Neural and Circulatory Monitoring of Cognition

Posthumous Publication Statement

Please note that the author(s) of this book sadly passed away between the book's writing and publication. In order to honour the original work of the authors, this book has been published as it was submitted by the authors with no external changes. We hope that the reader can excuse any inconsistencies or incompletion that may arise as a result of this.

Neural and Circulatory Monitoring of Cognition

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PREFACE

The authors are brothers. One of them, Leslie, is a Human Factors Engineer. The other, Richard, is a statistics professor. Over the years this has proved to be convenient for collaboration in many research projects. In addition, both of us have a keen interest in cognitive processes: Leslie primarily with changes in cognition related to injury, disease, or abrupt changes in ambient circumstances; Richard, cross-cultural differences in cognition.

This has naturally led us to collaborate in our research. But none of our projects would have been possible without others on the team. We owe an enormous debt to those who helped—and often provided essential leadership!

In many of the research projects that we have pursued regarding changes in cognitive processes, we have found that one or the other of two instruments were essential: either the familiar electroencephalograph (EEG) or the versatile bioimpedance device (REG). They are not only essential, but very inexpensive compared to the equipment often used now for brain research, such as the MRI. Moreover, there are situations, bedside, or emergency events, in which the portability of EEG and REG instruments is vital.

It is this experience that has led us to compose this small book. Not only do we wish to draw attention to the inexpensive and convenient nature of EEG and REG data collection, we also wish to explain certain ex-post data treatments that enhance the information obtained. We have found that an effective way to do this is to simply show a sample of the published journal articles regarding our projects. These are found at the end of each chapter—and are often referred to within the chapter. (All of the other authors as well as all of the publishers have given their kind assent to this.)

Chapter One is almost entirely focused on the conversion of conventional EEG data to a far more useful form. The conventional data is a set of traces showing, for each scalp electrode, the voltage difference relative to a 'ground' such as linked earlobes. This form of the data is quite appropriate for medical diagnoses, focusing attention on the frequency of voltage oscillation at each location. This can be an indicator related, for example, to certain kinds of dementia. However, we will show how it can easily be transformed to show the relative concentration, at each site, of scalp electrostatic energy. This is not only valuable in order to trace the location of cognitive processes. It is also valuable in revealing subjects' comparative response to an experimental stimulus, e.g., a change in ambient conditions or the difficulty of a continually repeated task.

Chapter Two introduces the reader to impedance plethysmography (IPG). It provides the physiologic principals of the measurement technique, a description of the instrumentation, method of application and the analysis of recorded data. This is followed by a brief description of the use of IPG used on the head to monitor brain blood flow. When used on the head, IPG is called rheoencephalography (REG). We also explain how REG can be used at the same time as EEG energy-density to provide cerebral blood flow responses to cognitive activity.

CHAPTER ONE

USING SCALP ELECTROSTATIC ENERGY DENSITY TO STUDY COGNITION

RICHARD W. MONTGOMERY, PH.D

Introduction

1. Using scalp electrostatic energy density to study cognition

In spite of great advances in brain science achieved through the development of fMRI scanning techniques, conventional electroencephalograph (EEG) will continue to play an important role in research. EEG is far less expensive, which makes it more often possible to repeat an experiment with a large number of subjects. It also makes it possible to replicate a procedure several times in order to track changes in brain function over time, or to observe responses to various changes in experimental conditions.

1.1 EEG research based on ERPs

For many research applications the EEG recording protocol is designed to produce Event Related Potentials (ERPs). These are brief stimulus-gated segments of a continuous recording, which are later electronically "cut, stacked, and averaged." For example, if the stimulus is presentation of a picture on a computer screen, the continuous EEG record is automatically marked to show the instant of presentation of each picture. Later, for each electrode, a time trace would be computed as the average of all of the brief post-stimulus segments deemed artifact free. The term ERP may refer either to the resulting stimulus-gated average time-trace for a given electrode or to an ensemble of such traces for all electrodes. If the experiment involved comparison of, say, two experimental conditions, the post-stimulus segments would, of course, have been sorted into corresponding batches, resulting in two ensemble ERPs.

An important feature of ERPs is that they “average-out” brain activity not associated with processing the stimulus (Vaughan, 1974). Each of the stimulus-gated segments is, of course, influenced by lots of brain activity. But those activities that are not systematically related to the stimulus become, in effect, random ‘noise’; experience has shown that an average of about 30-40 stimulus-gated segments is typically sufficient to wash it out.

Computer programs exist to produce ERPs. However, here we wish to provide detailed instructions for constructing a special kind of ERP – an “energy-density” ERP – in the form of a 3D ‘moving picture’ of the scalp spatial distribution of energy-density. The significance of saying that this is a special type of ERP stems from the fact that EEG recordings do not directly show the energy of the underlying electrical fields. Instead, they are records of changes in the voltage levels of the scalp electrodes, relative to a selected reference (e.g., linked earlobes). Changes in scalp electrode voltage levels are, in turn, the result of changes in the scalp distribution of electrical charge. But neither, by themselves, reveal the amount of brain energy being devoted to the experimental task – and this information is often dramatically different from what might be shown by either voltage or charge separately. By use of Ohm’s law, however, these two quantities can be combined to calculate the underlying changes in the scalp spatial distribution of energy density. (Although “ERP” stands for event-related potential, i.e. voltage, the term is so widely used to emphasize a stimulus-gated record, that it is commonly used for all event-related results, with a preface to show the type; e.g., “energy-density ERP”.)

