

Specifying and Developing References for Live Z-Score Neurofeedback

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Introduction

Live Z-Score neurofeedback training (LZT) has been in practice for close to 10 years, and has evolved considerably in that time (Collura et al, 2007; Collura, 2013). There is now a proliferation of methods that incorporate live Z-Scores for neurofeedback as well as for other purposes. One of the cornerstones of LZT is that there must be some reference as part of the system, which provides the basis for computing the live z-scores that are incorporated into the feedback process. As the field evolves, it is appropriate to ask what constitutes a useful reference for Live Z-Scores, and how a reference may be chosen or developed, with various priorities and concerns in mind. It will be shown here that there is a wide range of possible choices for LZT references, and that the field has only begun to explore how to develop and use references.

This article will discuss the choice of references for LZT training, as well as considerations with regard to the development of such references. For the purposes of qEEG assessment, it is generally accepted that references should be based upon a representative population of individuals, so that results put the client in the context of a particular group. While a normative sample is clearly important for qEEG assessment, when a reference database is to be used for LZT training, it is not clear that one can assume that a population of "normal" individuals constitutes an ideal reference. When working with individuals, it is more likely that the reference needs to reflect the individual profile of the cli-

ent, as well as the particular goals of the intervention.

All LZT training takes advantage of the same fundamental equation:

$$z = \frac{x - \mu}{\sigma}$$

Or in more recognizable terms,

$$zscore = \frac{measurement - mean}{stdev}$$

Where z is the resulting z-score, x or "measurement" is the current sample value, "mu" or "mean" is the reference mean value ("target") and "sigma" or "stdev" is the standard deviation value

There is more than one way to arrive at values that will be valid, useful, and effective.

in the reference table. So the z-score is no more complex than a number that tells you how far a measurement is from some target, in terms of the normal distribution. Although it is often assumed that the mean and standard deviation should represent a "normal" or "typical" population, this is not necessary in the definition of a z-score. These reference values might represent some "normal," "typical," or "desirable" values, but they might just as well represent some ideal, an individual, or someone in any particular state of self-regulation or dysregulation. The key point is that a reference for LZT neurofeedback consists ultimately of a set of means and standard deviations, and there is more than one way to arrive at

values that will be valid, useful, and effective.

LZT training is accomplished in real time by computing instantaneous metrics, and then comparing them with some reference values and standard deviations. The simple choice of these two numbers completely determines the resulting z-scores. Generally, it is assumed that the reference mean and standard deviation are derived from some appro-

appropriate statistically representative sample. This is true, and is a requisite condition for the computation to have validity with respect to the intended sample. However, what constitutes a representative sample is open to interpretation. A statistical average and standard deviation from n individuals from a well-controlled sample is one way to derive a reference, and has until recently been the primary reference used not only for LZT but also for qEEG in general. However, as we shall see, a set of values from a chosen sample, or even from a single individual is also a valid source of reference data, and other methods, such as synthesizing values, or constructing references for specific purposes, is also possible.



Incorporating LZT References in biofeedback

The following block diagram shows the software design of a general-purpose Live Z-Score training system (figure 1). It provides several options for the selection (or development) of LZT references, as well as flexible feedback capability providing visual, auditory, vibrotactile, or electromagnetic feedback. Input data can include, in addition to z-scored values, convention qEEG metrics, Infra-Slow Fluctuations (ISF), and peripheral biofeedback modalities. One emphasis is to provide various options that can be combined or customized, rather than dictating a single, monolithic approach to LZT neurofeedback.

being monitored in accordance with the Lifespan protocol. Subjects were not performing any particular task, and they were not selected with any goal in mind other than representing a population of symptom-free individuals who were not diagnosed with any mental or emotional disorders.

More recently, the BrainDX database reference has been added (John et al.) as an option for mini-assessments, and for neurofeedback training. This latter reference consists of static data acquired, also at rest, and reflecting the population data when averaged over a minimum 2-minute epoch. As will be described below, the target values (means) for both references are theo-

particularly individuals who were not under any task, was not an appropriate reference. It was argued that the reference EEG might not well represent the EEG that would be desirable for any particular client at any particular time. An additional concern was that individuals may or may not have EEG characteristics that were not typical, but that were appropriate for them. The idea of individualized references, as well as “optimal functioning” or “peak performance” references was elevated early on, and remained in the background as a concern as LZT continued to develop and proliferate.

What is “normal?”

Because the typical “normal” reference is based upon a population statistic, certain observations may be made at the outset. The first is that this reference EEG does not in fact represent any particular functioning brain. In fact, there may be no brain that meets these conditions at all. As an example, if we were to compute the typical “normal” man in terms of height, weight, body proportions and muscle and fat proportions, hair color, blood chemistry, and so on, we would have a portrait of an average man.

However, not only does no such individual necessarily (or likely) exist, but also there is no a priori reason to expect that someone would benefit by becoming more “typical.” Surely, normalizing critical levels such as excess blood sugar, hypertension, or obesity, would be expected to be of general benefit. However, if an individual has a personal profile that puts their optimal functioning at some other level, then the normative comparison cannot take this into account. To put this in perspective, one might ask, how often a practitioner tells a client “your problem is that you are not more average.”

In relation to EEG z-scores, or for

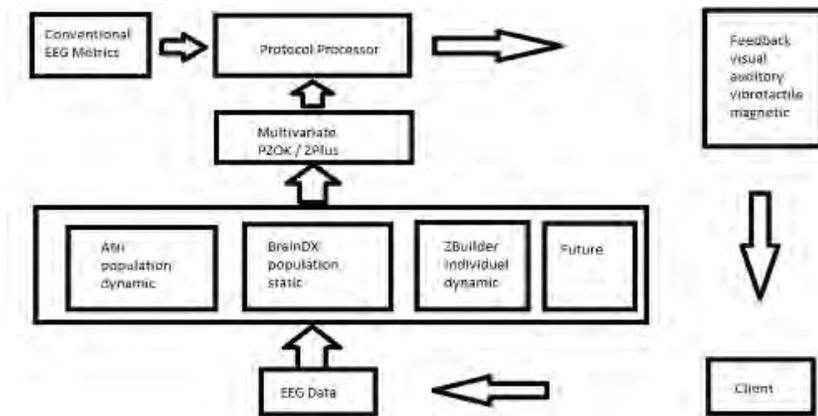


Figure 1: Software design of a general-purpose Live Z-Score training system.

When the LZT method emerged, the reference chosen was the Lifespan database, which is comprised of 725 individuals meeting specific acceptance and rejection criteria, and derived according to well documented principles (Thatcher). It includes eyes-open (EO) and eyes-closed (EC) conditions, which must be selected by the user, along with specifying age, when initializing the software. Therefore, each client receives feedback that indicates how well that client’s EEG matches, in certain ways, the EEG of a population of selected individuals who were sitting still,

retically, and in practice, the same, and the only difference in principle is in the variation of the data. This difference, which has long been recognized as a scale factor of approximately 2X, is easily compensated for in practical training and assessment, by accounting for the simple fact that the observed z-scores will be larger when using the static database reference.

One of the early concerns that was raised with the emergence of LZT was the appropriateness of the reference. It was suggested that by using a population average of typical individuals,

any biologically-related metric, we can ask the question, do we really expect everyone's brain to be the same, such as these dancers all lined up in a row?



Or is this not a more realistic scenario, with individuals expressing their own individual characteristics, strengths, and weaknesses?



It is clear, intuitively and practically, and has been borne out by research and clinical experience, that not everyone who is asymptomatic and with an unremarkable medical history ("normal") has the same EEG pattern (Johnstone et al). Even normal individuals, including those in the database, reveal particular patterns that reflect personal style, strengths, and weaknesses, but do not necessarily imply pathology. That is the reason that the z-scores have their par-

ticular standard deviations. The values vary within the sample population, and a certain percentage are, by necessity, not near the center of the distribution.

