related modulation during *n*-back task performance. For example, figure 2.1 displays spectral power in the 4–14 Hz range at a frontal midline (Fz) and a parietal midline (Pz) scalp location computed from the continuous

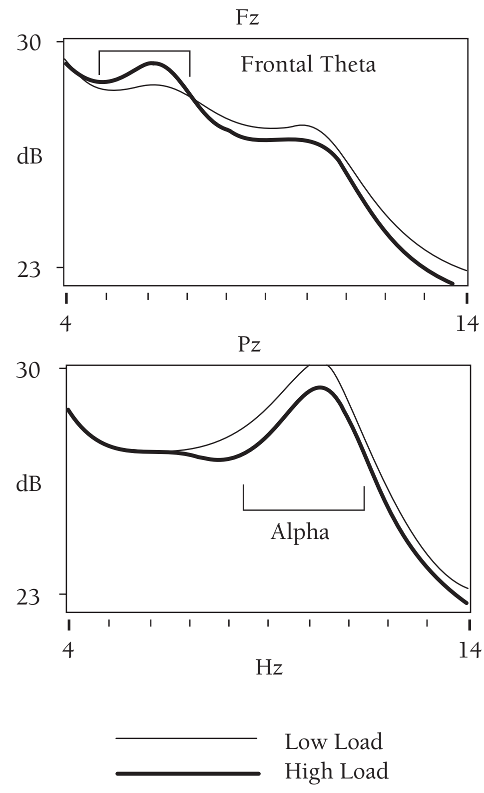

Figure 2.1. Effect of varying the difficulty of an *n*-back working memory task on the spectral power of EEG signals. The figure illustrates spectral power in dB of the EEG in the 4–14 Hz range at frontal (Fz) and parietal (Pz) midline electrodes, averaged over all trials of the tasks and collapsed over 80 subjects. Data from Gevins and Smith (2000).

EEG during performance of low-load (0-back) and moderately high-load (2-back) versions of a spatial *n*-back task. The data represent the average response from a group of 80 subjects in a study of individual differences in cognitive ability (Gevins & Smith, 2000) and show significant differences in spectral power as a function of task load that vary between electrode locations and frequency bands.

More specifically, at the Fz site a 5–7 Hz or theta-band spectral peak is increased in power during the high-load task relative to the low-load task. This type of frontal midline theta signal has frequently been reported to be enhanced in difficult, attention-demanding tasks, particularly those requiring a sustained focus of concentration (Gevins et al., 1979; Gevins et al., 1998; Gevins, Smith, McEvoy, & Yu, 1997; Miyata, Tanaka, & Hono, 1990; Mizuki, Tanaka, Iogaki, Nishijima, & Inanaga, 1980; Yamamoto & Matsuoka, 1990). Topographic analyses have indicated that this task loading-related theta signal tends to have a sharply defined potential field with a focus in the anterior midline region of the scalp (Gevins et al., 1997; Inouye et al., 1994); such a restricted topography is unlikely to result from distributed generators in dorsolateral cortical regions. Instead, attempts to model the generating source of the frontal theta rhythm from both EEG (Gevins et al., 1997) and magnetoencephalographic (Ishii et al., 1999) data have implicated the anterior cingulate cortex as a likely region of origin. This cortical region is thought to be part of an anterior brain network that is critical to attention control mechanisms and that is activated by the performance of complex cognitive tasks (Posner & Rothbart, 1992). Indeed, in a review of over 100 PET activation studies that examined anterior cingulate cortex activity, Paus and colleagues found that the major source of variance that affected activation in this region was associated with changes in task difficulty (Paus, Koski, Caramanos, & Westbury, 1998). The EEG results are thus consistent with these views, implying that performance of tasks that require significant mental effort places high demands on frontal brain circuits involved with attention control.

Figure 2.1 also indicates that signals in the 8–12 Hz or alpha band tend to be attenuated in the high-load task relative to the low-load task. This inverse relationship between task difficulty and alpha power has been observed in many studies in which task difficulty has been systematically manipulated. In fact, this task correlate of the alpha rhythm has been recognized for over 70 years (Berger, 1929). Because of this load-related attenuation, the magnitude of alpha activity during cognitive tasks has been hypothesized to be inversely proportional to the fraction of cortical neurons recruited into a transient functional network for purposes of task performance (Gevins & Schaffer, 1980; Mulholland, 1995; Pfurtscheller & Klimesch, 1992). This hypothesis is consistent with current understanding of the neural mechanisms underlying generation of the alpha rhythm (reviewed in Smith, Gevins, Brown, Karnik, & Du, 2001). Convergent evidence for this view is also provided by observations of a negative correlation between alpha power and regional brain activation as measured with hemodynamic measures (Goldman, Stern, Engel, & Cohen, 2002; Moosmann et al., 2003) and the frequent finding from neuroimaging studies of greater and more extensive brain activation during task performance when task difficulty increases (Bunge, Klingberg, Jacobsen, & Gabrieli, 2000; Carpenter, Just, & Reichle, 2000).

In addition to signals in the theta and alpha bands, other spectral components of the EEG have also been reported to be sensitive to changes in effortful attention. These include slow-wave activity in the delta (<3 Hz) band (McCallum, Cooper, & Pocock, 1988), high-frequency activity in the beta (15–30 Hz) and gamma (30–50 Hz) band (Sheer, 1989), and rarely studied phenomena such as the kappa rhythm that occurs around 8 Hz in a small percentage of subjects (Chapman, Armington, & Bragden, 1962).