1.2 Illustrations of applications

The following examples demonstrate the difference that energy-density ERPs make in research projects.

Example 1: EEG response, before and after body cooling

As part of an investigation of the effect of therapeutic cooling on the cognitive performance of multiple scoliosis (MS) patients, healthy control subjects, as well as a sample of MS patients, participated in the following experiment: While instrumented for EEG they were asked to passively view a series of triangle figures presented on a computer screen, a new figure every two seconds. Equilateral triangles, all of the same size, were presented randomly either with the vertex pointed upward (75%) or pointed downward (25%). Subjects were instructed to watch for the latter, the 'rare' stimuli.

This is the so-called 'Odd Ball' experimental design. In various applications of this design, it has been found that a peak in the voltage ERP is commonly observed at the Pz electrode site (near the left angular gyrus) approximately 300 msec. after stimulus presentation (i.e., 'P300') – and that it is more pronounced for the less-expected ('rare') stimulus.

The first figure below shows the voltage ERP at the Pz electrode site for the 'rare' stimulus, for a normal control subject (an adult female). It will be noted that cooling induced a slight decrease in the latency of the P300 peak, and a slight increase in amplitude. Since both traces are for the 'rare' (less expected) stimulus, this decrease in latency and increase in amplitude is interpreted as a measure of the subject's ability to note the occasions of that stimulus. Evidently, cooling improved the subject's attention and/or cognitive processing. What's important here is the comparison with the second figure, which shows the effect of converting the ERP data to show energy density rather than voltage.

Although the main purpose of this comparison is just to illustrate how ERPs are enhanced in this manner, we should explain why this enhancement was important. The broad objective of this NIH-sponsored research project was to demonstrate the value of a cooling jacket to aid MS patients. As a step toward that objective, it was necessary first to demonstrate that cooling does have an effect on cognitive processing – indicated in this case by the patient noticing a small change in a visual stimulus. If the research had depended upon the familiar voltage ERP, this pre-post cooling difference might well have been dismissed as insignificant. However, it is clear from the second figure below, which compares energy density ERPs, that there is a significant difference.

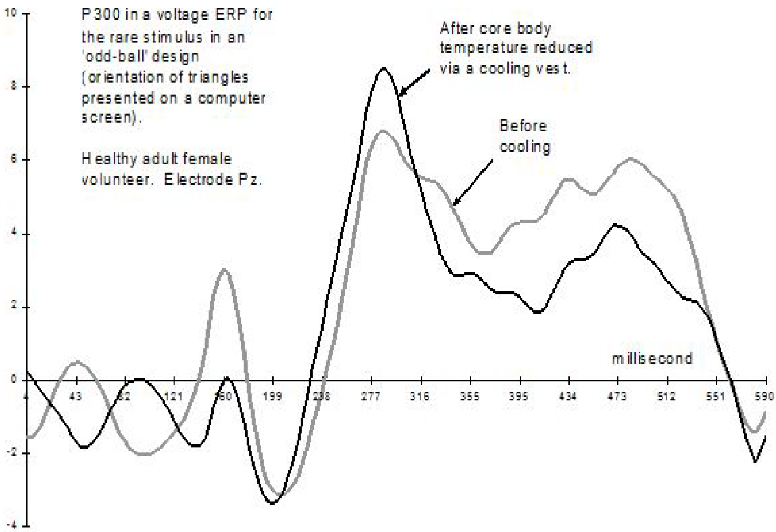

Figure 1. Effect of cooling upon the voltage P300 event related potential.

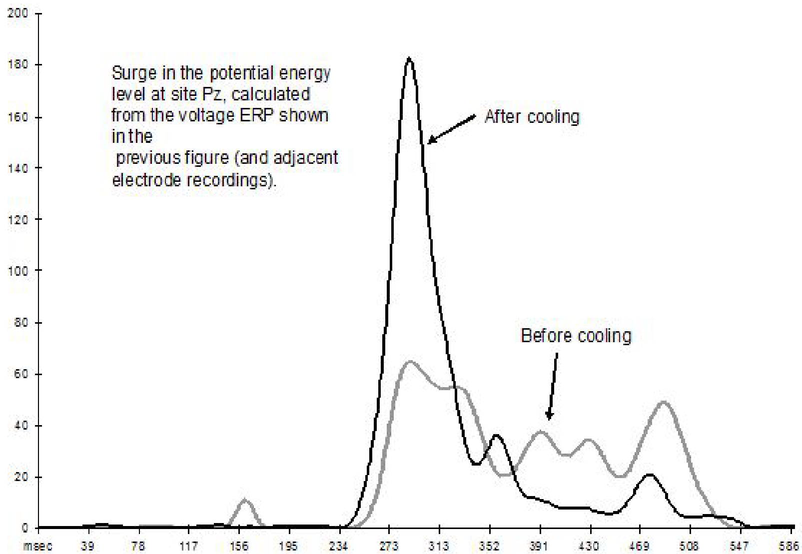

Figure 2. Effect of cooling upon the potential energy P300 event related potential.

Example 2: Eating a chocolate bar

All disturbances to the scalp electrostatic field due to cortical activity must, of course, originate in metabolic energy transformations. Brain scanning techniques such as positron emission tomography (PET) exploit this linkage. They rely upon the fact that metabolites labeled with a radioactive tracer tend to accumulate in cortical sites where metabolic activity is unusually high.

