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Basic Principles of Quantitative EEG

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Abstract

Principles of quantitative electroencephalography (EEG) relevant to neurotherapy are reviewed. A brief history of EEG, the general properties of human EEG, and the issues and obstacles associated with quantitative methods are discussed. Fourier analysis is also described.

Keywords: EEG, principles, overview, fourier analysis, neurofeedback

Basic Principles of Quantitative EEG

The human electroencephalogram (EEG) may be the most complex set of signals in nature and is certainly the most complicated phenomenon routinely subjected to scientific experimentation. That electrical potentials are detectable at the scalp at all is the result of some fortuitous neural architecture. Human neocortex consists of tightly packed arrays of columns, six neurons deep, aligned perpendicular to the pia matter directly below the skull (Mountcastle, 1978). Any other orientation and the neuroelectrical activity would cancel each other out entirely, but because of this organization electrical potentials propagate to the scalp where their differences can be measured. Scalp potentials are exceedingly faint, mere millionths of a volt, a thousand times weaker than the heart's electrical rhythms, and even the blink of an eye can swamp the signal temporarily.

Each scalp electrode detects the electrocellular activity of about 10 billion cortical neurons. This information is smeared and distorted by the insulating layers between cortex and sensor (skin, skull, dura, blood, spinal fluid, pia) and if this was not enough of an obstacle to interpretation, negative and positive potentials cancel each other out so that we detect only the difference in valence, what's left over after cancellation, which accounts for only a fraction of the electrocellular activity beneath the sensor. And it is the difference in electrical potential between two sensors which registers. Finally, scalp recordings produce two-dimensional representations of brain activity (topography), but the brain is a volume and an irregular one at that (Meijs et al, 1987). Mathematical techniques can generate three-dimensional pictures of internal structures (tomography) by identifying likely sources of surface potentials, but it's difficult and dubious to estimate volume dynamics from surface activity (Pascual-Marqui et al, 1994). And because only columnar structures contribute to surface recordings most subcortical structures appear silent. Altogether, it makes interpreting EEG data a bit like trying to discern the comings and goings of marine life from the eddies and swells on the surface of a lake. But it's not impossible. In fact EEG has been reliably interpreted for many conditions and contexts including epilepsy, sleep, and psychological research for 70 years (e.g., Gibbs et al., 1937; Loomis et al., 1935). In its favor is its remarkably high temporal resolution (millisecond range), comparable to cortical and thalamic cell firing rates (Steriade et al, 1978). Whereas other functional neuroimaging techniques such as positron emission tomography and functional magnetic resonance imaging are based on metabolic transactions (e.g., blood flow, oxygenation), EEG and MEG (magnetoencephalography) allow us to eavesdrop on neural communication directly.

The field of human electroencephalography, a basic tool of clinical neurology for much of the last century, originated in the efforts of Hans Berger, a German psychiatrist working alone. Between 1929 and 1938 Berger published 14 reports on human EEG and its relation to cognition and neurological disturbances (Millett, 2001). Much of what we know about human EEG was first documented by him, especially in the middle frequencies. For instance, Berger described the phenomenon of alpha blocking, an abrupt suspension of alpha waveforms in ongoing EEG when an individual opens her eyes (Berger, 1929). Quantitative EEG begins and ends with alpha blocking, at least metaphorically. If we cannot explain this very reliable and unmistakeable aspect of human EEG and use it to calibrate cognition and attentional states, we cannot do much more with the other less predictable features of this phenomenon. Alpha blocking is independent of respiratory, vascular, or motoric responses and occurs when individuals pay attention to objects in the environment, even when the eyes are closed (Etevenon, 1986; Adrian & Matthews, 1934). Opening one's eyes in a darkened room will not affect alpha activity (Bohdanecky et al., 1984) whereas stimulus intensity, complexity, familiarity, and meaningfulness will, presumably due to changes in attention (Gale & Edwards, 1983; Baker & Franken, 1967; Boiten et al., 1992). When alpha blocking was subjected to quantitative methods, it showed itself to be one of degree, not all-or-nothing. The term "alpha blocking" was replaced by "desynchronization" to better reflect this gradation. Alpha rhythms may become partially desynchronized (instead of wholly desynchronized or blocked) when sensory information is anticipated, attended to, or otherwise processed (Pfurtscheller, 1986). Alpha desynchronization need not involve the entire cortex all at once; uncommitted cortical areas can remain in an "idling" synchronized state while other areas are desynchronized (Pfurtscheller, 1992). Regional patterns of simultaneous desynchronization and synchronization reflect different cognitive and behavioral states such as sensorimotor performance (Sterman et al., 1996).

