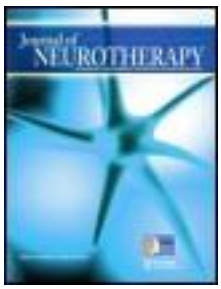


Journal of Neurotherapy: Investigations in Neuromodulation, Neurofeedback and Applied Neuroscience

EEG Connectivity Patterns in Childhood Sexual Abuse: A Multivariate Application Considering Curvature of Brain Space

Lisa M. Black PhD [a] , William J. Hudspeth PhD [b] , Alicia L. Townsend PhD [c] & Eugenia Bodenhamer-Davis PhD [d]

[a] Alternative Behavioral Health Solutions , Norman, Oklahoma

[b] Neuropsychometrix, Inc , Los Osos, California

[c] PsychoNeuroPlasticity Center , Lewisville, Texas

[d] Department of Rehabilitation , Social Work and Addictions, University of North Texas ,
Published online: 12 Dec 2008.

To cite this article: Lisa M. Black PhD , William J. Hudspeth PhD , Alicia L. Townsend PhD & Eugenia Bodenhamer-Davis PhD (2008) EEG Connectivity Patterns in Childhood Sexual Abuse: A Multivariate Application Considering Curvature of Brain Space, Journal of Neurotherapy: Investigations in Neuromodulation, Neurofeedback and Applied Neuroscience, 12:2-3, 141-160, DOI: 10.1080/10874200802398808

To link to this article: http://dx.doi.org/10.1080/10874200802398808

EEG Connectivity Patterns in Childhood Sexual Abuse: A Multivariate Application Considering Curvature of Brain Space

Lisa M. Black, PhD
William J. Hudspeth, PhD
Alicia L. Townsend, PhD
Eugenia Bodenhamer-Davis, PhD

ABSTRACT. *Introduction*. A limitation of the bivariate electroencephalogram (EEG) coherence measure is low precision in location specification in anatomical space and functional connectivity. A more powerful use of functional connectivity of distributed brain systems maybe evaluation of patterns of correlations obtained through the functional connectivity matrix of Principal Component Analysis. The eigenimages that result from such analysis represent a descriptive characterization of anatomically distributed changes in the brain. There is little research exploring the relationship between childhood sexual abuse (CSA) and connectivity patterns in the brain. This study explored the connectivity patterns between 24 high-functioning, unmedicated adults with a history of CSA and age, gender, and handedness matched high-functioning adults with no history of CSA.

Method. Resting eyes closed quantitative EEG (QEEG) was recorded from 19 scalp locations with a linked ears reference from 60 unmedicated adult research participants. The QEEG was subjected to measures of connectivity for analysis.

Results. A robust analysis of QEEG cortical coherence revealed moderate to large effect sizes indicating patterns of both increased and decreased connectivity between brain locations, which differentiated the groups.

Conclusion. The EEG coherence information extended previous work in nonclinical, unmedicated adults and suggested CSA impacts cortical function resulting in lateralized differences.

Lisa M. Black is affiliated with Alternative Behavioral Health Solutions, Norman, Oklahoma.
William J. Hudspeth is affiliated with Neuropsychometrix, Inc., Los Osos, California.
Alicia L. Townsend is affiliated with PsychoNeuroPlasticity Center, Lewisville, Texas.
Eugenia Bodenhamer-Davis is affiliated with the Department of Rehabilitation, Social Work and Addictions, University of North Texas.
Address correspondence to: Lisa M. Black, PhD, Alternative Behavioral Health Solutions, 4003 24th Avenue N.E., Norman, OK 73071 (E-mail: dr.black@wildblue.net).

The Early Trauma Project is an ongoing study orginally conducted at the Neurotherapy Lab of the University of North Texas, Denton, Texas. Special thanks go to Rich Herrington, PhD, fo his valuable advice in the research design of this project. Implementation of the robust statistical procedures used would not have been possible without his expertise in this area.

Journal of Neurotherapy, Vol. 12(2–3) 2008

doi: 10.1080/10874200802398808

Statistical methods for preventing small distribution changes from making large changes in power or probability coverage because of small and nonnormal samples is also discussed.