Automated Detection of Mental Effort or Fatigue-Related Changes in the EEG

The results reviewed above indicate that spectral components of the EEG vary in a predictable fashion in response to variations in the cognitive demands of tasks. While this is a necessary condition for the development of EEG-based methods for monitoring cognitive workload, a number of other issues must also be addressed if such laboratory observations are to be transitioned into practical tools. Foremost among them is the problem of EEG artifact. That is, in addition to brain activity, signals recorded at the scalp include contaminating potentials from eye movements and blinks, muscle activity, head movements, and other physiological and instrumental sources of artifact. Such contaminants can easily mask cognition-related EEG signals (Barlow, 1986; Gevins, Doyle, Schaffer, Callaway, & Yeager, 1980; Gevins, Zeitlin, Doyle, Schaffer, & Callaway, 1979; Gevins, Zeitlin, Doyle, Yingling, et al., 1979; Gevins, Zeitlin, Yingling, et al., 1979), an essential but difficult and often subtle issue that, unfortunately, is too often given lip service but not actually dealt with. In laboratory studies, human experts review the raw data, identify artifacts and eliminate any contaminated EEG segments to ensure that data used in analyses represent actual brain activity. For large amounts of data, this is an expensive, labor-intensive process which itself is both subjective and variable. To be practical in more routine applied contexts, such decisions must be made algorithmically.

We have directed a great deal of research toward automated artifact detection. This has led to the development and testing of multicriteria spectral detectors (Gevins et al., 1975; Gevins, Yeager, Zeitlin, Ancoli, & Dedon, 1977), sharp transient waveform detectors (Gevins et al., 1976), and detectors using neural networks (Gevins & Morgan, 1986, 1988). In some cases, automated detection algorithms can perform about as well as the consensus of expert human judges. For example, in a database of about 40,000 eye movement, head/body movement, and muscle artifacts, we found that algorithmic methods successfully detected 98.3% of the artifacts with a false detection rate of 2.9%, whereas on average expert human judges found 96.5% of the artifacts with a 1.7% false detection rate. Thus, while further work on the topic is needed, it is reasonable to expect that the problem of automated artifact detection will not be an insurmountable barrier to the development of EEG-based cognitive monitoring methods.

A closely related problem is the fact that, in subjects actively performing tasks with significant perceptuomotor demands in a normal fashion, the incidence of data segments contaminated by artifacts can be high. As a result, it can be difficult to obtain enough artifact-free data segments for analysis. To minimize data loss, effective digital signal processing methods must also be developed to filter contaminants out of the EEG when possible. One powerful approach to this problem has been to implement adaptive filtering methods to decontaminate artifacts from EEG signals (Du, Leong, & Gevins, 1994). We have found such methods to be effective at recovering most of the artifact-contaminated data recorded in typical laboratory studies of subjects working on computer-based tasks. A variety of other methods have been employed by different investigators in response to this problem, including such techniques as autoregressive modeling (Van den Berg-Lensssen, Brunia, & Blom, 1989), source-modeling approaches (Berg & Scherg, 1994), and independent components analysis (Jung et al., 2000). A difficult issue with contaminant removal is that bona fide brain signals can also be removed with the artifacts. As with the problem of artifact detection, continued progress in this area suggests that, at least under some conditions and for some types of artifacts, decontamination strategies will evolve that will enable the automation of EEG processing for continuous monitoring applications.

Presuming then that automated preprocessing of the EEG can yield sufficient data for subsequent analyses, questions still remain as to whether the type of load-related changes in EEG signals can be measured in a reliable fashion in individual subjects, and whether such measurements can be accomplished with a temporal granularity suitable for tracking complex behaviors. That is, in the experiments described above, changes in the theta and alpha bands in response to variations in WM load were demonstrated by collapsing over many minutes of data recorded from a subject at each load level, and then comparing the mean differences between load levels across groups of subjects using conventional parametric statistical tests. Under normal waking conditions, such task-related EEG measures have high test-retest reliability when compared across a group of subjects measured during two sessions with a week between them (McEvoy, Smith, & Gevins, 2000). However, for the development of automated EEG analysis techniques suitable for monitoring applications, load-related changes in the EEG would ideally also be replicable when computed over short segments of data and would need to have high enough signal-to-noise ratios to be measurable within such segments.

Prior work has demonstrated that multivariate combinations of EEG variables can be used to accurately discriminate between specific cognitive states (Gevins, Zeitlin, Doyle, Schaffer, et al., 1979; Gevins, Zeitlin, Doyle, Yingling, et al., 1979; Gevins, Zeitlin, Yingling, et al., 1979; Wilson & Fisher, 1995). Furthermore, neural network-based pattern classification algorithms trained on data from individual subjects can also be used to automatically discriminate data recorded during different load levels of versions of the type of *n*-back WM task described above. For example, in one experiment (Gevins et al., 1998) eight subjects performed both spatial and verbal versions of 3-, 2-, and 1-back WM tasks on test sessions conducted on different days. For each single trial of data in each subject, spectral power estimates were computed in the theta and alpha bands for each electrode site. Pattern recognition was performed with the classic Joseph-Viglione neural network algorithm (Gevins, 1980; Gevins & Morgan, 1988; Joseph, 1961; Viglione, 1970). This algorithm iteratively generates and evaluates two-layered feedforward neural networks from the set of signal features, automatically identifying small subsets of features that produce the best classification of examples from the sample of data set aside for training. The resulting classifier networks were then cross-validated on the remaining data not included in the training sample.