EEG may be analyzed qualitatively, as Berger did, or quantitatively, as those who followed. In qualitative analysis, common to neurology and sleep studies, the features of an EEG chart are characterized in a general way, in a more categorical fashion. Some evidence of abnormality or physiological state exists, or it doesn't, or is or isn't likely. In quantitative analysis, common to psychological research and neurotherapy, these features are subjected to mathematical and statistical analyses and the extent of each feature being examined is calculated. Each approach classifies the EEG record in terms of "frequency or period, amplitude, phase relations, morphology (waveform), topology, abundance, reactivity and variability of these parameters… (e.g., continuous, random, paroxysmal, etc.) “ (Brazier et al, 1961). Little has changed conceptually in 40 years except our experience and the speed and computational power of our tools.

Quantitative EEG commenced 70 years ago when Dietsch (1932) applied Fourier analysis to seven records of EEG. Fourier analysis remains one of the most popular analysis technique in this field, though hardly alone. Given the profound difficulties associated with EEG signal acquisition and analysis, EEG researchers have always been early adopters of technology (Berger, 1929; Brazier et al., 1961), but it was the advent of powerful personal computers and the invention of the fast fourier transform (Cooley & Tukey, 1965) which launched this field. Ironically, fast fourier transforms (FFTs) are avoided in operant conditioning (neurofeedback) because they require intervals, which introduces an unacceptable time lag for training. Real-time or near instantaneous spectral techniques such as digital filters are employed instead. Fourier analysis is a very accurate spectral analysis technique so it is often used offline, for assessment, when time is not an issue. As the discipline matures, quantitative EEG will likely emerge as a mainstay of neurology, sleep medicine, as well as psychiatry and psychology, but at this point in time it remains controversial to some (Nuwer, 1997; but see Thatcher et al, 1999). Such reservation to quantitative methods is rare in science and medicine, and probably reflects the complexity of the phenomena under investigation as well as the ambitions of parties on both sides of the issue.

Quantitative EEG is regarded as noisy, unreliable, and imprecise in the minds of many psychologists, neuroscientists, and medical professionals (Nuwer, 1988; Begley, 1992), but this reputation is undeserved and being shed. It came about partly because complexity fosters freedom, at least until things are better understood. A researcher interested in quantitative EEG analysis confronts a gauntlet of largely arbitrary methodological choices about reference electrodes, recording electrodes, and artifact management techniques, as well as epoch parameters, windowing functions, bandwidths, and other spectral parameters when spectral analysis is performed, and every choice has been thoroughly criticized in one way or another (see Kaiser, 2001a). Different methodologies produce incompatible and conflicting results, which fosters confusion, but there is no immediate solution to this problem due to the range of variables addressed and our current lack of understanding (Remond & Lairy, 1972). Given the variety of methodologies, combined with the computational intricacies of EEG, it's understandable why many psychologists and physicians have ignored the promise and potential of this evaluative and diagnostic tool. What is known is that EEG is a chaotic signal consisting of non-periodic (spikes, "random noise"), non-sinusoidal and periodic (mu), or sinusoidal and periodic (alpha, delta) signals (Nunez, 1981). Neurotherapists tend to focus on sinusoidal signals and divide the frequency spectrum into four or five relevant frequency bands (e.g., theta at 4-7 or 4-8 Hz, SMR or sensorimotor rhythm at 12-15 Hz) to capture these periodic features. As wide frequency bands encompass a variety of physiological processes (Lorig & Schwartz, 1989), some clinicians opt for narrower frequency bands including single-Hertz bands (Kaiser, 2001b).

In any investigation we should ask ourselves, what am we trying to do? (Sterman, 2003). With EEG spectral analysis we convert voltage amplitudes into frequencies. Why? Because we believe that mental processes are better reflected in the periodicities we identify than the raw values we detect. We should be able to observe these periodicities in the visual record, and note their actions and possible functions, else we may just be fooling ourselves.The further removed our analysis takes us from the raw signal, the more likely error has crept in. Non-linear and highly derived indexes of EEG activity run the risk of being empirically meaningless, uninterpretable, or fraught with unproven or untestable assumptions. We already know that on one level neural coding is linearly related to perception (e.g., Johnson, Hsiao, & Blake, 1996). Such psychophysical efforts are a far cry from a brain activity index of thought processes but it is a starting point and we dare not tread too far away from the actual recording, whatever approach we take.