KEYWORDS. Childhood sexual abuse, EEG coherence, functional connectivity, QEEG, quantitative EEG

The development of the electroencephalogram (EEG) lead to a better understanding the functional relationship between areas of the brain through evaluation of the degree of similarity between two signals produced in different regions of the brain. Years ago, Brazier and Casby (1951) studied the similarity between two EEG signals using a cross-correlation computation. More recent work examined measures of EEG cortical coherence between pairs of EEG signals recorded simultaneously at different scalp locations to examine human development (Marosi et al., 1992; Thatcher, 1992; van Ball, van Beijsterveldt, Molenaar, Boomsma, & de Geus, 2001), cognitive processing (Harmony et al., 1993; Reiterer, Hemmelmann, Rappelsberger, & Berger, 2005; Sauseng, Klimesch, Schabus, & Doppelmayr, 2005; Schack, Chen, Mescha, & Witte, 1999; Thornton, 2003), and psychiatric conditions and treatment (Clarke et al., 2005; John, Prichep, Fridman, & Easton, 1988; Knott, LaBelle, Jones, & Mahoney, 2002; Prichep & John, 1992; Sritharan, Sergejew, Silberstin, Egan, & Copolov, 2005; Suffin & Emory, 1995, 1996). Otnes and Enochson (1972) defined the coherence function at each frequency as

$$Coh^2_{xy}(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f)G_{yy}(f)}$$

where $G_{xy}(f)$ is the cross-spectrum between the signals x and y and $G_{xx}(f)$ and $G_{yy}(f)$ are autospectrums of the respective signals x and y, and values are filtered and normalized. Often the correlation function rather than the coherence function is used to evaluate the similarity between two signals with a high degree of comparability of results using either method (Guevara & Corsi-Cabrera, 1996). Coherence can therefore be described as the accumulation of the squared cross-correlations of the power/amplitude of activity between pairwise EEG time series. Hughes and John (1999) described coherence as "a measure of synchronization between activity in two channels" (p. 192). Thus, coherence can be thought of as the morphological similarity between two sites in the brain irrespective of time synchronization, with a correction for absolute magnitude. It is reasonable to assume the sites that covary highly possess high connectivity or are processing related cortical/subcortical information, as they share a significant number of neurons whose dynamic interactions occur within the same time frame. The term *functional connectivity* has been used when discussing coherence between spatially distant sites (Friston, Frith, Liddle, & Frackowiak, 1993). The value of coherence is the ability to infer activity of intrahemispheric pathways (uncinate) and interhemispheric collosal tracts, which connect sites and invisible to the EEG. Coherence adds substantial clinical value to surface EEG data because it enables inferences about deeper structures, like the limbic system.

Although an understanding of pairwise functional connectivity is certainly interesting, it is limited. One limitation of EEG coherence is that it is not precise in its specification of location in anatomical space because the pairwise comparisons assume a flat space and provide a flat space estimate. The description of hypercoherence at an electrode site is analogous to describing a person as "big" without specifying height and width. Although EEG coherence estimates can prove to be quite accurate when comparing near neighbor sites, the estimates quickly move toward erroneous conclusions when comparing more distant sites (Kus,

Kaminski, & Blinowska, 2004; Liberati, Cursi, Locatelli, Comi, & Cerutti, 1997).

Kus et al. (2004) utilized simulation procedures to compare different coherence measurements (e.g., Granger causality, directed transfer function, direct directed transfer function, bivariate coherence, and partial directed coherence). The researchers found pairwise estimates to be incorrect in most cases, when compared to multichannel estimates. Volume conduction in the brain can enlarge estimates of coherence for near neighbor sites but reduce signal phase differences for sites at larger distances, which contribute to random errors. Barry, Clarke, McCarthy, and Selikowitz (2005) adjusted coherence measures to remove such random distance effects and found that systematic interelectrode distance effects still remained and accounted for greater than 50% of the variance. When the researchers removed this systematic variance, more accurate coherence estimates were achieved. This research makes an important contribution to our understanding that both random and systematic distance effects contribute to variance to make pairwise coherence estimates based on binary models inaccurate.