Utilizing these procedures, test data segments from 3-back versus 1-back load levels could be discriminated with over 95% ($p < .001$) accuracy. Over 80% ($p < .05$) of test data segments associated with a 2-back load could also be discriminated from data segments in the 3-back or 1-back task loads. Such results provide initial evidence that, at least for these types of tasks, it is possible to develop algorithms capable of discriminating different cognitive workload levels with a high degree of accuracy. Not surprisingly, they also indicated that relatively large differences in cognitive workload are easier to detect than smaller differences, and that there is an inherent trade-off between the accuracy of classifier performance and the temporal length of the data segments being classified.

High levels of accurate classification were also achieved when applying networks trained with data from one day to data from another day and when applying networks trained with data from one task (e.g., spatial WM) to data from another task (e.g., verbal WM). It was also possible to successfully apply networks trained with data from a group of subjects to data from new subjects. Such generic networks were found on average to yield statistically significant classification results when discriminating the 1-back from the 3-back task load conditions, but their accuracy was much reduced from that achievable with subject-specific networks. On the one hand, such results indicate that there is a fair amount of commonality across days, tasks, and subjects in the particular set of EEG frequency-band measures that are sensitive to increases in cognitive workload. Such commonalities can be exploited in efforts to design efficient sensor montages and signal-processing methods. Nonetheless, they also indicate that to achieve optimal performance using EEG-based cognitive load-monitoring methods, it will likely be necessary to calibrate algorithms to accommodate individual differences. Such conclusions are also consistent with the observation that patterns of task-related EEG changes vary in conjunction with individual differences in cognitive ability and cognitive style (Gevins & Smith, 2000).

In addition to being sensitive to variations in attention and mental effort, the EEG also changes in a predictable fashion as individuals become sleepy and fatigued, or when they experience other forms of transient cognitive impairment. For example, it has long been known that the EEG of drowsy subjects has diffusely increased lower theta band activity and decreased alpha band activity (Davis, Davis, Loomis, Harvey, & Hobart, 1937; Gevins, Zeitlin, Ancoli, & Yeager, 1977). These changes are distinct from those described above characterizing increasing task load based on topography and spectral characteristics. Because such EEG changes are robust and reliable, a number of laboratories have developed and tested computerized algorithms for automated detection of drowsiness (Gevins, Zeitlin, et al., 1977; Hasan, Hirkoven, Varri, Hakkinen, & Loula, 1993). Such methods have produced highly promising results. For example, in one study we used neural network-based methods to compare task-related EEG features between alert and drowsy states in individual subjects performing the *n*-back WM tasks described above (Gevins & Smith, 1999). Utilizing EEG features in the alpha and theta bands, average test set classification accuracy was 92% (range 84–100%, average binomial $p < .001$). In another study, we explicitly compared metrics based on either behavioral response measures during an *n*-back WM task, EEG recordings during task performance and control conditions, or combinations of behavioral and EEG variables with respect to their relative sensitivity for discriminating conditions of drowsiness associated with sleep loss from alert, rested conditions (Smith et al., 2002). Analyses based on behavior alone did not yield a stable pattern of results when viewed over test intervals. In contrast, analyses that incorporated both behavioral and neurophysiological measures displayed a monotonic increase in discriminability from alert baseline with increasing amounts of sleep deprivation. Such results indicate that fairly modest amounts of sleep loss can induce neurocognitive changes detectable in individual subjects performing computer-based tasks, and that the sensitivity for detecting such states is significantly improved by the addition of EEG measures to behavioral indices.

Extension of EEG-Based Cognitive State Monitoring Methods to More Realistic Task Conditions

The results described above provide evidence for the basic feasibility of using EEG-based methods for monitoring cognitive task load, mental fatigue, and drowsiness in individuals engaged in computer-based work. However, the *n*-back WM task makes minimal demands on perceptual and motor systems, and only requires that a subject's effort be focused on a single repetitive activity. In more realistic work environments, task demands are usually less structured and mental resources often must be divided between competing activities, raising questions as to whether results obtained with the *n*-back task could generalize to such contexts.

Studies have demonstrated that more complicated forms of human-computer interaction (such as videogame play) produce mental effort-related modulation of the EEG that is similar to that observed during *n*-back tasks (Pellouchoud, Smith, McEvoy, & Gevins, 1999; Smith, McEvoy, & Gevins, 1999). This implies that it might be possible to extend EEG-based multivariate methods for monitoring task load to such circumstances. To evaluate this possibility, a subsequent study (Smith et al., 2001) was performed in which the EEG was recorded while subjects performed the Multi-Attribute Task Battery (MATB; Comstock & Arnegard, 1992). The MATB is a personal computer-based multitasking environment that simulates some of the activities a pilot might be required to perform. It has been used in several prior studies of mental workload and adaptive automation (e.g., Fournier, Wilson, & Swain, 1999; Parasuraman, Molloy, & Singh, 1993; Parasuraman, Mouloua, & Molloy, 1996). The data collected during performance of the MATB were used to test whether it is possible to derive combinations of EEG features that can be used for indexing task loading during a relatively complex form of human-computer interaction.