It is a necessary fact that, for example, 40% of the population will be outside the plus or minus one standard deviation limits, for any arbitrary metric. That

is how the metrics are constructed. It also means that 1 in 20 readings will, statistically, be expected to be at or beyond two standard deviations. Given that an individual may be characterized by thousands of different z-scores, we must necessarily expect deviant z-scores, even among normal individuals. Furthermore, there is no particular reason that anyone is any better off if they are near the centers of the distribution. In particular, it is not necessarily true

that anyone with a z-score of two on any metric will necessarily be any better off if that parameter moved toward the center of the population mean.

As a theoretical ideal, the best and only "pure" reference for a given individual during a neurofeedback task would be the EEG of that individual, in a more desirable state. Whether that corresponds to characteristics of a population average is not a presumptive fact. The concept of normative qEEG was introduced independent of the idea of live training to z-score norms. It is not at all clear that the normative average sample is the only, or even an optimal, target for operant learning. However, this view may be taken a priori based upon a mechanistic, interventional model that subscribes to the idea that all brains should be the same.

As a more specific example of a limitation of normative database reference is that a certain percentage of individuals will, by definition, be on a deviant part of a distribution. However, since all entrants into the database are purportedly "normal," a given percentage of the population will necessarily be significantly deviant. For example, the following figures show the EEG of an asymptomatic, high-performing individual who happens to have a fast posterior dominant rhythm (PDR). Based on a visual inspection, it is clear that this individual simply has an alpha peak frequency at or near 12.0 Hz, which is at the high end of the "normal" distribution. By definition, some percentage of the normal population will present with this finding.

Two findings are evident from this analysis; one is that because the EEG alpha frequency is significantly fast, yet normal for this individual, the z-score computations produce misleading results. It appears that this individual has elevated levels of beta activity, as well as high beta. The excess beta is due

to the fact that some of the EEG alpha actually exists in the beta band, as defined. A second fact, which is a limitation of any Fourier-based method, is that there appears to be a second harmonic to the fundamental, evident as a broad spectrum of energy, centered at exactly twice the dominant alpha. This harmonic is not due to any aspect of the equipment, aside from the fact that Fourier analysis uses simple sinewaves as the basis function, and any deviation from a simple sinewave appearance will produce higher harmonics. The alpha is visibly nonsinusoidal in this case, consisting of a sharper top wave and a flatter bottom wave. This does not constitute any “real” beta activity, but simply shows that the wave is not a simple sinewave. There is no a priori reason that EEG waves should be sinusoidal, and in many cases they are not, such as the boxlike shape of theta, or the wicket shape of mu waves.

We therefore see several limitations of a sinewave-based metric that assumes the presence of exact frequency bands and pure sinewaves. The following example (figures 2 and 3) shows a perfectly functional, asymptomatic individual, who happens to have a peak alpha frequency at the high end of the population distribution. Moreover, the alpha waves are not purely sinusoidal, and have a different shape at the top of the wave, compared to the bottom of the wave. These two characteristics combine to produce a qEEG result that appears to show excess energy in the beta range. Of particular concern is the fact that the nonsinusoidal wave morphology introduces a first harmonic at twice the fundamental, so that the FFT analysis shows abnormal energy in the vicinity of 24 Hz, in a broad band. This phenomenon will occur with any Fourier-based method, including JTFA analysis. Therefore, whether one uses an FFT

or JTFA-based method, the presence of rhythms in the boundaries of the component bands, or with a nonsinusoidal waveform, will produce these types of anomalous readings.

map is interpreted on its own, one might consider this individual significantly abnormal, and having excess beta and high beta. However, this is not at all the case. This example shows that a norma-

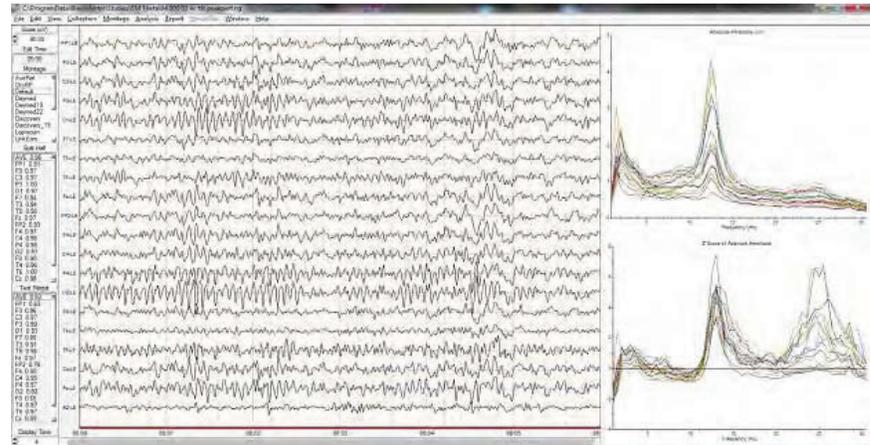


Figure 2: Spectral distribution. Non-sinusoidal peak alpha at the high end of the population distribution, producing g artifactual beta.

The resulting maps show these excesses. They are not related to any aspect of the equipment, but reflect rather the vagaries of using an FFT to analyze a peculiar, yet normal, waveform. If the

diverse sample may fall short of providing a useful assessment basis for those at the extreme of the population. It also suggests that LZT training that depends strongly on normalizing these aspects is likely to emphasize factors that are either irrelevant, or even counterproductive, to appropriate clinical progress. For example, not only is it not clear that reducing the amplitude of these signals, or the frequency of alpha would be beneficial, but anecdotal experience has shown that a client may or may not find that a training bias toward “normalization” will produce positive results.

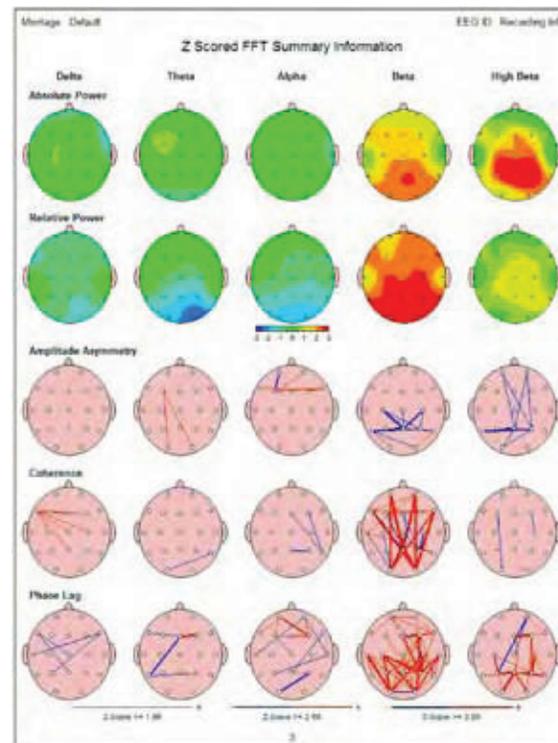


Figure 3: Topographical z-score map. Non sinusoidal peak alpha at the high end of the population distribution, producing g artifactual beta. Using FFT or JTFA-based method, the presence of rhythms in the boundaries of the component bands, or with a nonsinusoidal waveform, will produce anomalous readings.

Figure 4 (courtesy of D. Kaiser) shows the distribution of alpha peak frequency in a normal population. It is evident from this graph that a significant segment of the normal population will have a peak alpha that is either at or below 9 Hz, or at or above 11 Hz. Because these individuals lie at the edges of a typical qEEG alpha band, their EEGs will tend to produce “abnormal” results when subjected to a statistical comparison such as a z-score.

A further complicating factor occurs with respect to aging. A database can attempt to compensate for age-related changes by either using a “bin” method, or by regressing values against age. This will effectively ensure that the database has age-appropriate norms for the chosen bands. It does not, however, ensure that the bands chosen are appropriate for any age.

Figure 5, (from <http://www.iomonitoring.pro/eeg.htm>) shows the typical values of posterior dominant rhythm (PDR) as a function of age. It shows that the PDR changes quickly from ages one through five, in particular. One result of this fact is that, as the PDR moves from one band (theta) into the other (alpha) in the analysis, abrupt changes in scores may be observed (Mulder, 2013). For example, a child of age 4 will have a PDR that lies at the cusp of the two bands, and will not be adequately represented. This suggests that, particularly with respect to age, fixed bands may be a limitation. Furthermore, customized bands may be more desirable, both with regard to age, and with regard to individual differences.