Because diverse regions of the brain become activated and work together during information processing, multivariate models have been increasingly used in order to consider all signal components together and to deal with the variance problems inherent in bivariate coherence measurements of the EEG (Anderson, Stolz, & Shamsunder, 1998; Arnold, Miltner, Bauer, & Braun, 1998; Harner, 1990; Harner & Riggio, 1989; Liberati et al., 1997; Moller, Schack, Arnold, & Witte, 2001; Nunez et al., 1997; Valdes-Sosa, 2004). Valdes-Sosa pointed to multivariate autoregressive time series models as being limited in the number of time series they can handle, thus, requiring a priori region selection, which sacrifices a full spatio-temporal understanding of the brain data. This limitation led Valdes-Sosa to specify a Bayesian spatial-temporal multivariate autoregressive time series model, which reduced dimensionality of many computations through single-value decomposition.

A more powerful use of functional connectivity is the characterization of distributed brain systems through the evaluation of patterns of correlations. Electrode space must be corrected for the curvature of space in the brain, which requires multiple descriptors. This is obtained through subjecting the functional connectivity matrix to Principal Component Analysis. This is a multivariate estimate that discovers only those variables critical to the description of the curved space around which the generators cluster. The analysis discards unessential variables. The eigenimages that result from such analysis represent a descriptive characterization of anatomically distributed changes in the brain—mapping anatomy into a functional space (Hudspeth, 1993). It is analogous to describing a person in terms of several dimensions (e.g., height, width, and breadth) rather than in terms of only one dimension. It is proposed that simple mathematical coherence calculations based on flat space may be useful with adjacent electrodes, but a more complex system that accounts for a curved space and uses multiple estimates is necessary to understand the full spatio-temporal nature of continuous time series brain data. An analogy can be drawn from the contrast between Riemannian (Gallot, Hulin, & Lafontaine, 2004) and non-euclidian geometry. Although non-euclidian geometry was certainly useful in the description of smaller systems, Riemannian geometry with N spatial dimensions was necessary for a more accurate understanding of the universe.

Between 1985 and 1988, Hudspeth (1993) and his students carried out detailed analyses related to the underlying structure of the human EEG. They discovered a basic principle by which three basis waveform eigenstructures could be extracted from the EEG and used to reliably predict the global integration of different brain systems. These three basis waveforms were found to account for 85% of the covariation within a multichannel EEG recording and were furthermore found to exhibit neuroanatomical accuracy in the horizontal, sagittal, and coronal planes. This methodology, based on coherence information in the EEG, has been used in the development of Hudspeth's (1999–2004a) "Neuroelectric Eigen Images" (NEI) in the NeuroRep QEEG analysis

software, making the study of connection patterns in the brain available to inspection.

In the next issue of *Journal of Neurotherapy*, Hudspeth provides further explanation of this technique and provides evidence for its validity. Especially compelling is his magnetic resonance imaging showing white matter tracts in the cortex with electrodes superimposed according to their anatomically grounded solution position (not their 10–20 system position). The anatomical solution provided by the NEI appears to line up with known anatomical locations or positions in which white matter tracts perforate the cortex. In addition, the eyes closed versus the eyes open conditions produce functional changes that are reflected in the NEI. This type of face validity is helpful in understanding more practical aspects of the NEI. The calculations used in this methodology are explained later in this article.

CHILDHOOD SEXUAL ABUSE (CSA) AND EEG COHERENCE

CSA has been hypothesized to change neural circuitry (Teicher, Glod, Surrey, & Swett, 1993), but little research in the CSA considers the influence of CSA on connection patterns in the brain. Researchers at McLean Hospital in Belmont, Massachusetts (Ito, Teicher, Glod, & Ackerman, 1998) were the first to look at the relationship between EEG coherence and early abuse. They found higher levels of left hemisphere alpha coherence and significant left greater than right asymmetries in the alpha band in children experiencing CSA and/or physical abuse. In addition, it was found that left hemisphere coherence decayed more rapidly across electrode distance in normal individuals as compared to abused individuals, implicating deficits in left-sided brain functional differentiation among abused individuals. Unfortunately, this study was limited by its focus on alpha band (8–12 Hz) coherence only, its failure to control for drug effects, and its failure to assess posttraumatic stress disorder (PTSD) status.