The MATB task included four concurrently performed subtasks in separate windows on a computer screen (for graphic depictions of the MATB visual display, see Fournier et al., 1999; Molloy & Parasuraman, 1996). These included a systems-monitoring task that required the operator to monitor and respond to simulated warning lights and gauges, a resource management task in which fuel levels in two tanks had to be maintained at a certain level, a communications task that involved receiving audio messages and making frequency adjustments on virtual radios, and a compensatory tracking task that simulated manual control of aircraft position. Manipulating the difficulty of each subtask served to vary load; such manipulations were made in a between-blocks fashion. Subjects learned to perform low-, medium-, and high-load (LL, ML, and HL) versions of the tasks. For comparison purposes they also performed a passive watching (PW) condition in which they observed the tasks unfolding without actively performing them.

Subjects engaged in extensive training on the tasks on one day, and then returned to the laboratory on a subsequent day for testing. On the test day, subjects performed multiple 5-minute blocks of each task difficulty level. Behavioral and subjective workload ratings provided evidence that on average workload did indeed increase in a monotonic fashion across the PW, LL, ML, and HL task conditions. This increase in workload was associated with systematic changes in the EEG. In particular, as in the prior study of workload changes in the *n*-back task paradigm, frontal theta band activity tended to increase with increasing task difficulty, whereas alpha band activity tended to decrease. Such results indicated that the workload manipulations were successful, and that spectral features in the theta and alpha range might be useful in attempting to automatically monitor changes in workload with EEG measures.

Separate blocks of data were thus used to derive and then independently validate subject-specific,

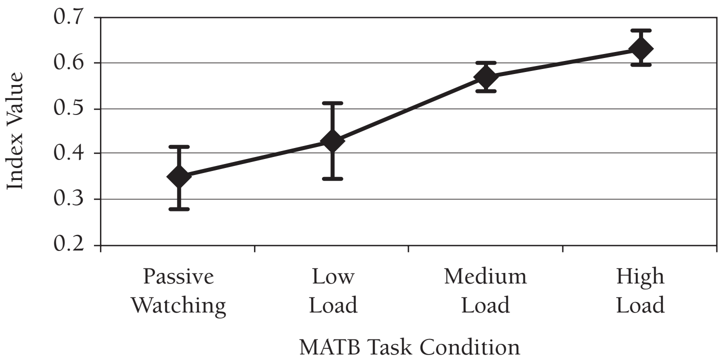

Figure 2.2. Mean and *SEM* (N = 16 subjects) EEG-based cognitive workload index values during performance of the MATB flight simulation task. Data are presented for each of four task versions (PW = passive watch, LL = low load, ML = moderate load, HL = high load). Average cognitive workload index scores increased monotonically with increasing task difficulty. Data from Smith., Gevins, Brown, Karnik and Du (2001).

EEG-based, multivariate cognitive workload functions. In contrast to the two-class pattern detection functions that were employed to discriminate between different task load levels in the prior study, we evaluated a different technique that results in a single subject-specific function that produces a continuous index of cognitive workload and hence could be applied to data collected at each difficulty level of the task. In this procedure, the EEG data were first decomposed into short windows and a set of spectral power estimates of activity in the theta and alpha frequency ranges was extracted from each window. A unique multivariate function was then defined for each subject that maximized the statistical divergence between a small sample of data from low and high task load conditions. To cross-validate the function, it was tested on new data segments from the same subject. Across subjects (figure 2.2), mean task load index values were found to increase systematically with increasing task difficulty and differed significantly between the different versions of the task (Smith et al., 2001). These results provide encouraging initial evidence that EEG measures can indeed provide a modality for measuring cognitive workload during more complex forms of computer interaction. Although complex, the signal processing and pattern classification algorithms employed in this study were designed for real time implementation. In fact, a prototype online system running on a circa 1997 personal computer performed the requisite calculations online and provided an updated estimate of cognitive workload at 4-second intervals while subjects were engaged in task performance.

It is worth reiterating here the critical role that effective automated artifact detection and filtering plays in such analyses. Effective artifact detection and filtering is particularly important during complex computer-based activities such as videogame play, as these types of behaviors tend to be associated with a great deal of artifact-producing head, body, and eye movement that might confound EEG-derived estimates of cognitive state. For example, figure 2.3 illustrates the average workload indices obtained from data from a single electrode (frontal central site Fz) in an individual subject during the MATB, obtained after calibrating a multivariate index function for that electrode using artifact-decontaminated examples of data from the low-load and high-load MATB conditions and then applying the resulting function to new samples of EEG data that were either decontaminated with state-of-the-art EEG artifact detection and filtering algorithms (leftmost and center columns) or without systematic artifact detection and correction (rightmost column), with $N = 50$ 4-second index function scores per task condition. A linear discriminant function applied to the data was able to correctly discriminate 95% of the individual clean samples of LL MATB data as coming from that category rather than from the HL category (binomial $p < .000001$). In contrast, an equivalent linear discriminant function applied to the artifact-contaminated LL data performed at chance level.