Effects of eye and task conditions

A further consideration relates to the conditions of the reference acquisition. Most existing reference databases include an eyes-closed (EC) and an eyes-open (EO) condition. Some also include one or more task-related conditions.

Any of these references might be used either for assessment, or for LZT training. Therefore, it is important to understand how the brain responds to these conditions, with respect to particular EEG frequency bands and amplitudes.

The following graphs (developed in collaboration with D. Kaiser) show the typical effect of closing the eyes in a normal adult population (figure 6), as well as task-related changes (figures 7 and 8). This confirms the well-known observation that alpha increases by a factor of up to 2.2, maximally in the occipital leads. Because this set of curves is based upon a population statistic, it ac-

curately represents the differences that will exist in a z-score reference of eyes-closed EEG, when compared to the corresponding eyes-open EEG. It may be noted that the particular sets of leads can be separated by their response to the eyes-closed condition, and break naturally into bands such as 8-12, 4-7, and 12-15, based upon the observed separation of curves. This provides an interesting validation of the choice of the standard bands, showing that they do reflect something about how the brain is wired, and how it responds to changes, in this case, the closing or opening of the eyes.

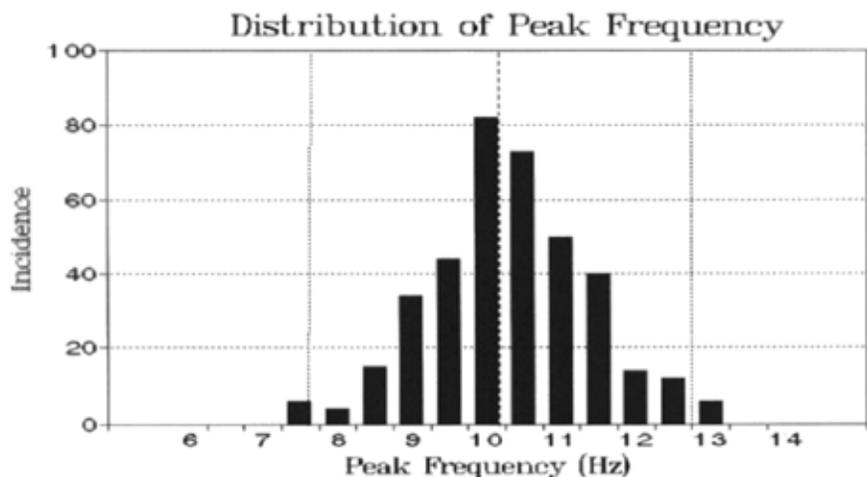
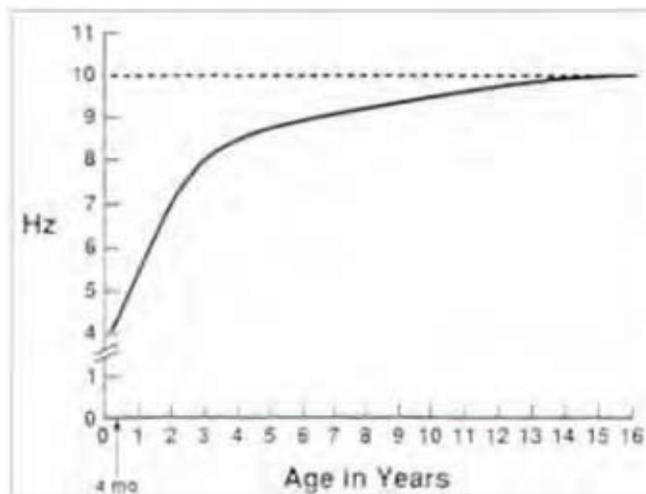


Figure 4: Distribution of alpha peak frequency in a normal population (courtesy of D. Kaiser).

The following



Typical values of PDR as a function of age

Figure 5: Posterior dominant rhythm as a function of age.

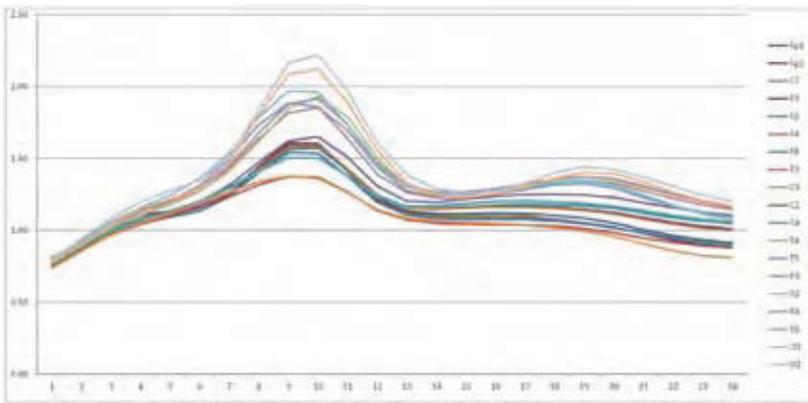


Figure 6: Effect of eyes closing on EEG amplitude.

The following graph shows the EO EEG compared to a task (age-appropriate reading). In this case, we observe that the population shows increases of up to 100% in the low delta range, increases up to 1.5 in the alpha range, and less change in the theta and beta ranges.

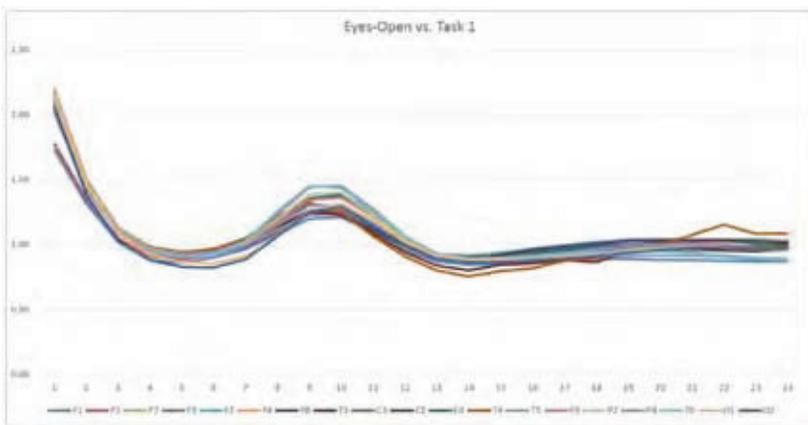


Figure 7: EEG amplitude. Eyes open vs. Task 1.

The following graph shows the EO EEG compared to a different task (serial 7's). In this case, the changes are even more pronounced. In this case, the difference in alpha increases to a factor of up to three, and a further dependence on beta occurs, in both directions, in the range of 15 to 24 Hz.

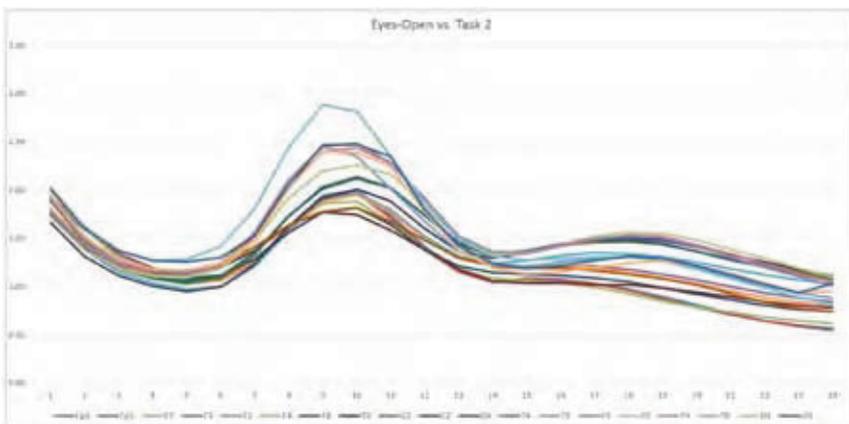


Figure 8: EEG amplitude. Eyes open vs. Task 2.

These two comparisons between eyes-open resting condition and task conditions provide several important observations. One is simply that a brain under a task can have an EEG amplitude pattern that differs significantly from that at rest. Another observation is that the differences are frequency dependent, and are most significant in the alpha range.