Ito et al. (1998) also found higher levels of left hemisphere alpha coherence and reversed asymmetry in physically and/or sexually abused children to an adult sexual trauma group. This study also explored activity in additional EEG frequency bandwidths and included an adult nonclinical group for comparison. Specifically, the CSA group was compared with the non-CSA (NCSA) group for overall left versus right hemisphere coherence as well as focal coherence differences. Townsend, Black, and Bodenhamer-Davis (2001) examined QEEG variable and Minnesota Multiphasic Personality Inventory (Butcher, Dahlstrom, Graham, Tellegen, & Kaemmer, 1989) patterns of 12 adult outpatients reporting CSA and compared them with a matched sample of outpatients who reported they had not experienced CSA. They found the CSA group had significantly lower alpha relative power in nearly all leads of the International 10–20 electrode placement sites. Alpha is a brain rhythm associated with suspended processing, and relative percent power provides an index for the allocation of energy in the brain to the various frequency bands. Exploratory post hoc analyses found differences between the groups in the relationship between variability of alpha relative power in the posterior regions and frontal-posterior coherence. Specifically, focal versus diffuse alpha relative power in posterior regions was related to frontal-posterior connectivity only in the NCSA group. These preliminary findings implicate a lack of regulation of the posterior sites via the frontal cortex in individuals with a history of CSA.

In follow-up, Black, Hudspeth, Townsend, and Bodenhamer-Davis (2002) examined QEEG abnormalities and coherence patterns based on the complex eigenimages of 15 adult outpatients reporting CSA and compared them with a matched sample of outpatients who reported they had not experienced CSA. Increased EEG abnormalities were found to be associated with the CSA group, including decreased connectivity (functional differentiation) in the left frontal regions in the theta and beta bands, whereas increased connectivity (functional redundancy) characterized posterior central regions across all bands in the CSA group compared to the control group. Important caveats of this study were that it did not control for drug effects and did not assess PTSD status. The aforementioned

EEG studies provide preliminary evidence for neuropsychological consequences associated with CSA, more specifically, left hemisphere coherence deficits.

The purpose of our study was to describe the methodology QEEG-based neuroelectric coherence measure developed by Hudspeth (1994–2004a) and report results of an application of this measure to an investigation of QEEG characteristics of adults reporting CSA. It was expected that, consistent with Black et al. (2002) findings, the two groups would exhibit differences of right and left hemisphere coherence in at least one of the bandwidths. Specifically, it was expected that Black et al. findings of theta hypercoherence on the right and alpha hypercoherence on the left in CSA adults as compared to NCSA adults and Ito et al.'s (1998) findings of greater average alpha left hemisphere coherence in abused children as compared to normals would be replicated. The two groups were expected to exhibit a different degree and pattern of coherence in at least one of the bandwidths at the level of the individual electrode as was demonstrated in the Black et al. study. However, because an unmedicated, nonclinical sample was recruited, it was not known prior to the study what frequency or localization patterns might be exhibited.

METHOD

Participants

Forty-eight individuals participated in this study. The CSA group participants ($n = 24$) were recruited from the Dallas/Fort Worth area by fliers posted in university and area clinics, and areas designated for public postings across the University of North Texas (UNT) campus. Each person was interviewed to assess exclusionary criteria and CSA. Twenty-four age-matched control participants who had not experienced CSA were recruited in the same manner for the NCSA group. Incoming new clients of the UNT Neurotherapy Lab clinic and new practicum students of the UNT Neurotherapy Lab were also recruited as participants. Similarly, these individuals were interviewed to assess exclusionary criteria and CSA.

Other requirements for participant inclusion were sexual trauma experienced before age 14, no history of traumatic brain injury, no loss of consciousness greater than 5 min, no current alcohol or substance abuse, and no current use of medication suspected to affect the EEG. Requirements for control inclusion were denial of any type of childhood trauma (e.g., physical abuse) plus no major head injuries, no current depression, no sleep disorders, no current psychiatric diagnoses, no current overuse of drugs or alcohol, no neurological disease, and absence of convulsion or seizure. Participants were matched based on age (within 7 years), gender, and handedness. All participants were asked to meet medication wash-out times (5 to 7 times the half-life) for all substances except caffeine and nicotine, for which 1 to 4 times the half-life was considered sufficient to avoid withdrawal effects on the EEG. In addition, all participants were 18 years of age or older. All participants meeting selection criteria were given a free topographic map of their eyes closed QEEG results and a 20-min explanation upon completion.