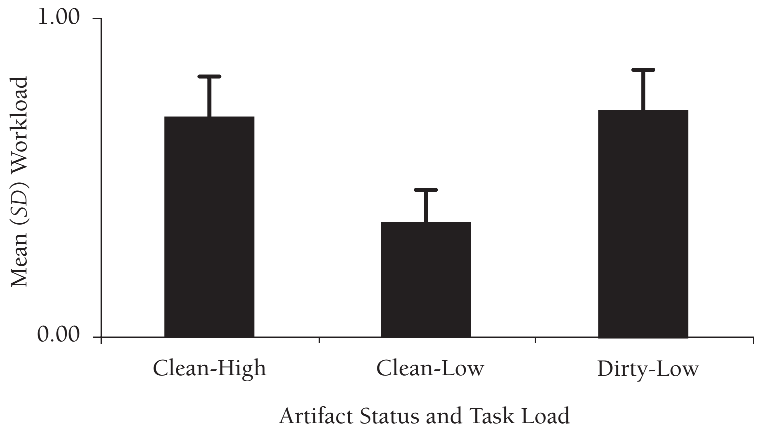

Figure 2.3. Individual subject workload index function scores from a single EEG channel (frontal central electrode Fz) can discriminate low from high load levels during MATB task performance when effective EEG artifact decontamination is employed (left and center columns), but load can be misclassified without such correction (right column).

Analogous methods have also been used in a small exploratory study that involved more naturalistic computer tasks. In that experiment (Gevins & Smith, 2003), the EEG data were recorded while subjects performed more common computer-based tasks that were performed under time pressure and that were more or less intellectually demanding. These more naturalistic activities required subjects to perform word processing, take a computer-based aptitude test, and search for information on the Web. The word processing task required subjects to correct as many misspellings and grammatical errors as they could in the time allotted, working on a lengthy text sample using a popular word processing program. The aptitude test was a practice version of the Computer-Adaptive GMAT test. Subjects were asked to solve as many data-sufficiency problems as possible in the time allotted; such problems make a high demand on logical and quantitative reasoning skills and require significant mental effort to complete in a timely fashion. The Web-searching task required subjects to use a popular Web browser and search engine to find as many answers as possible in the time allotted to a list of trivia questions provided by the experimenter. For example, subjects were required to use the browser and search engine to "convert 98.6 degrees Fahrenheit into degrees Kelvin," "find the population of the 94105 area code in the 1990 U.S. Census," and "find the monthly mortgage payment on a $349,000, 30-year mortgage with a 7.5% interest rate." Each type of task was structured such that subjects would be unlikely to be able to complete it in the time allotted. Data were also recorded from subjects as they performed easy and difficult *n*-back working memory tasks, and as they rested quietly, for comparison with the more naturalistic tasks.

The same basic analysis procedure described above that was applied to the EEG data recorded during MATB performance was also employed in this study to derive personalized continuous functions indexing cognitive workload. The resulting functions were then applied to new samples of that subject's data.

A summary of the results from these analyses, averaged across data segments within each task condition and compared between conditions, is presented in figure 2.4. These comparisons indicate that the cognitive load index performed in a predictable fashion. That is, the condition in which the subject was asked to passively view a blank screen produced an average EEG-based cognitive workload load around the zero point of the scale. Average index values during 0-back task performance were slightly higher than those during the resting condition, and average index values during the 3-back task were significantly higher than those recorded either during the 0-back WM task or during the resting state. All three naturalistic tasks produced workload index values slightly higher than those obtained in the 3-back task, which might be expected given that the *n*-back tasks had been practiced and

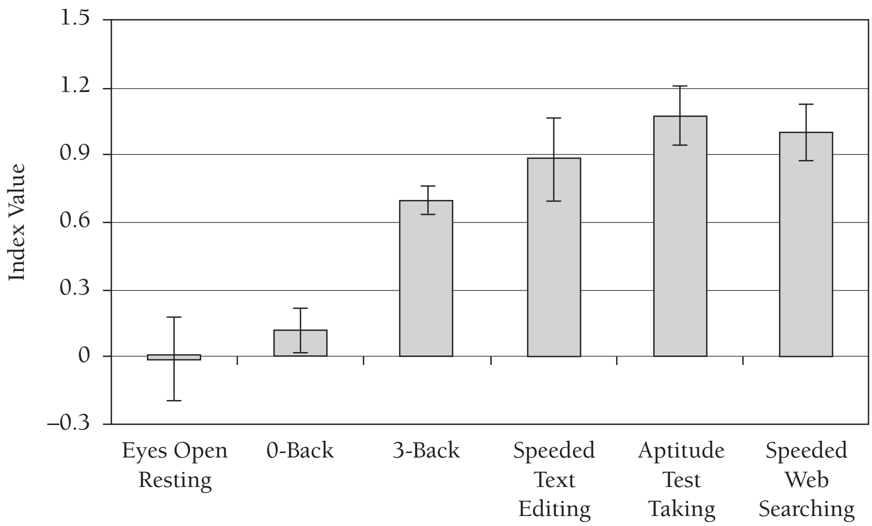

Figure 2.4. Mean and *SEM* ($N = 7$ subjects) EEG-based cognitive workload index values during resting conditions, easy and difficult versions of the *n*-back working memory tasks, and a few naturalistic types of computer-based work (see text for full description of tasks and procedure). The data represent average index values over the course of each type of task. The easy WM and resting conditions produced significantly lower values than the more difficult WM condition or the naturalistic tasks.

were repetitive in nature, whereas the other tasks were novel and required the use of strategies of information gathering, reasoning, and responding that were less stereotyped in form. Among the naturalistic tasks, the highest levels of cognitive workload were recorded during the computerized aptitude-testing task—the condition that was also subjectively experienced as the most difficult.