Metabolic energy exchanges must also underlie EEG patterns. So, one might hypothesize that energy density ERPs would reflect metabolic changes in brain activity better than the raw voltage ERPs. This hypothesis was tested with the following simple experiment.

A healthy male volunteer, instrumented for EEG, was asked to passively view a small white spot on a computer screen, which repeatedly blinked on for two seconds, off for two seconds. This stimulus was designed to be as ‘minimal’ as possible. ERPs of responses to such minimal visual stimuli, recorded at the central occipital electrode Oz are often called visual evoked responses, VEPs. A common stimulus is a reversing black-and-white checkerboard.

The figure below shows the subject’s (electrode Oz) VEP – as a conventional voltage ERP – before and after eating a large chocolate bar which was intended to induce a ‘sugar high’.

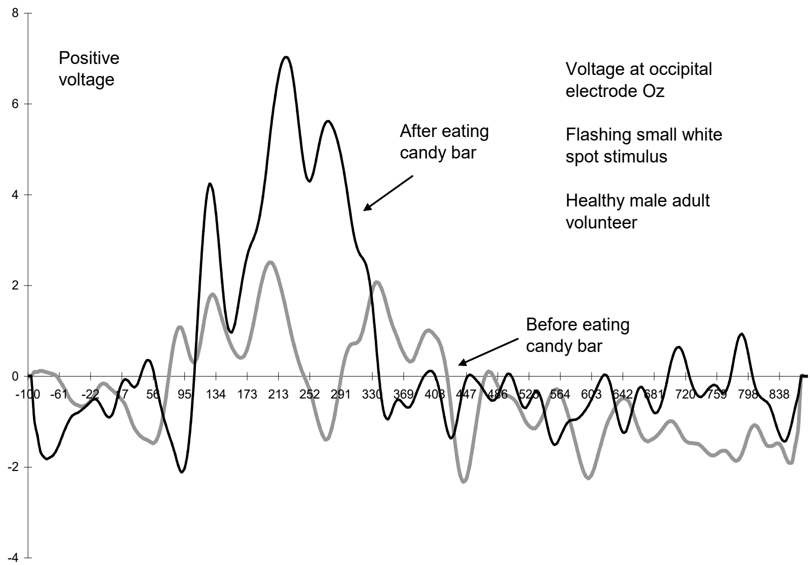

Figure 3. Voltage ERP before and after eating a candy bar.

The following figure shows an energy-density ERP computed from the same data.

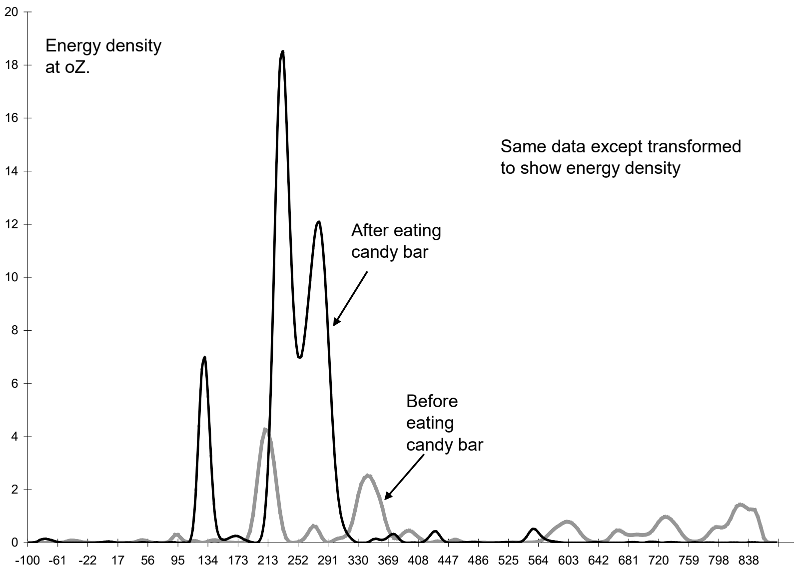

Figure 4. Energy density ERP before and after eating a candy bar.

Example 3: Synonym-antonym discrimination

The next example was selected to illustrate how the energy-density transformation facilitates statistical analysis. The term ‘cortical activity’ is widely used in the EEG literature, and it would seem that the time-integral of the energy level at a particular electrode site, over a brief period, could be used as a measure of cortical activity near that site. However, voltage data is not suitable for this approach because voltage waveforms usually contain negative as well as positive excursions that cancel each other in a time integral. Half or full-wave rectification could be used to avoid cancellation, but this seems rather artificial, compared to the straightforward time-integration of energy density, which is always positive.

In this experiment, eight female graduate students were asked to view a series of word-pairs presented on a computer screen. The subjects were matched in all respects (handedness, age, IQ, etc.) except reading skill. They represented a wide range of reading skills. Half of the subjects had

been diagnosed as developmental dyslexics, while the other half were considered 'normal' readers. The word-pairs were randomly presented without repetition from a very long file of word-pairs, and the subjects were asked to indicate via a keypad whether the words were antonyms or synonyms. Performance was measured as an error-index: the proportion of erroneous responses made by the subject, weighted by their average reaction time.