When put into practice, the intent of the LZT reference may be open for interpretation, and there is room for creativity in this aspect. For example, a reference may be designed to place a demand on the client, other than to simply “be more normal.” There is an analogy to other forms of therapy, such as paradoxical intention in psychotherapy, which facilitates change by moving the client into an extreme position, and then allowing for learning to occur. There is no authoritative reason why neurofeedback must be done using a reference that purports to be some “ideal” or “most efficient” pattern.

Neurofeedback, flexibility, and variability

The primary issue with neurofeedback can be considered to be one of flexibility, not necessarily adherence to a particular norm. For example, figure 9 shows mean z-scores (colored bars) as well as z-score variation (“error” lines) for a 1-minute sample of EEG. It is evident that the z-scores that are closest to normal also exhibit the greatest variation. The few z-scores that are the most deviant also show the least amount of variability. It is almost a rule that any variable that is more deviant will have a tendency to be less variable, in a system in which variability is one of the key elements of self-regulation.

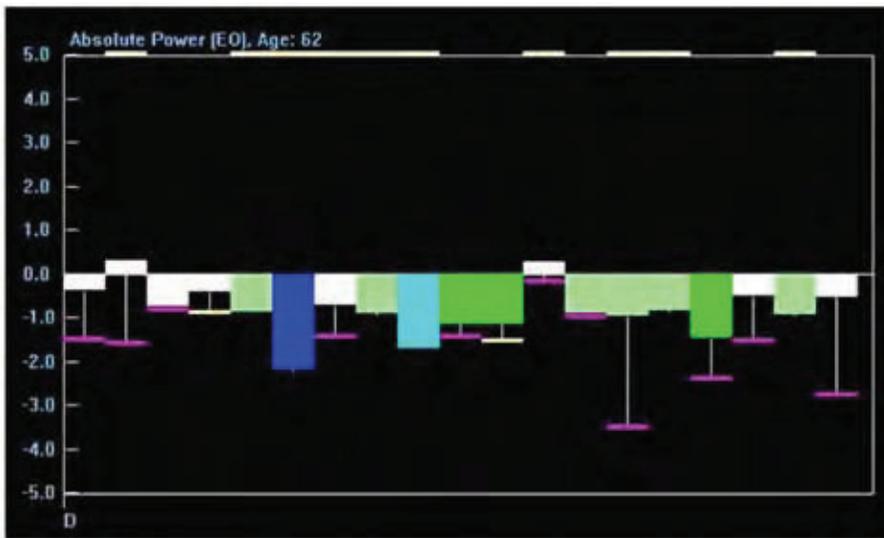


Figure 9: Mean z-scores (colored bars) as well as z-score variation (“error” lines) for a 1-minute sample of EEG.

certain percentage (usually 10% to 40%) to lie outside the target range, while the client still gets positive rewards. This allows the client’s brain to adjust in an individual manner, and to allow some values to remain “deviant.” Without this provision, the necessity would arise to pay more attention to the specific choices of z-scores, and to avoid z-scores that do not specifically relate to the complaint or disorder under care. This also provides

a robust approach to “optimal functioning” and “peak performance” z-score training, because an individual’s unique characteristic(s) would naturally tend to occupy the population of outliers that is ignored, hence neither reinforced nor inhibited, by the training protocol.

The concept of paradoxical training has existed in other areas of psychotherapy. By challenging an individual in a particular way, it becomes possible

to enable a system to explore different boundaries and modes of behavior. As one example, a golfer might temporarily place a weight on a club, in order to exaggerate the motor activities associated with a swing. When the weight is removed, the swing is improved in the unweighted case, as well.

Choice of population (or individual) references

It is important that a reference can be associated with a normally distributed population of values. However, this does not require a population of individuals. A series of samples from any individual, taken over time, is in itself a statistical sample. Once the relevant values are reduced to simple tables of means and standard deviations, all that matters is that the reference values are correct, and that there is some normal distribution that underlies them. As an example of a normal population of values derived from a single individual, figure 10 shows the distribution of instantaneous values over a 1-minute epoch. The gaussianity of this distribution is visually evident.

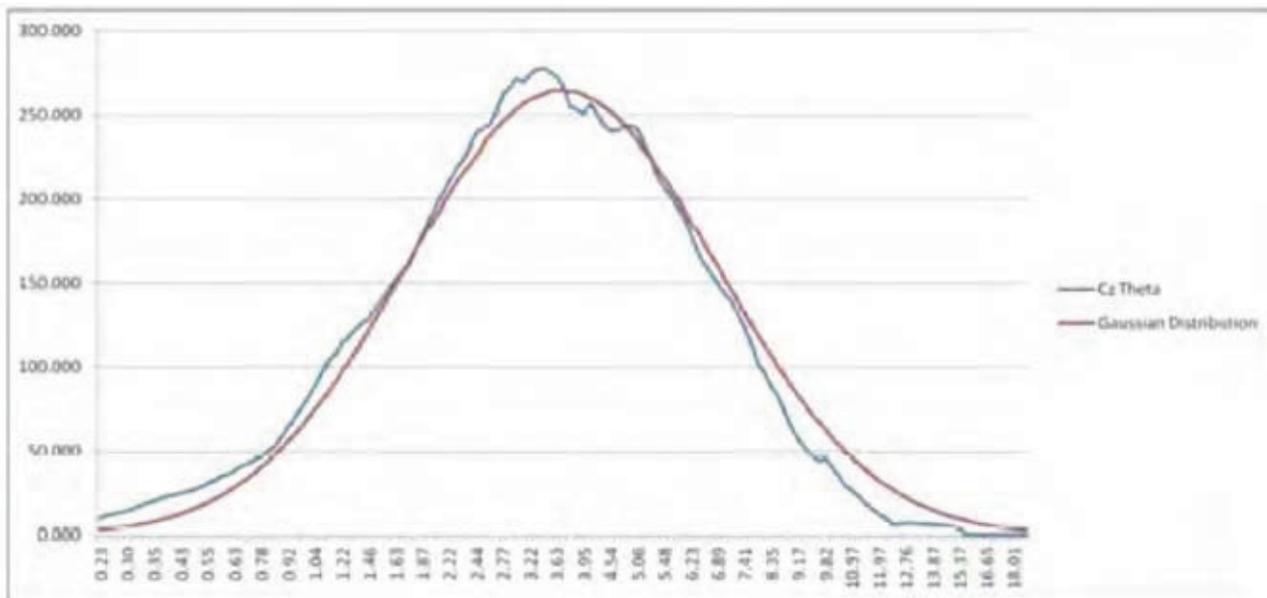


Figure 10: Distribution of instantaneous values from a single individual over a 1-minute epoch. The gaussianity of this distribution is visually evident.

och. The gaussianity of this distribution is visually evident.

The validity of an individual reference for LZT use can be further validated statistically. The following table summarizes an example of goodness-of-fit values for all 19 10-20 sites, for 10 frequency bands, for an example 1-minute sample. Figure 11 shows these values in graphical form. The bars represent the goodness of fit for every site, and for every component band. It is evident that

EEG with a known healthy condition. In the practice of optimal aging, it is also possible to capture EEG from individuals in healthy states, before age-related decline sets in. By training to one's own EEG during healthy phase, one can avoid the possibility of less than optimal results if one's neurofeedback is directing the client away from their own healthy operating parameters.