This pattern of results is interesting not only because it conforms with a priori expectations about how workload would vary among the different tasks, but also because it provides data relevant to the issue of how the workload measure is affected by differences in perceptuomotor demands across conditions. Since in the *n*-back tasks stimuli and motor demands are kept constant between the 0-back and 3-back load levels, the observed EEG differences in those conditions are clearly closely related to differences in the amounts of mental work demanded by the two task variants rather than other factors. However, in the study of MATB task performance described above, the source of variation in the index is somewhat less clear. On the one hand, performance and subjective measures unambiguously indicated that the mental effort required to perform the high-load version of the MATB was substantially greater than that required by the low-load (or passive watching) versions. On the other hand, the perceptuomotor requirements in the high-load version were also substantially greater than those imposed by the other version. In this latter experiment, such confounds were less of a concern. Indeed, both the text editing task and the Web searching task required more effortful visual search and more active physical responding than the aptitude test, whereas the aptitude test had little reading and less responding and instead required a great deal of thinking and mental evaluation of possibilities. Thus, the fact that the average cognitive workload values during performance of the aptitude test were higher than those observed in the other tasks provides convergent support for the notion that the subject-specific indices were more closely tracking variations in mental demands rather than variations in perceptuomotor demands in these instances. Nevertheless, the results remain ambiguous in this regard.

From Unidimensional to Multidimensional Neurophysiological Measures of Workload

Another approach to resolving the inherent ambiguity of the sort of unidimensional “whole brain” metric used to quantify mental workload in the studies described above is to generalize the metric to separate index loading of different functional brain systems. That is, the applied psychology and ergonomics literature has long posited a relative independence of the resources involved with higher-order executive processes and those involved with perceptual processing and motor activity (Gopher, Brickner, & Navon, 1982; Wickens, 1991). Furthermore, related topographic differences can be observed in regional patterns of EEG modulation. For example, it is clear that alpha band activity over posterior regions is particularly sensitive to visual stimulation and that increases in motor demands are associated with suppression of alpha and beta band activity over sensorimotor cortex (Arroyo et al., 1993; Jasper & Penfield, 1949; Mulholland, 1995). Such regional differences can also be observed during performance of complex tasks. In one study, the EEG was recorded from subjects while they either actively played a videogame or watched the screen while someone else played the game (Pellouchoud et al., 1999). Across the group of subjects, the amplitude of the frontal midline theta rhythm was larger in the active performance condition than in the resting or passive watching conditions. In contrast, a posterior alpha band signal was attenuated during both the playing and the watching conditions relative to the resting condition, suggesting that it was responding primarily to the presence of complex visual stimulation rather than active task performance. Finally, a central mu (10–13 Hz) rhythm recorded over sensorimotor cortex was attenuated during the active game-playing condition, but not during the passive watching condition, presumably reflecting activation related to the game's hand and finger motor control requirements (Pellouchoud et al., 1999). In another study where subjects were allowed to practice a videogame until they were skilled at it, the alpha rhythm recorded over frontal regions increased in amplitude with progressive amounts of practice, suggesting that smaller neuronal populations were required to regulate attention as the task became automated. In contrast, the alpha rhythm recorded over posterior regions displayed no such effect, suggesting that neural activation related to visual processing did not diminish (Smith et al., 1999).

Such considerations have led to an extension of the method described above to create multidimensional indices that provide information about the relative activation of a local neocortical region. In particular, instead of defining a single load-sensitive multivariate function for the whole head, we have worked toward extracting three independent topographically regionalized metrics from multielectrode data (Smith & Gevins, 2005) recorded in the MATB experiment described above. One metric was derived from data recorded over frontal cortical areas. Since this region of the brain is known to be involved in executive attention control and working memory processes, we refer to this metric as a measure of cortical activation related to frontal executive workload. A second metric was derived from data recorded from central and parietal regions. Since these regions are activated by motor control functions, somatosensory feedback, and the coordination of action plans with representations of extra personal space, we refer to this second metric as a measure of sensorimotor activation. A third metric was derived from electrodes over occipital regions. Since this region includes primary and secondary visual cortices, we refer to this third metric as representing variation in cortical activation due to visuoperceptual functions. While these labels are convenient for discussion, they of course are highly oversimplified with regard to describing the actual operations performed by the underlying cortical systems. They may, however, be seen as consistent with the results of fMRI studies of simulator (driving) operation (Calhoun et al., 2002; Walter et al., 2001), which have also reported activation in frontal attention networks, sensorimotor cortex, and visual cortices (see also chapter 4, this volume).