Energy-density ERP profiles were produced for each subject at electrode site t5 in the international 10-20 system. This site was selected on the basis of PET and other brain-scanning data that indicate localization of semantic processing in the posterior inferior parietal cortex in the vicinity of the angular gyrus (Frackowiak, et. al., 1997). Two pairs of regression analyses were conducted, in which the subjects' error index values were regressed on the time integrals of their energy-density ERPs. In each pair, one regression is for all subjects combined; the other uses a category variable to test group separation (i.e., the difference between 'dyslexic' and 'normal' readers).

In the first pair of regression analyses the integral was taken over the post-stimulus period from 140 to 190 milliseconds. As shown below, there is evidence of close relationship between semantic task performance and 'brain activity' represented by the time integral of scalp electrostatic energy density at site t5 during that period. But introduction of a 'category variable' (0 for normal readers, 1 for diagnosed dyslexics) to distinguish between the normal and dyslexic readers hardly improved the result. The regression coefficient for that variable was not statistically significant. (T-values are shown in parentheses.)

$$\text{Error Index} = 74.12 - 12.49 \ln(\text{t5 energy})$$
$$R^2 = .97 \qquad\qquad (-14.75)$$

$$\text{Error Index} = 79.18 - 13.27 \ln(\text{t5 energy}) - 2.16\,(\text{category})$$
$$R^2 = .98 \qquad\qquad (-17.64) \qquad\qquad (-1.52)$$

However, a second pair of regression analyses were computed from the same data, but for a later stage of processing; the post-stimulus period from 200 to 500 milliseconds. Also, in this case, the regressor was the time integral of the (unsigned) difference between energy-density recorded at right and left parietal electrode sites p3 and p4 over this time period. This pair of electrode sites and this time-period was selected in the hope of observing the effect of inter-hemisphere interaction during 'higher level' processing in the parietal association centers. In this case, there is a distinct difference between the dyslexic and normal readers.

Error Index = 106.84 −15.24 ln (p3 energy – p4 energy)
R^2 =.81 (−5.06)

Error Index = 100.19 −14.77ln (p3 energy – p4 energy) + 7.37 (category)
R^2 = .96 (−9.77) (4.33)

Even though the sample was small (n = 8) and the second regression used up 3 degrees of freedom, the t-value for the category coefficient indicates that there is a less than 1% chance that the observed group separation was due to chance alone.

One may construe from these results that: 1.) Semantic discrimination is a positive function of cortical energy. 2.) In the early stage of processing, which PET localizes near t5, the dyslexic subjects are undistinguished from the normal readers. 3.) The factor which distinguished these two groups is related to a later stage of semantic processing, involving inter-hemispheric interaction. Of course, dyslexia relates to a wide variety of deficiencies in reading-related cognitive processing, not just semantic processing, and experts in these fields would have much more to contribute. The main point here is simply to show how statistical hypothesis-testing can be aided by converting ERPs to show energy-density. (The referenced paper by Farmer and Montgomery presents more on the cortical path of reading-related activation, as it was tracked by energy-density ERPs.)

1.3 Brain Energy Allocation and Cognitive Fatigue

Here we present a more elaborate demonstration of the value of the energy-density ERPs. The previous examples emphasized their practical value in simply enhancing ERP peaks or in facilitating statistical analysis. This section is intended to show that the scalp spatial distribution of electrostatic energy is not just a convenient post-hoc data treatment. Rather, this transformation of the raw voltage ERPs should be viewed as a means of recovering information that is more fundamentally related to brain function.

We assume that the brain has (at any moment) only limited resources. These resources may take the form of functionally specialized neural assemblies and/or general metabolic energy. The various compensatory strategies by which individuals cope with a high cognitive workload under stress can be viewed as an example of strategic reallocation of these brain resources. The process of reallocating resources may be mediated by a hierarchy of feedback control loops, in which higher-level loops determine the set points for lower-level loops. But whatever the details, one can reasonably assume that the brain does continually adjust the allocation of its resources in order to use them as efficiently as possible. Major shifts in resource allocation may be required as priorities change, for example, due to unanticipated events in the ambient environment or changes in work priorities. Also, shifts in resource allocation may be required in order to offset the cumulative effect of postponing various system-maintenance or homeostasis tasks essential to personal comfort, safety, or long-term effective performance.

If one assumes that the brain strives (either automatically or under volitional control) to achieve maximum efficiency in allocation of limited processing resources, then it is appropriate to explore this from the perspective of optimal resource allocation. We assume that the healthy human brain is normally efficient in allocating limited brain resources. In general, economic theory emphasizes the comparison of the extra (or "marginal") benefits of allocating more resources to some particular activity, versus the extra (or "marginal") costs, which are assessed by considering the benefits that are sacrificed as the resources are taken from some alternative activity.

In the present case only two assumptions are required. The first is that the brain does attempt to optimally allocate limited resources among several concurrent activities. The manner in which the brain does this need not be specified. The second necessary assumption is that beneficial brain activity adds less and less to the individual's welfare as it is pursued more and more extensively. The incremental gains are smaller and smaller – until they are simply not worth the effort. This is the universal "law of diminishing marginal utility", which is the foundation of all economic theory. Mathematically, the first partial derivative of welfare or benefit with respect to the level of the activity is downward sloping. For present purposes one need not know the degree of slope, just that it is negative (Wilde & Beightler, 1967).