In many practices, the qEEG reference database is used for both assess-

ment, and for LZT neurofeedback. In the original embodiment, one set of computed references was used for the assessment phase, and a different set was used for LZT neurofeedback. This was done so that the instantaneous values used for training would correspond to the instantaneous variation observed in the reference sample. For the instantaneous references, both the between-subject variation and the within-subject variation were included in the data. As a result, since the reference standard deviations are larger, the resulting computed live z-scores are smaller, typically by 1 to 1.5 standard deviations. When this was first observed, there was some confusion and concern, and it was necessary to explain the statistics before users became comfortable with this difference. The question then arose, why cannot the instantaneous values correspond to the assessment values, so that an EEG that produced a 3.0 SD excess of beta on a report, would also produce a 3.0 SD excess in the live display. The fact is that this is possible, and

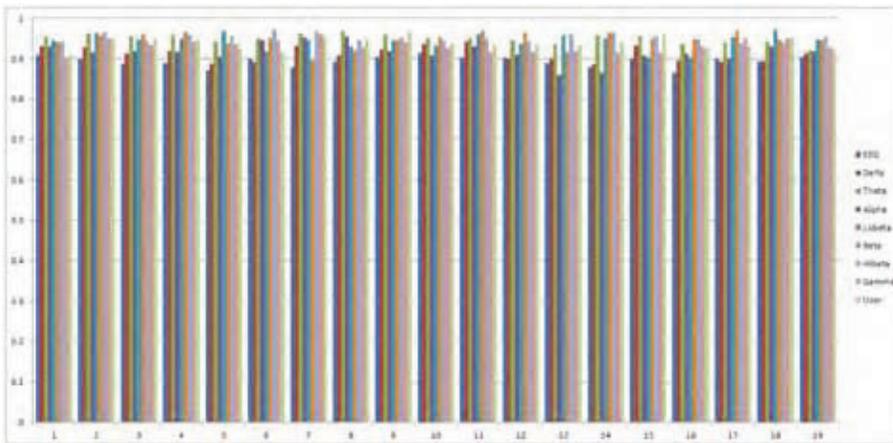


Figure 11: Goodness-of-fit values for all 19 10-20 sites, for 10 frequency bands, for a 1-minute sample.

a high-quality fit is achieved for every value and every site, from this sample of EEG.

qEEG Z-Score cryogenics

The ability to construct an LZT target from an arbitrary sample of EEG opens the door to many possibilities. One is to capture EEG signatures from individuals as a precaution for future events or conditions. For example, if EEGs are taken from all participants in athletic competition or other potentially dangerous activities, these can be used as references to assess the effects of injury or other adverse events or conditions. Decisions regarding whether an athlete has been significantly impaired, and should or should not return to play, can be well addressed by comparing the

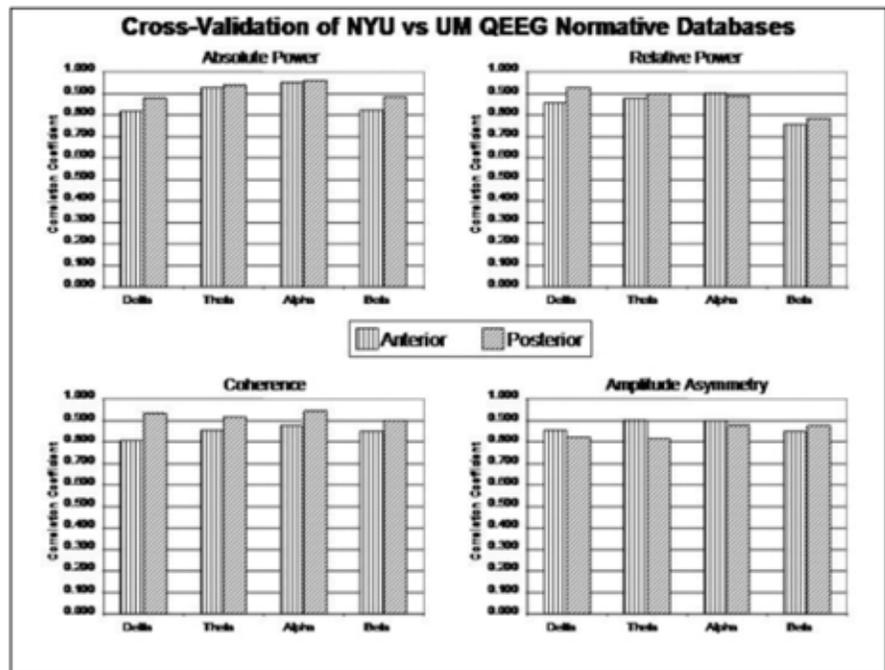


Figure 12

by using a static reference for live training, the expected correspondence can be observed.

Static versus Dynamic Z-Score References

When normative databases are constructed using similar principles, it is an expected, and observed, result that they will produce similar references. Figure 12 (from Thatcher & Lubar) shows the match, for example, between the Lifespan and the BrainDX databases. This match therefore demonstrates that different databases can be used as references, and will produce equivalent results.

Figure 13 shows the relationship between the dynamic EEG data and the population values, as well as how the static distribution compares with a dynamic distribution. The static norms reflect the average values for multiple individuals, but do not reflect indi-

vidual variation. The dynamic population norms, by incorporating all of the variation, both between and within individuals, produces a very large distribution. However, this distribution does not represent the range of any particular individual's optimal functioning. The figure also shows three individual distributions, representing individuals on the high, middle, and low parts of a population.

Consider Mr. "Red" for example. His normal range of function is represented by the red parameter values, and the red bell curve describing his distribution. If Mr. Red is somehow dysregulated or meets with some adverse conditions, his EEG may deviate from that normal set of values, either by becoming hyperactive (excess) or hypoactive (deficit) in that particular value. If a standard normative reference is used to train Mr. Red to recover, then the system will, by

definition, tend to reward Mr. Red when his values move more toward a "normal" level, which may not be optimal for him. The assumption that a population statistic is optimal for all individuals is tantamount to assuming that everyone is a "Mr. Green" or would be better off by being more like Mr. Green. However, this contradicts the foundational assumption of the database, which is that everyone in the population is healthy, even if they occupy outer regions of the normal distributions.

There is a need to demonstrate the equivalence between obtaining live training data from more than one possible real-time implementation. In particular, although static references are generally computed using FFT's, the live data is more often obtained using real-time method such as using digital filters or a related complex demodulation technique (Collura, 1990)

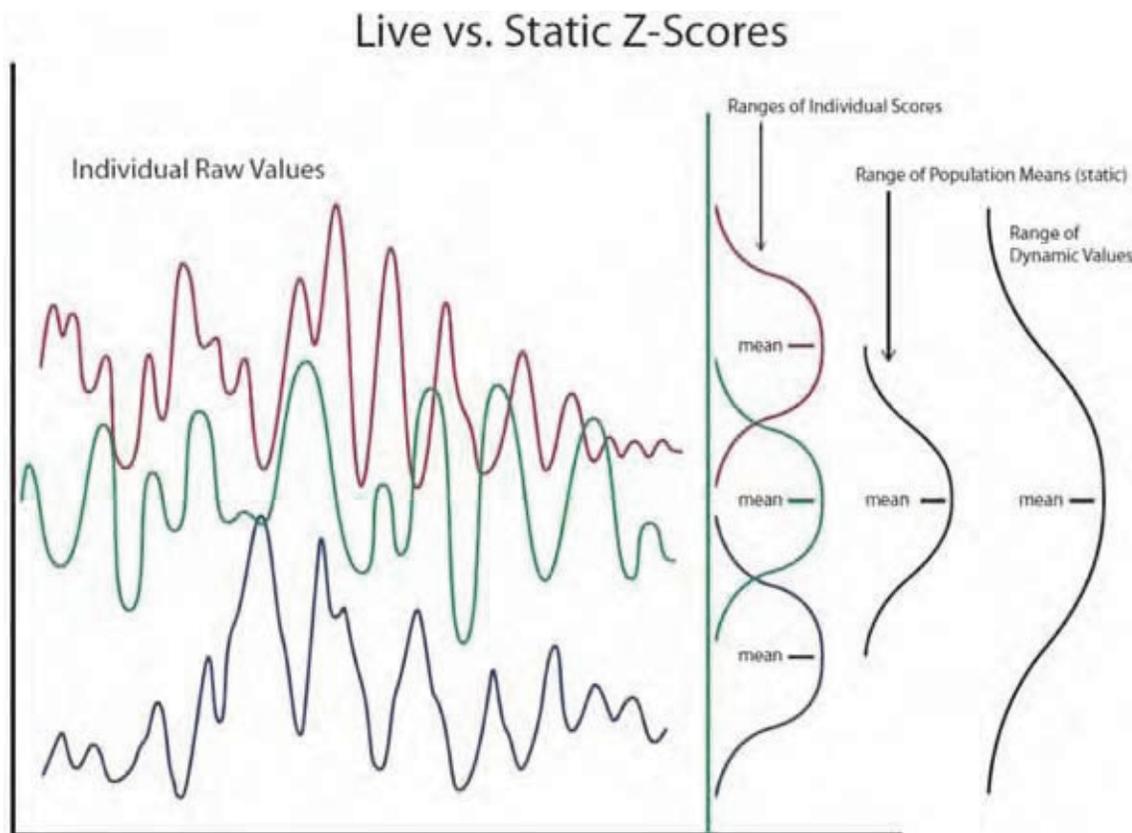


Figure 13: Relationship between the dynamic EEG data and the population values.