Figure 2.5 summarizes how the three regional cortical activation metrics changed as a result of task manipulations, describing the mean output of the regional metrics computed across all of the cross-validation data segments for each task difficulty level for each subject. Each regional metric was found to be significantly affected by the task difficulty manipulation, consistent with the notion that the MATB task increased workload on multiple brain systems in parallel. Furthermore, both subjective workload estimates and overt task performance were found to covary with the regional EEG-derived workload estimates, indicating the metrics were tracking changes in brain activity that were functionally significant.

In a second experiment, these regional workload metrics were tracked over the course of an

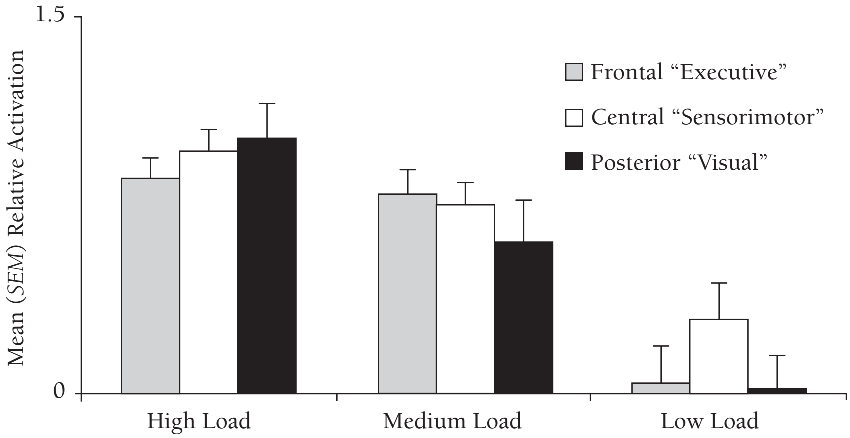

Figure 2.5. Average normalized (*SEM*) values for regional cortical activation metrics over frontal, central, and posterior regions of the scalp derived from multivariate combinations of EEG spectral features recorded from $N = 16$ participants performing 5-minute blocks of high-, medium-, and low-load versions of the MATB task.

all-night experiment during which subjects performed the HL version of the MATB and other tasks in a more or less continuous fashion without sleeping since early the prior morning (Smith & Gevins, 2005; Smith et al., 2002). During this extended wakefulness session, cortical activation as indexed by the regional EEG workload scores was observed to change with time on task despite task difficulty being held constant and despite the fact that subjects were highly practiced in the task. The changes are illustrated in figure 2.6. The daytime values are contrasted with values representing the first block of data from the overnight session, where testing on average began around 11:00 p.m. They are also contrasted with late night values from the time period within the last four test inter-

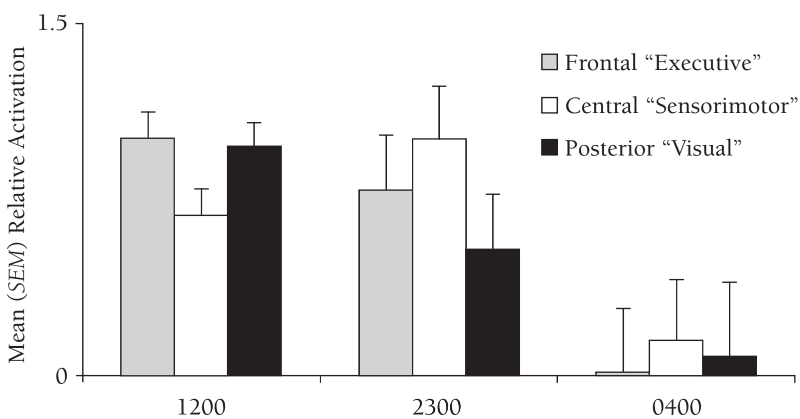

Figure 2.6. Average normalized (*SEM*) values for regional cortical activation metrics over frontal, central, and posterior regions of the scalp derived from multivariate combinations of EEG spectral features recorded from $N = 16$ participants performing 5-minute blocks of the high-load MATB task during alert daytime baseline periods (around noon or 1200 hrs), during the first test interval of an all-night recording session (2300 hrs or 11:00 p.m.), and during the test interval between 1:30 and 5:30 a.m. in which they displayed a cortical activation minima (across subjects this minimum occurred on average at 0400 hrs or 4:00 a.m.).

vals for each subject when he or she displayed a minimum in total cortical activation (for 15/16 subjects this minimum occurred between 1:30 and 5:30 a.m.). Average values for each region declined with sleep deprivation, with the largest overall declines for the frontal region.