Tables 1 and 2 show the demographic characteristics of both groups. The ages ranged from 18 to 59 ($M \pm SD = 32.31 \pm 11.42$). Women comprised 92% of the sample, and a European/White ethnic background comprised 83% of the sample. Participants with some undergraduate college education comprised 50% of the sample, whereas participants with a graduate-level education comprised 46% of the sample.

Measures

For the CSA group, a medical, developmental, and CSA history was gathered by clinical interview providing information on the perpetrator; participant's age at the time of the first abuse; and duration, frequency, nature, and severity of the abuse. Sexual abuse was defined as sexual intrusion, genital or digital penetration, molestation with genital contact, or fondling at or before the age of 14 by others exhibiting some sort of

TABLE 1. Age and IQ characteristics for CSA and NCSA groups.

Characteristics	CSA[a]		NCSA[b]	
	M	*SD*	*M*	*SD*
Age	31.6	10.4	33.0	12.4
Verbal IQ	115.0	11.2	115.5	11.5
Performance IQ	115.1	8.1	112.6	10.8
P-V difference	.13	11.8	−2.8	9.0

Note. CSA = childhood sexual abuse; NCSA = no childhood sexual abuse; P−V (Performance IQ–Verbal IQ)=.
[a]$n = 24$; [b]$n = 24$.

TABLE 2. Sociodemographic characteristics for CSA and NCSA groups.

Variable	CSA[a]		NCSA[b]	
	n	%	*n*	%
Gender				
Male	2	8	2	8
Female	22	92	22	92
Ethnicity				
Caucasian	21	87	19	79
African American	3	13	2	8
Asian	0	0	3	13
English as 2nd language	0	0	4	17
Education				
12 years	0	0	2	8
13–14 years	9	38	4	17
15–16 years	7	29	4	17
17 + years	8	33	14	58
PTSD	4	17	0	0

Note. CSA = childhood sexual abuse; NCSA = no childhood sexual abuse; PTSD = posttraumatic stress disorder.
[a]$n = 24$; [b]$n = 24$.

power over the child by virtue of being older or more powerful physically or mentally than the child.

Additional psychological measures administered in the investigation included the Clinician-Administered PTSD Scale (Blake et al., 2000), the Wechsler Abbreviated Scale of Intelligence (Wechsler, 1999), and the Minnesota Multiphasic Personality Inventory (Butcher et al., 1989), including supplementary scales of PK (Keane, Malloy, & Fairbank, 1984) and PS (Schlenger & Kulka, 1989) to assess PTSD. Results of these additional measurements are beyond the scope of this article and will be reported elsewhere. Only the results from the QEEG measures are reported here and additional results are reported elsewhere.

Procedures

All procedures for this study were approved by the Committee on the Use of Human Subjects at UNT, and all data collection procedures for the study were performed by the researcher and a QEEG-qualified colleague. Prior to the EEG collection appointment, potential participants completed an initial phone screening where the study was explained and eligibility on some of the inclusion/exclusion criteria was assessed, most important the criteria that related to drug usage. If initial criteria were met, potential participants were given an appointment time and a list of instructions for complying with standard procedures. Those included double washing the hair with

a stripping shampoo, obtaining a good night's rest for 2 nights prior to the appointment, eating a substantial meal 1½ to 2 hr prior to appointment time, abstaining from caffeinated beverages the morning of the appointment, and abstaining from alcohol and over-the-counter drugs according to wash out times. Upon arrival, a face-to-face interview was conducted to explain the study, obtain written informed consent, and determine eligibility for the remaining inclusion/exclusion criteria. Those who met criteria were prepared for EEG collection.

During EEG collection, participants were seated comfortably in a sound-attenuated room with windows allowing for natural light. Brain electrical activity was digitally recorded on a Lexicor digital EEG system (NRS-24) from 19 scalp electrodes on a Lycra cap (ElectroCap International, Inc., Eaton, OH), according to the International 10–20 System of electrode placement (Jasper, 1958), and referenced to linked ear electrodes and to a forehead ground contained in the cap. Eye movements were detected using a bipolar vertical electro-oculogram lead. Electrode resistances were kept below 5 Kohms and equal to within ±1 Kohm between leads. Bandpass filters were set at .5 to 30 Hz, and the sampling rate was set at 128 samples per second. Recordings were obtained in the awake state with eyes closed (two collections of 5–8 min) and in the awake state with eyes open (two collections of 5–8 min). Scalp electrodes were sterilized after collection from each participant. After EEG collection, participants completed the clinical interview and, following a break, psychological testing.