When comparing static and dynamic results, it is important to consider relevant similarities, and differences, in the methods used to compute parameters.

If one method is used to compute the reference values, and a different method is used to compute the real-time values, then it will be of concern whether there is concordance, or consistency, between the methods. If one chooses a particular method, e.g. FFTs of 2-minute samples, for the static values, and uses a different method, e.g. some other transformation, for the dynamic values, there may not be sufficient consistency to consider them to provide similar information. For example, if I use height as a measure of growth each month and weight as a measure every year, and attempt to correlate them, there will be a poor match, because these two parameters measure essentially different characteristics. With regard to waveforms, there are parameterizations that relate to, for example, height (e.g. peak-to-peak amplitude), while others relate to weight (e.g. total power). The assumed or actual match between two different metric approaches cannot be assumed; it should be demonstrated.

There are implementations in which the static data are derived from FFT analysis of long samples, while the dynamic data are derived from a different type of transform, such as a Hilbert or Gabor transform. When one examines these transforms, they are all essentially Fourier-like methods, but with variations in the kernel of the integral. When these methods are compared, differences of up to 18% between different types of transforms can arise, due primarily to differences in the windowing or kernel function.

The value of JTFA transforms is that they produce information in time as well as in frequency. However, all such

transforms are technically defined over an infinite time interval, and for them to produce output related to the signal of interest, the signal must be in the center of the window. Signals near the epoch edges are effectively reduced or even removed by the windowing function.

For this reason, a transform might be selected for the real-time computation, as well as for the reference database. However, transform methods are not well suited to real-time implementation, because of the inherent delay associated with the epoch and windowing operation. With a 1-second analysis epoch, any transform-based method will experience a response delay on the order of $\frac{1}{2}$ of the epoch length, or 500 milliseconds. This is rather long, when compared with the response times of methods based on digital filters.

Most neurofeedback software employs digital filters, or a related method, to compute real-time data for biofeedback purposes. This is because a digital filter provides a faster response time than any transform-based method. Digital filters provide a continuous processing of the data, and proceed one data point at a time, without having to use any particular epoch size or windowing technique. Digital filters emphasize the most recent data, and gradually de-emphasize earlier data, with a continuous function that is defined by the filter type. Digital filters are designed using different methods, such as Butterworth, Chebychev, Elliptical, or other methods. All digital filters proceed by adding a single data point to the computation, and combining it using weighting coefficients, with the previous data and results. This is in contrast with transforms, which always look at a finite extent of past data, usually on the order of 1 second, and analyze it in isolation, so as to estimate the immediate value of a relevant parameter. It is this window-

ing and epoch selection that causes all transforms to suffer from a built-in delay that is independent of how fast the computer is. Even if a computer is infinitely fast, a transform will always introduce a response delay because of the way that it looks at the data.

The ability to match static references and dynamic calculations cannot be taken for a given, unless either the same method is used for both, or if the correlation can be justified and demonstrated. As an example, if one takes weight on a clinical medical scale, and also at home on a cheap scale, the match may be as poor as 5 pounds, maybe more. But if both scales are at least calibrated to the same reference, a match within 1 pound or so can be expected. Similarly, if one takes care of the relationship between a static and a dynamic computation, and can demonstrate the appropriate relationship, then dynamic measures can be referenced to static data, even if the methodology of the computations is not identical.

In the results shown here, care was taken to implement a digital filter using the method of complex demodulation (Childers), which ensures that the instantaneous values converge to match values that would be obtained from an FFT of the same time frame. Rather than being another epoch-based transform, the filter used here is continuous, and provides output that instantaneously reflects the most recent data, without any delay due to fixed epoch size or windowing. In the steady state, the values would match identically. Due to the effects of the time-variation in the signal, small differences will occur, because the digital filter is actually doing a better job than the FFT of tracking changes in the EEG. However, the ultimate degree of matching can be shown to be within a few percent, even in the face of a dynamic EEG. This matching would not be

possible if the dynamic method used a transform such as Hilbert or Gabor. It is made possible by the fact that the digital filters are designed with an eye to producing results that are comparable to FFT results, even when dynamic and static data are compared.

In summary, rather than there being a hard distinction between dynamic and static data, there is a continuous relationship. As dynamic data are considered over longer time periods, they converge to match the static data, if the computations are done correctly. A long damping factor, or time-constant, when applied to dynamic statistics, produces a result that necessarily matches that of a long-term analysis. If the basic scaling factor between a windowed method (e.g. FFT) and a digital filter is taken into account, the agreement is essentially perfect. In the results shown here, the responses of each filter band were carefully matched between the static norms (BrainDx/NxLink) and the dynamic data (BrainMaster digital filters) so that the agreement is obtained. When a played-

back EEG is viewed, revealing short-term changes in z-scores, maps, and sLORETA images, and the damping factor is increased to slow down the responses, the resulting data are essentially identical to that which would be obtained if a longer segment were selected and processed as a unit, providing averaged results. This provides the bridge between dynamic and static data, bringing the worlds of traditional qEEG assessment and live neurofeedback training together into one connected whole.

There are two key advantages to this approach, when contrasted to one that uses one method for static data and another method for dynamic data. One is that the maps and z-scores are entirely consistent. Live maps “look like” static maps, and reveal similar z-score deviations. This eliminates the previous confusion that has resulted when live z-scores did not match static z-scores, but required a compensation of 1 to 1.5 standard deviations to convert from one to the other. A second, more important advantage is that one database can

be used for both live neurofeedback and for summary statistics. Rather than having to have one set of norms for assessment and a different set of norms for training, a single set of targets can be used. The difference between short-term and long-term variations can be accounted for by adjusting the size of z-score targets. In the method that uses a single set of references, it is found that z-score targets are more often in the range of 1.0 to 2.0 standard deviations, which is what is intuitively expected, rather than the 0.5 to 1.0 standard deviations that is used when a separate database constructed using a different dynamic computation method is employed.

Figure 14 shows, in real-time, a comparison of results obtained from an FFT (top) with those obtained from a quadrature digital filter that implements complex demodulation (bottom). It is clear that both signals have the same behavior in time, and one appears to be essentially a replica of the other.