Interestingly, subjective workload was found to be negatively correlated with the magnitude of the fatigue-related decline in the frontal region—but not the other regions—suggesting that as frontal activation decreased the subjects found it increasingly difficult to confront the demands of the high-load MATB task. The fact that perceived mental effort was observed to be positively correlated with changes in frontal cortical activity in alert individuals, yet negatively correlated with frontal cortical activation with increases in mental fatigue, might be seen as problematic for the eventual development of adaptive automation systems that aim to dynamically modulate the cognitive task demands placed on an individual in response to momentary variations in the availability of mental resources as reflected by real-time analysis of neural activity. That is, it has sometimes been suggested that it might be possible to use measures of brain activation as a basis for automated systems to off-load tasks from an individual if he or she was detected to be in a state of high cognitive workload, or allocate more tasks to an individual that appeared to have ample reserve processing capacity and was in danger of becoming bored or inattentive. The current results indicate that a decrease in cortical activation in frontal regions may reflect either a decrease in mental workload or an increase in mental fatigue and a heightened sense of mental stress. Assigning more tasks to an individual in the former case may indeed serve to increase his or her cognitive throughput. In the latter case, it may result in the sort of tragic accident that is too often reported to occur when fatigued personnel are confronted with unexpected increases in task demands (Dinges, 1995; Miller, 1996; Rosekind, Gander, & Miller, 1994). Thus, while measures of brain function during complex task performance may serve to accelerate research into the sources of performance failure under stress, it seems likely that a great deal of future research will be needed before such measures can be adapted to the problem of developing technology for adaptively augmenting the capabilities of mission-critical personnel working in demanding and stressful computerized-task environments.

Conclusion

In summary, the results reviewed above indicate that the EEG changes in a highly predictable way in response to sustained changes in task load and associated changes in the mental effort required for task performance. It also changes in a reliable fashion in response to variations in mental fatigue and level of arousal. It appears that such changes can be automatically detected and measured using algorithms that combine parameters of the EEG power spectra into multivariate functions. While such EEG metrics lack the three-dimensional spatial resolution provided by neuroimaging methods such as PET or fMRI, they can nonetheless provide useful information about changes in regional functional brain systems that may have important implications for ongoing task performance. Such methods can be effective both in gauging the variations in cognitive workload imposed by highly controlled laboratory tasks and in monitoring differences in the mental effort required to perform tasks that more closely resemble those that an individual might encounter in a real-world work environment. Because this sensitivity can in principle be obtained with technology suitable for use in real-world work environments, the EEG can be seen as a critical tool for research in neuroergonomics.

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Main Points

1. The EEG recorded at the scalp is a record of instantaneous fluctuations of mass electrical activity in the brain, primarily summated postsynaptic (dendritic) potentials of large cortical neuronal populations.
2. Spectral components of the EEG signal show characteristic changes in response to variations in mental demands or state of alertness. As

with all other means of measuring brain function, EEG signals are also sensitive to the perceptual and motor activities of the subject in addition to mental activity. It is essential to separately measure these perceptual and motoric neural processes to have a strong inference that the brain function signals one would like to use as a measure of mental activity actually in fact do so.
3. The high temporal resolution of the EEG in combination with the simplicity and portability of the technology used to record and analyze it make it suitable for use in unrestrained subjects in a relatively wide range of environments, including real-world work contexts.
4. The sensitivity of EEG signals to particular task demands differs depending on the spatial positioning of scalp electrodes and, in many but not all cases, reflects functional specialization of nearby underlying cortical regions.
5. As with all brain function measurement technologies, the EEG signal is sensitive to artifactual contaminants not generated in the brain, which must be removed from the signal in order to make valid inferences about mental function. This is easier said than done.
6. There is no simple one-to-one mapping between a change in a measure of brain activation and the cognitive loading of an individual. Additional factors, such as the state of alertness, must be taken into account. Simplistic approaches to neuroadaptive automation that do not take this complexity into account will fail.

Key Readings

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3

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Event-Related Potentials (ERPs) in Neuroergonomics

Event-related potentials (ERPs) represent the brain's neural response to specific sensory, motor, and cognitive events. ERPs are computed by recording the electroencephalogram (EEG) from the scalp of a human participant and by averaging EEG epochs time-locked to a particular event. The use of ERPs to examine various aspects of human cognitive processes has a long history. Pioneering work on ERP correlates of cognitive processes such as attention (Hillyard, Hink, Schwent, & Picton, 1973), working memory (Donchin, 1981), and language (Kutas & Hillyard, 1984) were carried out in the 1970s and 1980s. These studies were important because they established the use of ERPs as a tool for *mental chronometry* (Posner, 1978), or the examination of the timing of the neural events associated with different components of information processing. However, these landmark studies did not greatly influence theory or empirical research in cognitive psychology in the era in which they were carried out. Moreover, because of their poor spatial resolution in localizing sources of neuronal activity underlying scalp electrical potentials, ERPs were not well regarded by neuroscientists accustomed to the spatial precision of single-cell recording in animals. The mid-1980s were a period when the cognitive neuroscience revolution was in its early phases (Gazzaniga, 1995). Consequently, ERP research did not enjoy much currency in the mainstream of either cognitive psychology or neuroscience.

The situation changed a few years later. The development of other neuroimaging techniques such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) led to their growing use to examine the neural basis of human cognitive processes, beginning with the seminal work of Posner, Petersen, Fox, and Raichle (1988). Neuroimaging allowed for the rediscovery of ERPs in cognitive psychology and cognitive neuroscience. As a result, ERPs made a comeback in relation to both psychology and neuroscience and today enjoy an acknowledged status in both fields. The importance of ERPs as a tool in cognitive neuroscience was further enhanced with the realization that PET, fMRI, and related neuroimaging techniques had serious limitations in their temporal resolution of assessing neural processing, despite their great advantage over ERPs with respect to spatial localization of neuronal activity.

At the present time, therefore, ERPs hold a unique position in the toolshed of cognitive neuroscientists. Because of the inherent sluggishness (several seconds) of neuroimaging techniques (PET