Let us look at an example of human EEG:

INSERT FIGURE 1 here:

Rhythmicities in the signal are generally thought to be caused by neuronal synchronization from extensive inhibitory processes within the thalamocortical system (Andersen & Andersson, 1968; Steriade et al, 1990), or from negative feedback among excitatory and inhibitory neurons (Freeman, 1975), or both, depending upon the frequency of interest. By its definition, rhythmic signals are periodic and relatively easy to analyze given the regularity of features. However clinicians are often interested in tasks that involve challenges, that a client performs poorly on, such as reading, math, or visual processing. But as shown in Figure 1, any mental challenge, even opening the eyes, elicits faster frequencies and “random” noise. Fortunately even “flat” signals contain rhythmic components whose incidence and amplitudes can be quantified. Frequency analysis provides a good first pass at the data, reducing a large amount of information into a handful of coefficients. While information is necessarily lost during such data reduction, what's lost may not be pertinent to cognition -- an empirical question we have yet to answer definitively.

Frequency or spectral analysis involves selection of elementary shapes or frequencies (waveforms) which are added together like weights on a scale until their total matches the pattern under investigated, as shown in Figure 2. The height or intensity of a waveform, its amplitude, is computed in microvolts for each frequency. Different waveforms are captured by wide or narrow frequency bands or bands tailored to specific properties under investigation (e.g., Kaiser, 2001b; see Figure 3). Impurity is dealt with by decomposing and analyzing each frequency band separately or by comparing each frequency band's relative contribution to the entire signal. Stability of a signal across time (stationarity) is a prerequisite for accurate Fourier analysis, and a signal is often segmented into short time intervals of like signals to increase its stability. When two or more signals are compared, the stationarity of phase and amplitude difference (coherence and comodulation, respectively, Sterman & Kaiser, 2001), as well as spatial topography, come into play.

INSERT FIGURE 2 about here

INSERT FIGURE 3 about here

In QEEG assessment we assume that each behavioral and mental state such as rest, mathematical processing, or face recognition, is reasonably homogeneous in nature, that the various perceptual and cognitive operations underlying each state of action or mental process occur in like qualities and quantities whenever the state occurs. This assumption called the macrostate assumption and it is the basis for cognitive neuroscience. In QEEG and other functional neuroimaging techniques we also assume that these perceptual and cognitive operations exhibit a distinct and reliable profile of brain activity (Gevins, 1984). So far, the assumption has served us adequately. For instance, chronic alcoholics typically exhibit less alpha activity than most people. So one way to treat this disorder might be to simply increase the amount of this activity, at least until it reaches the normal range. The intriguing neurotherapeutic technique known as alpha-theta training does just that, and with often unpredictably positive effects (Jones & Holmes, 1976). Most if not all psychiatric and neurological disorders exhibit abnormal patterns of spectral activity (e.g., Hughes & John, 1999). This is the crux of neurotherapy. Using the well known rules of operant conditioning, neurotherapists train individuals to suppress abnormal patterns of neuroelectrical communication and to elicit more normal ones. In other words, clients learn their way to mental health. Learning is what differentiates psychological therapies (present) from medical ones (absent). Neurotherapy’s goal is to improve self-regulation of cerebral mechanisms. Bad behaviors are eliminated and good behaviors fostered, with the wrinkle being that these behaviors are imperceptible to the individual without the tools these therapists possess, as these behaviors are happening inside the skull and not outside of it. And quantitative EEG assessment identifies just exactly which behaviors these are.