The similarity in the time-progress

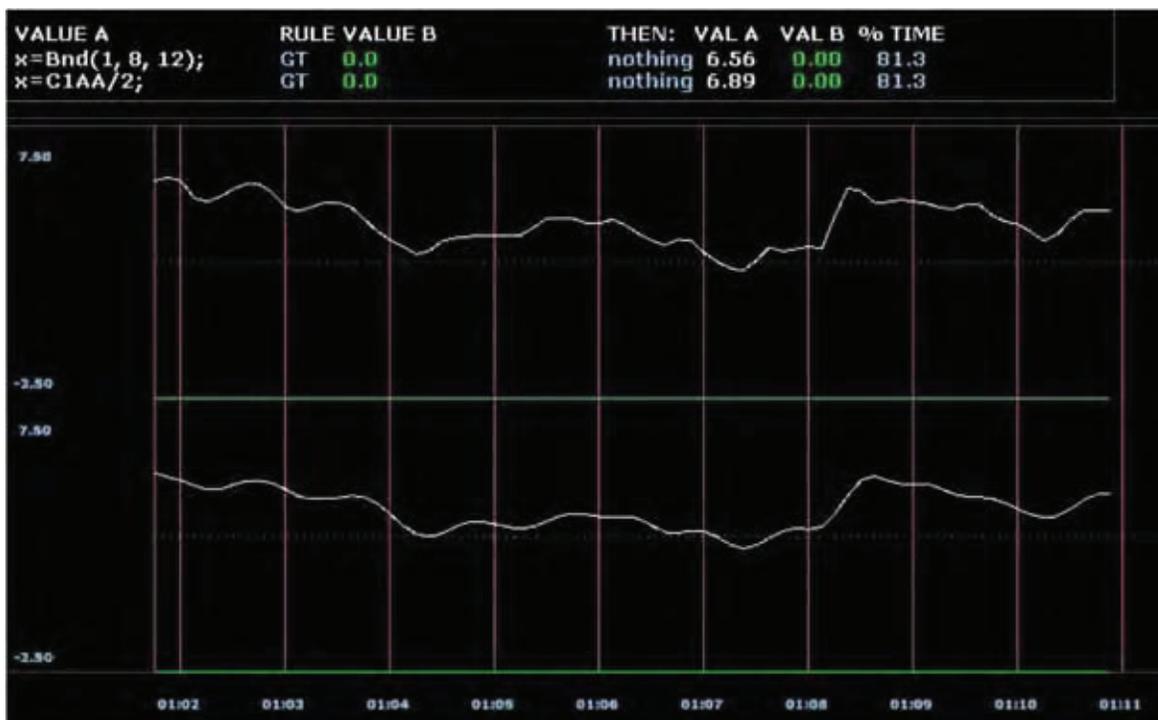


Figure 14: Real-time comparison of results obtained from an FFT (top) with those obtained from a quadrature digital filter that implements complex demodulation (bottom). Each signal has the same behavior in time, and one appears to be essentially a replica of the other.

of the two signals is visually apparent, and can be further confirmed by plotting the values against each other. Figure 15 shows a comparison of live values obtained from FFT, and from complex demodulation, plotted against each other. A scatter plot of this type is used to confirm a match between two variables, in a linear fit. In this case, a goodness of fit of 97.23 percent is observed. There is also a constant ratio, or scale factor, of 1.0629, which amounts to a consistent six percent ratio. This is explained by the difference in that an FFT uses a tapering “window,” while the JTFA does not. When this window is accounted for by this constant scale factor, the resulting accuracy is therefore roughly 2.8 percent, or plus or minus 1.4 percent. This difference is insignificant for z-scores, which, particularly if they are taking into account population and/or individual variation, must vary much more than a few percent, to produce a change of even a tenth of a standard deviation.

The following comparison shows

that this match is valid in practice, as it shows comparison maps taken from 10 seconds of EEG, and plotted using three methods. The top set is generated within NeuroGuide using the ANI database, the second set is generated within the BrainAvatar software using the BrainDX references, and the bottom set is generated within the BrainAvatar software,

using the ANI references. The maps are essentially identical in all bands, with the proviso that the BrainAvatar ANI maps, being derived from a dynamic reference, show slightly smaller z-scores. There is a further slight difference in the precise definitions of the frequency bands, which would account for some of the minor differences observed.

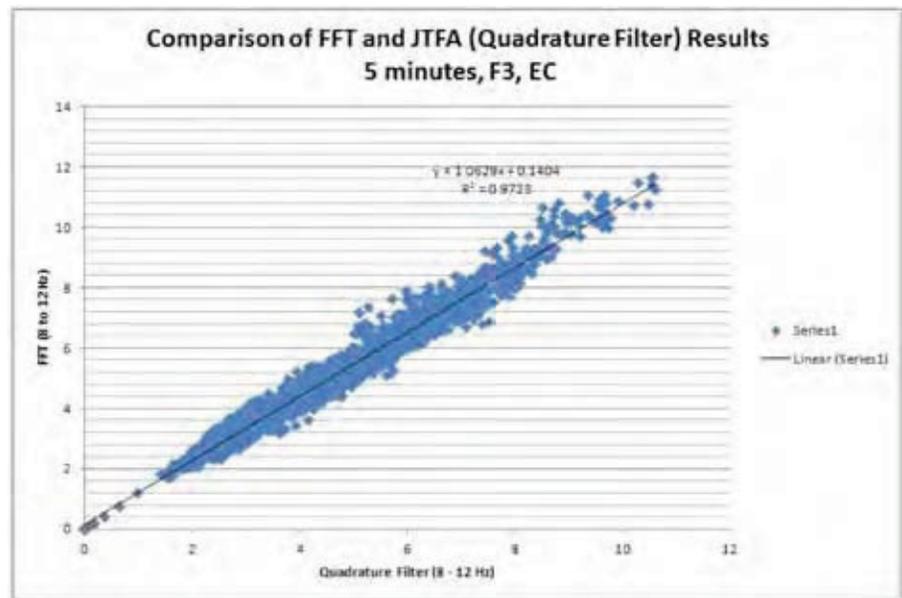


Figure 15: Scatter plot comparison of live values obtained from FFT, and from complex demodulation.

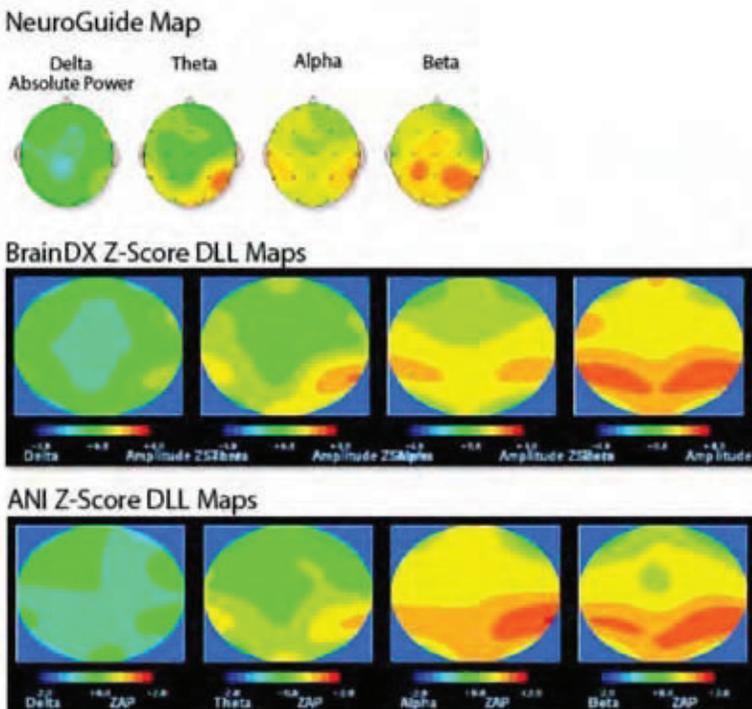


Figure 16: Comparison maps taken from 10 seconds of EEG, and plotted using three methods. Top row NeuroGuide using the ANI database. Middle row BrainAvatar software using the BrainDX references. Bottom row BrainAvatar software, using the ANI references.

As a further example of the ability to match dynamic with static statistics, Figure 17 from Collura shows the agreement between a coherence measurement derived from a digital filter implementation (BrainMaster) with those obtained using an FFT (NeuroGuide). It is clear from this example that both methods produce comparable results, across the entire range of coherence values from very low (<10%) to very high (80%).

As a verification that the static reference can be used for LZT neurofeedback, Figure 18 shows the progress of an LZT session with a client using the BrainDX Live Z-Scores and Percent Z-OK training:

The observed behavior in this session is typical, and is essentially the same as has been observed when using the original ANI LZT implementation. Z-Scores typically require a few minutes

to begin to adapt, and significant training effect is generally seen between 5 and 15 minutes into the session. It is also typical that sometime after the 10-minute mark, the client may begin to tire, and z-scores will begin to diverge again. At this point, the session should be ended. This session summary example confirms that even when using static targets, it is possible to perform effective LZT training, providing simply that the target ranges are chosen at an appropriate level.

Figure 19 shows a summary of the relevant raw values during this session, demonstrating that key EEG parameters shifted during the session as a result of the z-score feedback. This includes decreases in slow-wave activity (delta, theta, and alpha), as well as increases in beta activity.