1.4 Graphical depiction of the theory

Figure 1 shows the marginal benefit function (MB). The horizontal axis shows the level of performance of some activity. (Let us call it activity A.) The vertical axis actually shows two things: it shows the perceived extra benefit associated with each value on the horizontal axis – but since it would be irrational to 'pay' more for anything than the extra benefit of having it, the vertical axis also shows the amount of brain resources that would be allocated to (expended upon) the given activity: the necessary 'payment' or cost. Thus, the downward slope of the marginal benefit function shows that it is 'worth' less and less to the individual (in terms of resource expenditure) to move to each higher level of performance.

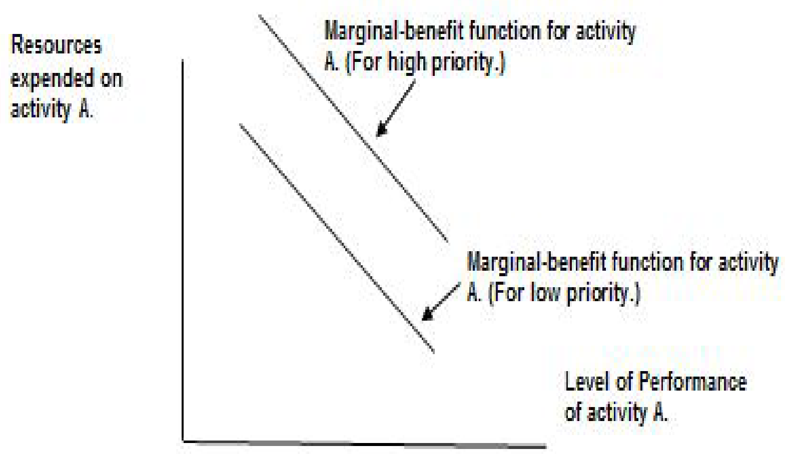

Figure 1. Marginal-benefit for two levels of activity.

Two possible locations of the marginal benefit curve are shown in Fig. 1, illustrating that if the given activity suddenly acquires a higher priority, the whole marginal benefit curve would shift upward. Such an upward shift in a marginal benefit curve is what we usually mean by increased 'motivation.' The activity has, for some reason, acquired greater significance to the individual, and any given level of performance is worth more resource expenditure than before.

Figure 2 shows a marginal cost function (MC) for "activity A," which is just the marginal benefit sacrificed by pursuing that activity at the expense of other brain activities. Its upward slope reflects the downward slope of their MB functions, since a higher level of performance of activity A would imply moving leftward along the horizontal axis of their marginal benefit functions. Figure 2 also shows the effect of those other activities becoming more significant to the individual: the marginal cost curve for activity A would shift upward, since every level of activity A would then entail a higher marginal cost that before. Marginal cost functions are often called marginal opportunity cost functions, since they reflect the sacrificed marginal benefit of other activities.

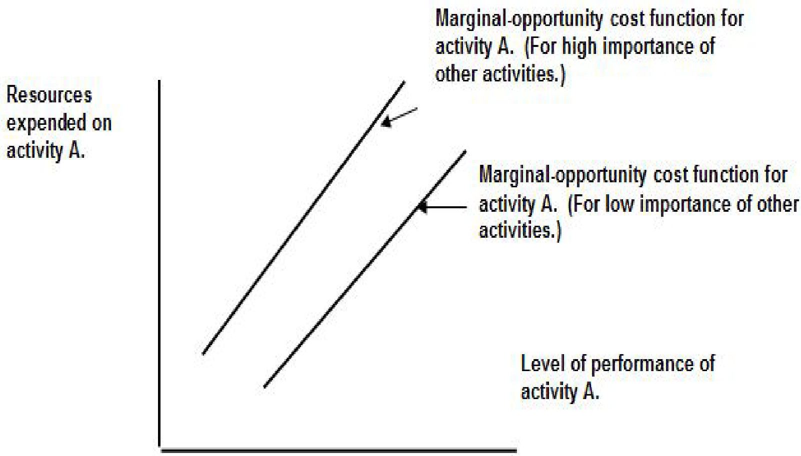

Figure 2. Marginal cost function (MC) for two levels of performance.

An upward shift in a marginal cost curve is the most useful way to abstractly characterize "cognitive fatigue". As a brain devotes more and more resources to a primary cognitive task, other brain activities must be denied those resources. Over time, or as the situation becomes more stressful, the opportunity cost of any particular level of performance of activity A will increase. Postponed system maintenance tasks will begin to become more urgent. Simple examples are the need to rest, or stretch, or go to the bathroom. A vast number of other activities, connected with perception, memory updating, maintenance of affective tone, and physiological homeostasis may also be partly postponed in order to concentrate attentional and other resources on the primary task. But the growing urgency of attending to any or all of these postponed activities will eventually shift the marginal opportunity cost function for the primary task – activity A – upward. Any given level of performance of activity A will cost more than before.

Clearly, a balance is achieved when each activity is pursued to the level that equates its marginal benefit with its marginal cost. This occurs at the intersection of the marginal benefit and marginal cost curves, as shown in Figure 3, below.