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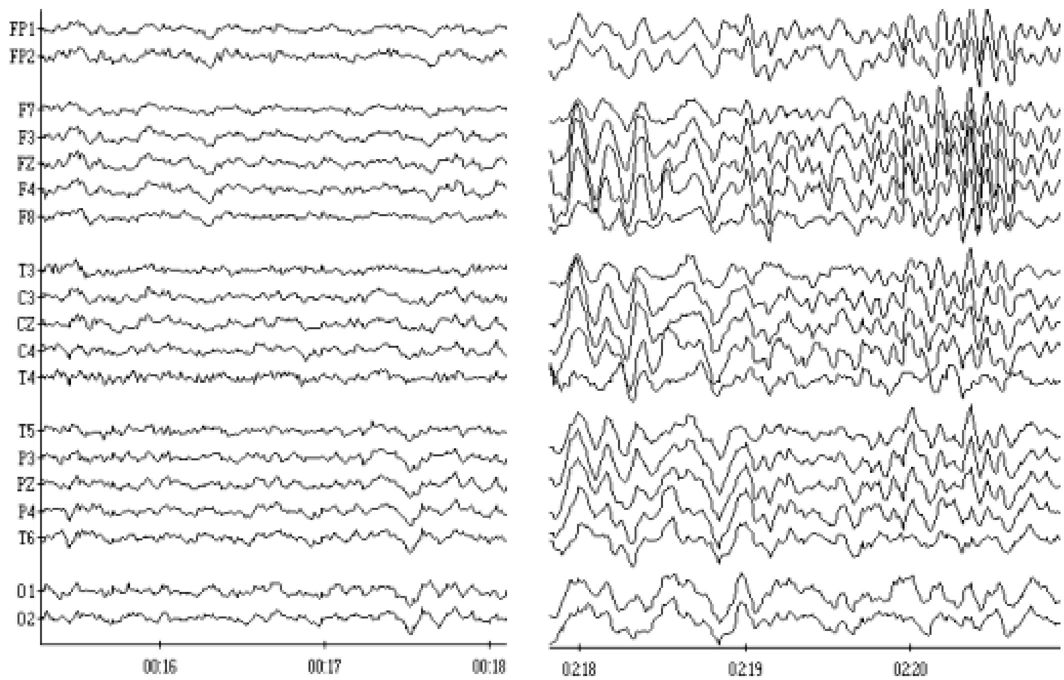
Figure Captions

Figure 1. Six seconds of EEG data recorded at 19 electrode sites from the same child recorded minutes apart. One might mistakenly characterize the intial 3-s segment as inactive and the latter as alert and active. The fast anterior sinusoidal rhythm in the latter segment is a sleep spindle. The child was alert with eyes open during the first part of the record but in stage two sleep a few minutes later.

Figure 2. Decomposing two seconds of an impure (multiple frequency) waveform that consists of the same three frequencies. The only difference between segments is the magnitude of the 2 Hz and 11 Hz contributions.

Figure 3. Illustration of selected spectral parameters described by Brazier et al. (1961).