To meet the objectives of the study, recordings were digitized, visually edited to reduce artifacts (contamination resulting from muscle tension and eye and body movements) according to field standards (Hammond & Gunkelman, 2001), and subjected to quantitative spectral analysis. A total of 30 to 100 sec of artifact-free recording were selected from each collection in the eyes closed condition for analysis. EEG was reformatted in a variety of referential and bipolar montages for visual evaluation of the presence or absence of regions of focal slowing, epileptiform activity, and/or asymmetries, by two trained QEEG technicians. Interrater reliability of ratings were 80% or greater for all visual evaluations of abnormality. Discrepancies were resolved for 100% agreement. The NeuroRep (Hudspeth, 1994–2004a) QEEG analysis and report system was used to analyze absolute magnitude and EEG coherence in each of the bands (delta, theta, alpha, and beta) and did not contain paroxysmal discharges.

Data Analysis

Editing was performed on the data according to field standards as outlined in Hammond and Gunkelman (2001). All data were coded so that the researcher was blind to group inclusion. Movement artifacts, muscle tension creating amplitudes greater than 5 microvolts, artifacts associated with drowsiness, electrode artifacts, and transients 50% greater than background activity were removed from the eyes-closed records. Reliability between the records was reviewed, and the best record or a combination of the two recordings was analyzed. If reliability measures for coherence bandwidths as well as individual channels were greater than or equal to 80%, the records were added together and analyzed. If the reliability between the records did not meet these standards, the record that included the participant's best performance was chosen for analysis according to the researcher's clinical judgment. The eyes-open records were used only to assess for alpha blocking and were not edited or analyzed.

The NEI connectivity indices were created by means of a complex demodulation program that computes auto- and cross-spectral power density for all 19 channels, using a second-order recursive digital filter developed by Neuromatics, Inc., expanded by Hrybyk and then extended to 19 channels by Hudspeth (Hudspeth, 1983; John et al., 1980; Thatcher, Krause, & Hrybyk, 1987). Coherence, phase, and asymmetry relationships between all pairwise combinations of 19 electrodes ($n = 171$) for 4 frequency bands

(delta, theta, alpha, and beta) and the unfiltered cross correlation are computed in the program. The results produced by the program are essentially identical to a fast Fourier transformation, though it is more efficient as results are computed only for the frequency bands (Otnes & Enochson, 1972).

To reduce measurement problems associated with the large number of statistical comparisons (171×19 matrixes) inherent in analysis of coherence, data were subjected to Principal Components Analysis (Hotelling, 1933; Pearson, 1901) as adapted for waveform data (John, Ruchkin, & Villegas, 1964). The component loadings were then used to determine the three dimensions (basis waveforms) inherent in each set of 19 waveforms, which reflect anatomical location (Hudspeth, 1993). The resulting three-dimensional eigenimage or NEI reflects a reduction of the data into a 19×3 matrix (Hudspeth, 1994–2004a).

NEI's were generated in the NeuroRep (Hudspeth, 1999a) software and based on the mean for each group. An example of an NEI can be seen in Figure 1. The NEI provides three different views of the coherence relationships for four frequency bands plus a combination of all frequency bands. The horizontal view provides left–right and anterior–posterior location information. The sagittal view provides anterior–posterior and dorsal–ventral location information. The coronal view provides left–right and dorsal–ventral location information. The horizontal and vertical dotted lines represent functional brain divisions. The intersection of the horizontal and vertical dotted line represents the point of origin, which is a point in brain space directly below CZ.

NEI's uniquely map brain anatomy into functional space so that the functional connectivities between sites are represented by the distance between brain locations (Hudspeth, 1994–2004a). Large distances are associated with hypocoherence or increased differentiation among sites, and small distances are associated with hypercoherence or redundancy among sites.