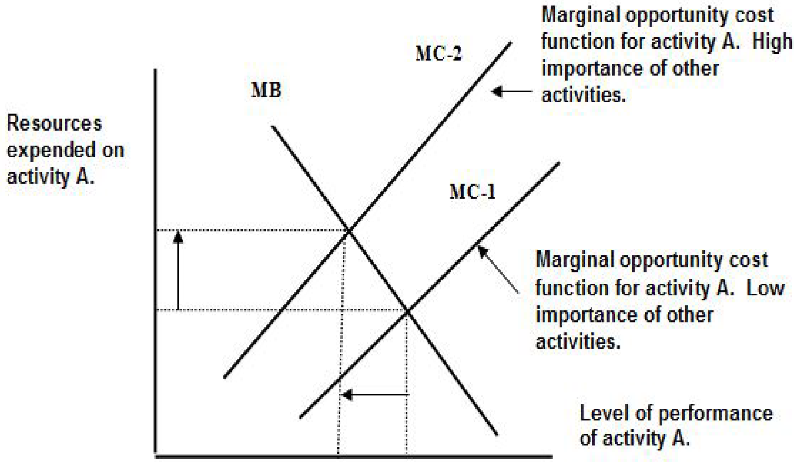

Figure 3. Intersection of marginal cost and marginal benefit functions

A shift (upward or downward) in either function, MB or MC, will of course require a rebalancing. A shift of either curve in Figure 3 will move the intersection along the curve that has not shifted. Although this is geometrically obvious, it is the most important feature of the analysis, for it allows us to relate shifts in the curves to, simultaneously, changes in the level of resource allocation to the task and changes in performance.

As an example, Figure 3 illustrates the effect of cognitive fatigue. Fatigue shifts the MC curve upward from MC-1 to MC-2, as the brain's resources must be reallocated to keep marginal cost equal to marginal benefit in all activities. For activity A, this reallocation is shown by the movement of the intersection upward to the left along the MB curve. At first, this may seem counter intuitive. The growing urgency of activity B, C, etc., leads, surprisingly, to an increase in resources expended on A. This result is easy to understand, however, if the movement is viewed in two steps: First, fatigue (urgency of other activities) requires activity A to be reduced. But that, in turn, increases the marginal benefit of activity A, making it worth the expenditure of added resources.

It is easy to see that this pattern of reallocation of resources may lead to catastrophe. As an example (one that is more physical than cognitive), picture a small boy in a playground, hanging by his hands from the crossbar of a jungle gym. As the child reaches the limit of his endurance, he will likely start to squirm, improve his grip, even grimace, as if that would help. What we see is an increase in energy devoted to the task. The metabolic cost of performing the activity has increased because tired muscles can no longer be starved of oxygen. Yet the prospect of falling increases the marginal value of hanging on, and hence justifies an even greater energy commitment. This is a self-reinforcing (positive feedback) loop, and it ultimately 'explodes'; the child gives up and drops to the ground.

Similar marginal cost-benefit analysis helps resolve a familiar ambiguity: Consider the problem that confronts an athletic coach in deciding if a player's poor performance is due to lack of motivation, or due to fatigue. Figure 3 shows that there is only one way in which performance and resource commitment to a task can both fall. That is, there is only one way in which the intersection of the marginal benefit and marginal cost curves can move inward toward the origin. This can only happen if the marginal benefit curve shifts downward, implying that the task is being regarded as less important. This is a decrease in motivation, not an increase in fatigue. This is a state that is perhaps best labeled as "boredom", not cognitive fatigue.

As implied above, empirical interpretation of behavior with respect to such 'constructs' as fatigue, learning, motivation, and boredom logically requires two forms of data: performance data, which is usually easy to collect, is insufficient by itself; it must be accompanied by resource-expenditure data – which is ultimately energy-expenditure data, and which can be provided by energy-density ERPs.

Although most of the energy used in brain activity is dissipated in the form of heat, carried away in the brain blood flow (Vasilescu & Margineanu, 1982), some part is dissipated as the energy that maintains the scalp electrical fields that are sensed by EEG. Therefore, it is assumed that the average energy density of an ERP is proportional to the extent of brain activation committed to the gating task. On this basis, marginal cost-marginal benefit analysis provides a needed framework for interpreting the data. It reveals that there are only four possible combinations of changes in resource commitment to a task and concurrent changes in task performance, and that these cannot overlap. Consideration of the following four contingencies is sufficient to determine which curve (MB or MC) is shifting, and in which direction (up or down) – and these serve to operationally define four corresponding states:

a) If both resource commitment and performance of an activity are increasing, then the MB curve is shifting upward (increased motivation).

b) If both resource commitment and performance of an activity are decreasing, the MB curve is shifting downward (decreased motivation).

c) If performance of an activity increases while less resources are committed to it, then the MC curve is shifting downward (learning).

d) If performance of an activity decreases while more resources are committed to it, then the MC curve is shifting upward (uncompensated fatigue).

1.5 Relation to energy density ERPs

As an example, this section shows how the economics concepts introduced above were applied in an investigation of mental exhaustion sponsored by NASA – one that exploited the energy density ERP transformation. NASA's concern was that operators performing mission-critical tasks might 'heroically' continue to perform a complex mental task beyond the point where it is safe to rely upon them. According to the MB-MC analysis, mental exhaustion occurs when compensatory strategies can no longer prevent an upward shift in the marginal cost function for the primary task, as other brain activities become increasingly urgent. The onset of this (self-reinforcing) stage would be signaled by a reduction in primary task performance despite a rapid increase in resources committed to it.