FP1
FP2
F7
F3
FZ
F4
F8
T3
C3
CZ
C4
T4
T5
P3
PZ
P4
T6
O1
O2
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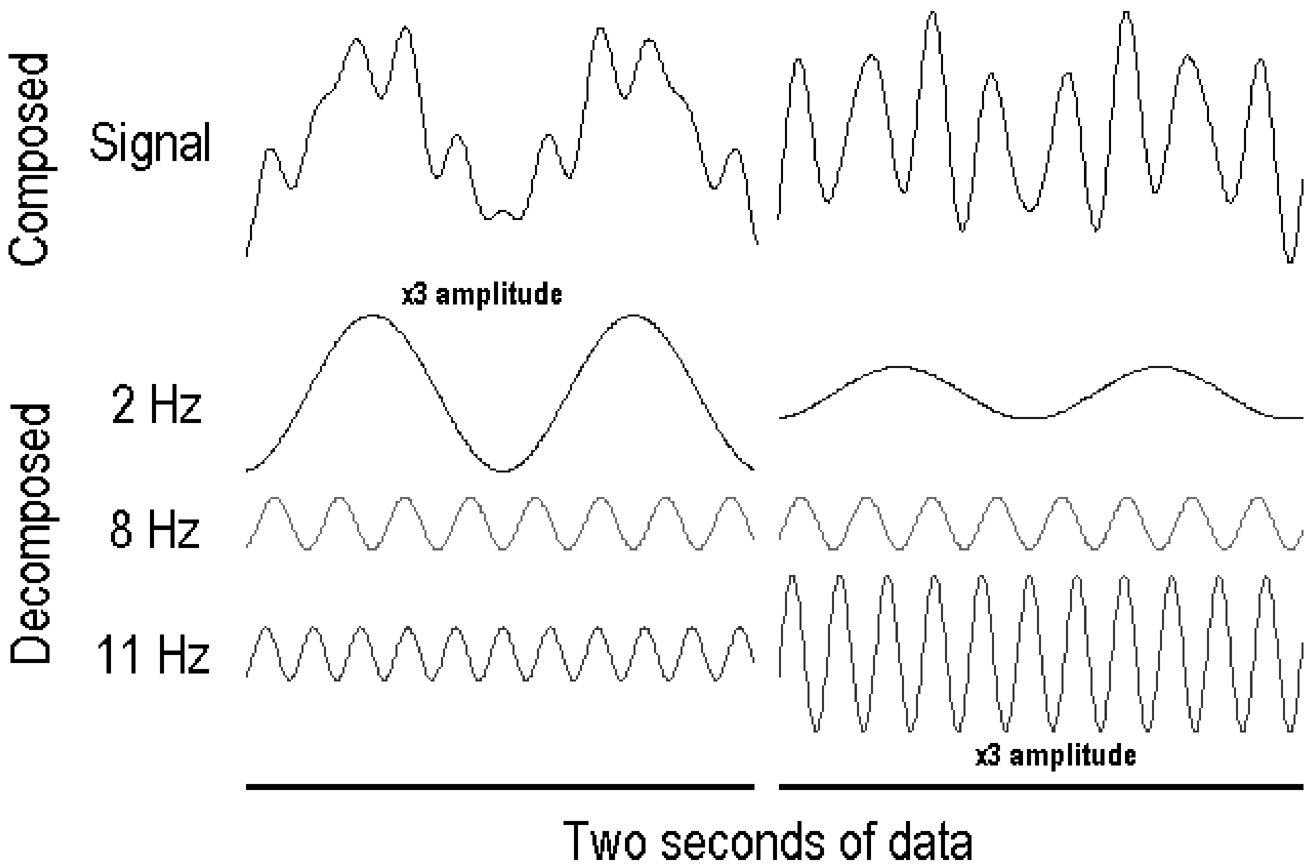
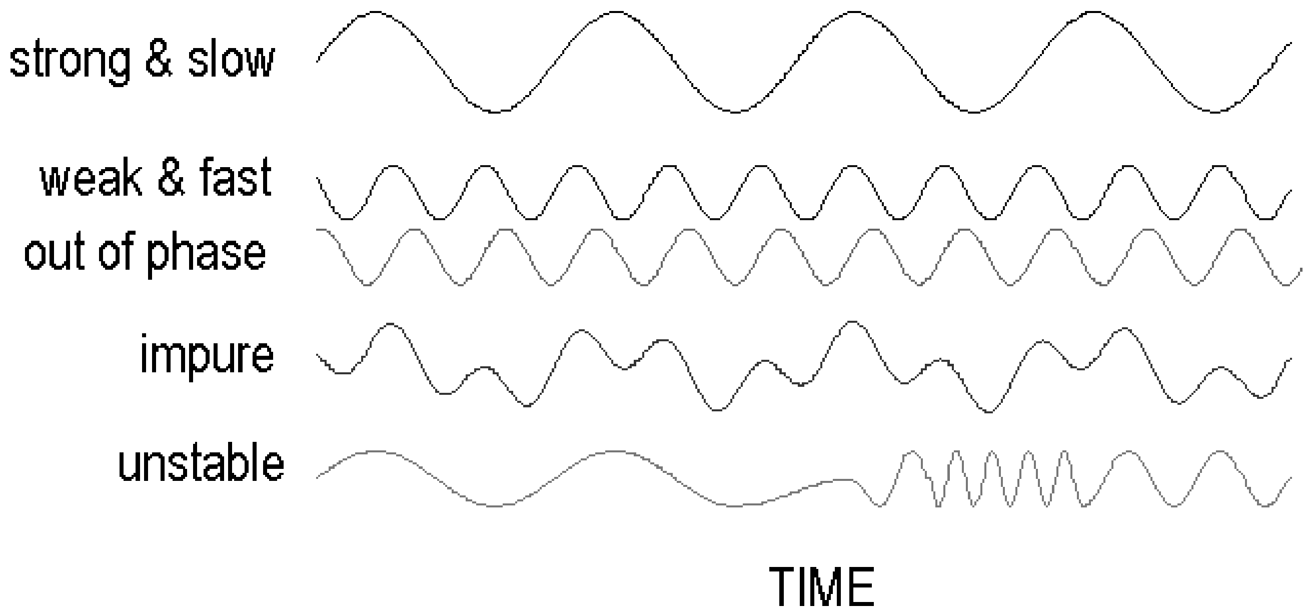
00:17
00:18
02:18
02:19
02:20


Composed
Signal
x3 amplitude
Decomposed
2 Hz
8 Hz
11 Hz
x3 amplitude
Two seconds of data


strong & slow
weak & fast
out of phase
impure
unstable
TIME