Online references and further detailed examples of static and dynamic z-

scores and maps can be accessed from: <http://www.brainm.com/kb/entry/540/>

Conclusions

Ultimately, neurofeedback therapy is as much an art as a science. While technical principles underlie its effectiveness, what occurs in the end is that the brain is informed, challenged, and lured into various conditions of awareness and responsiveness. How the brain responds is very much a function of each individual's unique characteristics, the approach of the clinician, and finally, the specifics of the equipment. There is often more than one way to achieve results, and the process is not a linear one, but a complex nonlinear interaction. For example, LZT training can be and is combined with other modalities such as conventional directed EEG training, HEG, or audiovisual or electromagnetic stimulation. Also, protocols can be designed to

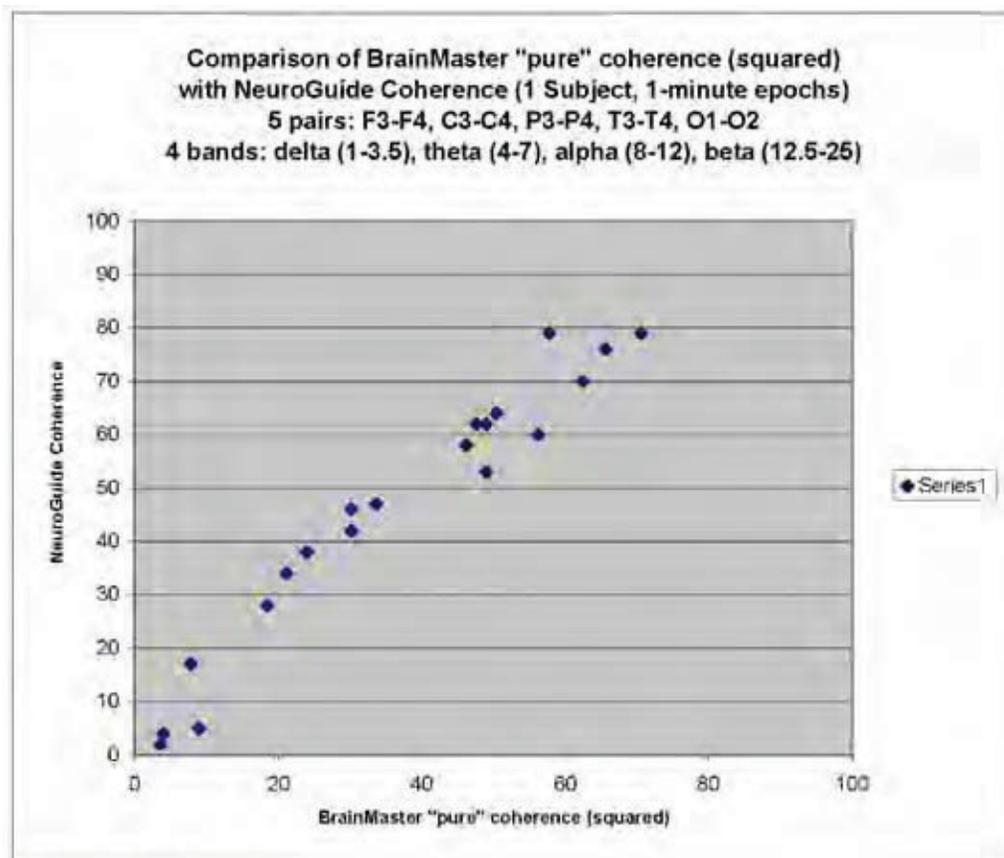


Figure 17: Agreement between a coherence measurement derived from a digital filter implementation (BrainMaster) with those obtained using an FFT (NeuroGuide).

ing/compensating, or individual qualities related to personal optimization or preference of brain state and function.

The brain's goals are effectively supplemented with additional goals related to its internal state and qualities of self-regulation (or not). By using various references and different ap-

proaches, it becomes possible to work with regard to the client's progress as a process that may include principles of direct challenge, alternating challenge and rest, paradoxical, and other types of information. The position taken here is that there is a wide range of possible approaches to creating z-score tem-

plate references, including individualized, specialized populations, and task-related methods, which have yet to be fully explored.

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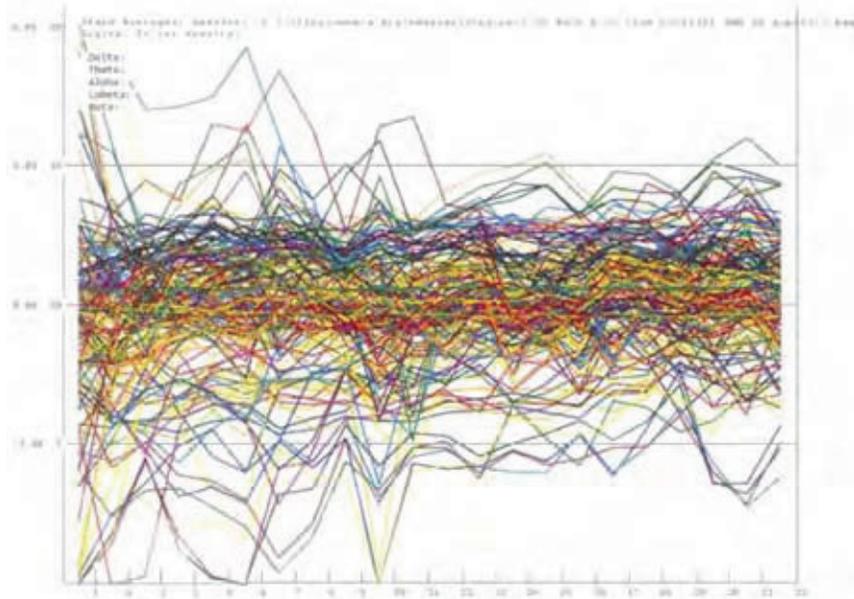


Figure 18: Progress of an LZT session with a client using the BrainDX Live Z-Scores and Percent Z-OK training

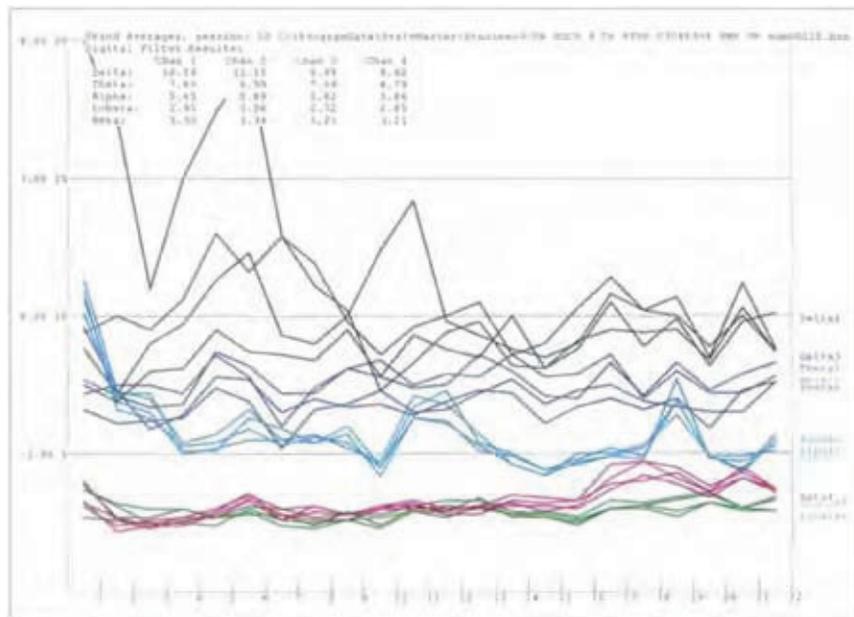


Figure 19: EEG parameters shifts during the session as a result of the z-score feedback included decreases in slow-wave activity (delta, theta, and alpha), as well as increases in beta activity.

Cantor, D. et al. see: <http://www.braindx.net/>

Thatcher, R. & Lubar History of the Scientific Standards of qEEG normative Databases. In: Budzynski, T., Budzynski, H., Evans, J., and A. Arbanal, (eds) *Introduction to qEEG and Neurofeedback: Advanced Theory and Applications*, Second Edition. New York: Elsevier. Note: Certain of the methods described herein are protected by US, Canadian, and foreign patents and patents pending.