Eleven subjects, college-educated, ages 20 through 35, all of them colleagues of the authors at NASA's Ames Research Laboratory, volunteered to compete in performing a computer-generated mental arithmetic task, repeatedly for as long as possible, while instrumented for EEG. Though unpaid and unrewarded, each volunteer was eager to "win" by excelling at both accuracy and endurance. Their scores were posted as they finished! (This competition is an important experimental condition that may be absent in studies that report "mental fatigue" as merely progressive inattention.)

The task consisted of calculating the sum of four one-digit numbers presented in the center of a computer screen. For example, 6 – 2 + 9 – 3. The numbers were random generated but were filtered to prevent obvious sums (such as 1– 1 – 2 + 2). An "answer" was also presented, which was, at random, often incorrect (75%), but close. The subject was required to determine if the sum was higher than, equal to, or lower than the proposed "answer," and indicate the decision by pressing one of three keys on a special hand-held keypad. Each response triggered presentation of a new problem after a five-second delay. Response times and number of errors were recorded automatically but were not revealed to the subject until the end of the session.

A 21-channel EEG recording was made while the subject performed the task, using a Lexicor NRS-24 system (Boulder, CO) with 3200x analog gain, 0.5 Hz high-pass filter, 60 Hz notch filter, and maximum scalp impedance of 5000 ohms. The analog signal was digitized at 256 samples per second. Scalp electrodes were applied according to the International Standard 10-20 pattern (Jasper, 1958; Homan, 1988), using the Physometric, Inc. eNET electrode cap (Billercia, MA) and EEG-Sol electrode paste (part number 16-004, Meditrace Products Division of Graphic Controls, Inc., Buffalo, NY).

Each response by the subject generated a marker in the continuous EEG recording that was later used to identify 600 millisecond stimulus-gated epochs. Those generated during each 15-minute period deemed to be artifact free by visual inspection were then averaged to produce ERPs. Depending upon the subject's reaction-time and the number of epochs that were rejected because they contained artifacts, the number of epochs generated during a 15-minute period varied but was never less than 30. Each 21-channel ERP was then mathematically converted to a measure of average scalp energy density (averaged over the 600 msec post-stimulus period and over the 21 electrode sites). This procedure is explained in the appendix to this book.

Some subjects endured longer than others. Two lasted for 150 minutes (2.5 hours: 10 ERPs). In each case it was the subject who decided to quit. All indicated they were too exhausted to continue. At this point most were visibly exhausted (sweaty, agitated, and anxious to get up and walk around); none were bored or drowsy.

Figures 4 and 5 illustrate how the MB-MC analysis was then used to track individual subjects' trajectories through the four possible states: Learning, Motivation, Fatigue, and Boredom. These figures pertain to one typical subject. Figure 4 shows the subject's ERP energy density levels compared to a "performance index". The performance index was simply the unweighted sum of the subject's average reaction time and number of errors during the period of each ERP. Note that the higher the value of this index, the worse the subject's performance; this performance deterioration would have been a leftward movement along the horizontal axis of figures like Figure 3 above.

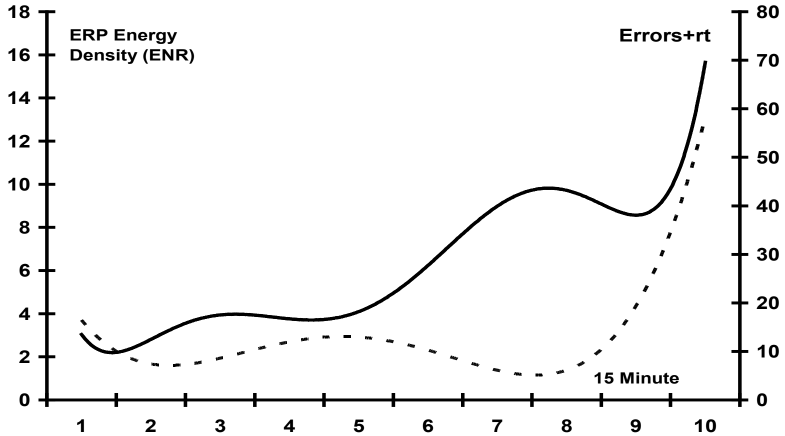

Figure 4. ERP energy density (solid line, left axis) and Error Index.
(dashed line, right axis).

The curves shown in Figure 4 for one subject are polynomial regression lines fit to the series of data points – each of which pertained to a single multi-electrode energy density integral ERP (R-sq. = 0.921). This measure was obtained as the spatial integral of a three-dimensional regression surface fitted to a grid of the individual electrode energy density ERP values. The successive data points were not spaced evenly, since the spacing would be determined by reaction time. For this purpose, a measure of 'whole head' energy density was used, since general brain activity related to the task was of interest, not the specific cortical location of the activity.

Figure 5 shows a "phase trajectory" derived from Figure 4. Each data point shows the concurrent values of the rate of change of the subject's ERP energy density and the rate of change of the subject's performance index – i.e., the first derivatives of the two curves in Figure 4 at each successive 1.5-minute intervals. A series of closely adjacent points indicates a longer period in that particular state compared to a series of widely separated points. Note that figures 4 and 5 are based on an index of "bad" performance (rt + errors), which is a leftward movement in figures like Figure 3.

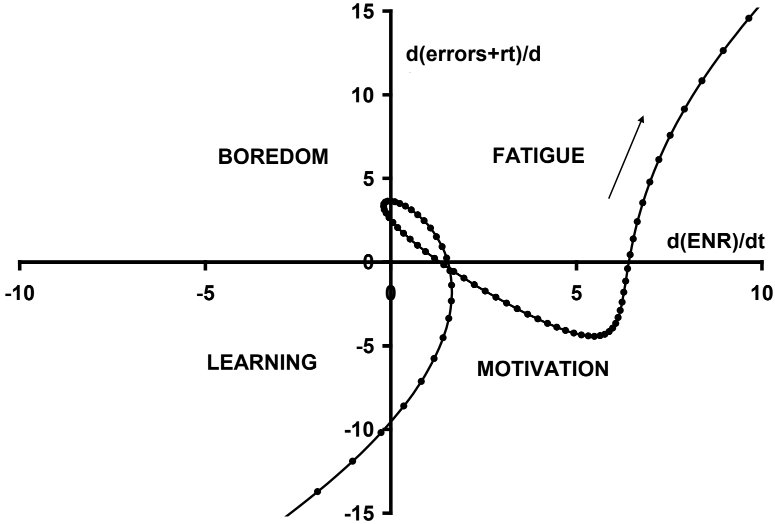

Figure 5. Phase diagram derived from Figure 4. Data points shown every 1.5 minutes.

The following table summarizes the logic behind the trajectory. It is the same as the summary at the end of Part 1, except that it makes clear that figures 4 and 5 are based on an index of "bad" performance (rt + errors), which is a leftward movement in figures like Figure 3.

Table 1, Logic behind cost and benefit function to determine performance.

energy	rt + errors	performance	Curve Shift	Interpretation
up	down	up	MB up	motivation
up	Up	down	MC up	fatigue
down	Up	down	MB down	boredom
down	down	up	MC down	learning

The subject whose state trajectory is shown in Fig. 5 was typical. Similar to most of the 11 subjects, he started by mainly learning the task, building skill through practice. That is, his performance improved while energy committed to the task also fell. Soon he further improved his performance by committing added energy to the task, i.e., the improvement in performance through practice was followed by a further improvement in performance through higher motivation. But then he began to tire: the marginal opportunity cost of performing the task began to rise, as shown by a concurrent increase in (bad) performance (errors + rt) and a decrease in energy. However, as with most subjects, this early period of fatigue was soon followed by a revival of performance through an increased energy commitment (higher motivation) – until finally he was overcome by uncompensated cognitive fatigue. Not all subjects followed this general trajectory, of course. Two started in the "Motivated" quadrant, moved almost immediately into the "Fatigue" quadrant, and quit.

Although the statistical analysis of group averages revealed a statistically significant pattern (rising energy accompanied by falling performance), what may be more important are the individuals' detailed phase trajectories. Differences and similarities among subjects may be just as important as the general trend toward mental exhaustion (which, after all, is not a surprising trend).

The way in which energy-density analysis was applied here could be combined with the scheduled introduction of special experimental treatments. Stress factors such as increases in ambient noise levels or temperature could be introduced at certain points during the experiment. Motivating factors could also be manipulated in a two-group experiment. In human factors engineering experiments, such analysis could be employed to compare instrument layouts and data displays, mission profile designs, training procedures, and crew selection criteria.

1.4.1 Constructing Energy Density ERPs

The task of constructing energy-density ERPs will doubtlessly be consigned to a computer program. The objective here is to explain the underlying logic. This will be done in three sections: an overview, then a more detailed discussion, followed by a set of pictures corresponding to the steps of the procedure.

First, an experimental stimulus (e.g., a mental arithmetic problem presented on a computer screen) triggers cortical activities that produce momentary electrical dipoles. We may speculate that these dipoles result from graded depolarization of apical dendrites of cortical pyramidal cells – which creates a difference in electrical charge density of the extracellular fluids between the cell soma and their apical dendritic fields. This, in turn, creates a minute electrical field. If many pyramidal cells are aligned radially to the scalp and experience similar dendritic depolarization in synchrony, the combined electrical field may be strong enough to rearrange the scalp distribution of electrostatic charge.

Work is required to rearrange a charge distribution. It takes energy. Therefore, localized changes in the energy of the scalp electrical field would offer an indirect, rough measurement of cortical activation. It might be thought that this is exactly what is measured by EEG recording. But there is a problem of 'units'. What is recorded is voltage, which is energy per unit of charge. The voltage data are proportional to the energy changes only if the charge concentration is assumed to remain constant. But this, of course, is unreasonable to expect, since the charge distribution is being changed by the electrical field being measured. Thus, the quantity that would be most useful, energy density, is measured only indirectly in EEG, and in a manner that confounds it with the changes in surface charge density that the energy produces.

Fortunately, all this can be untangled. By application of a standard physics result – Poisson's equation – it is possible to calculate the scalp distribution of charge, at any instant, from changes in the spatial distribution of voltage. The mathematics will be shown later, but it can be stated here that according to Poisson's equation, the charge distribution of an electrostatic field is proportional at each location to the spatial rate of change (the second partial derivative) of the voltage distribution. This mathematical procedure for computing charge density of an electrostatic field has been known for a long time; it was described over a century ago by Lord Kelvin (William Thompson, 1848). The procedure exploits the fact the charge distribution can be inferred from the geometry of the voltage levels within the field (its voltage surface) and that this, in turn, can be estimated from a grid of simultaneous voltage measurements.