NEI's provide an immense reduction of coherence information while preserving a parsimonious view of functional brain space (19×3 matrix). Despite this reduction, it is necessary to further reduce the data for statistical analysis because of the small sample size. Therefore, all three dimensions (component loadings) of the NEI were used to compute a vector length for each electrode and the resulting value represented the distance from the origin, which is a point directly below CZ:

$$\sqrt{x^2 + y^2 + z^2}$$

This equation represents a reduction of the 3×19 matrix to 19 vector lengths with a functional anatomic grounding. Each vector length represents functional distances, where larger distances from the origin are associated with less coherence or connectivity in that region and smaller distances from the origin are associated with more coherence or more connectivity in that region.

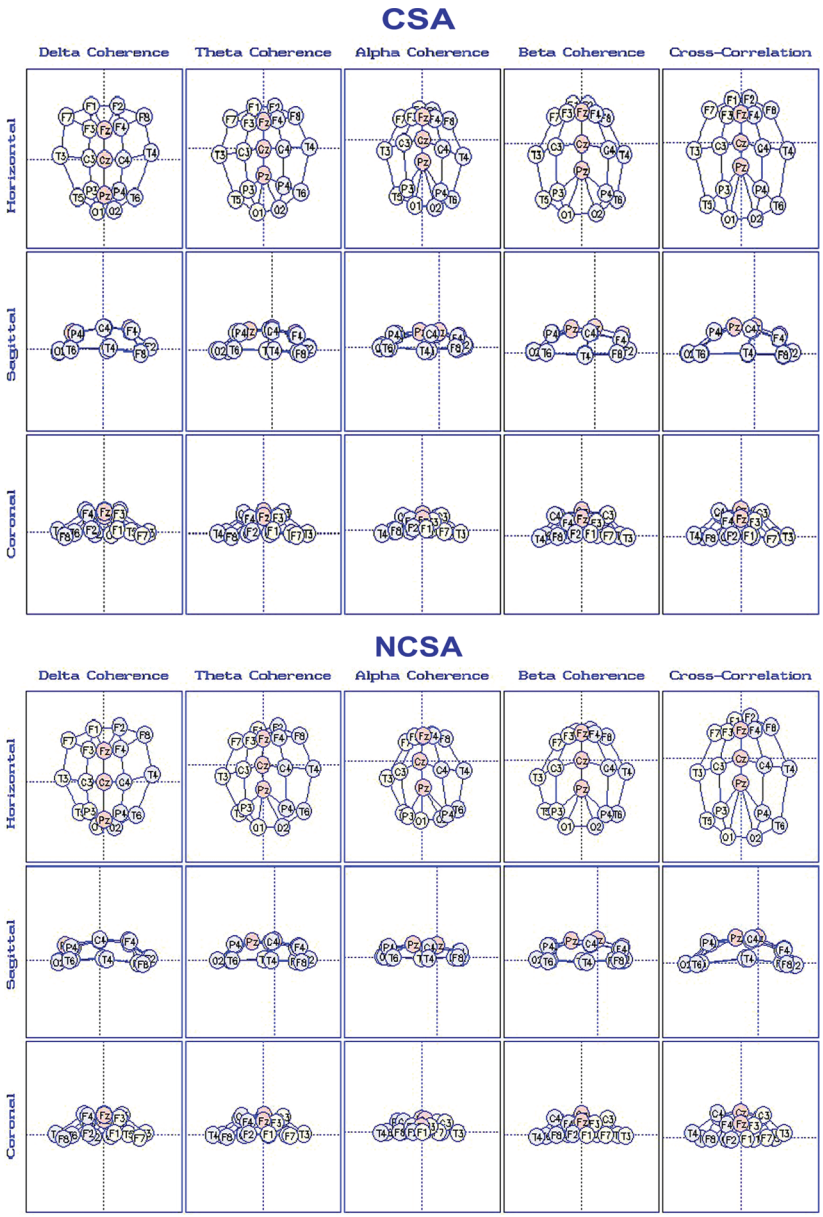
To compare these findings with those of Ito et al. (1998), the data were further reduced to reflect differences between left and right hemisphere coherence. To do this, vector lengths representing distance from the origin for each of eight electrodes per hemisphere (excludes vertex sites) were averaged to obtain composite hemisphere measures.

Statistical Analysis

Data were also analyzed for each site (electrode). Thus, vector lengths representing distance from the origin for each of 19 electrodes were compared. Descriptive statistics, graphs, and correlation matrices representative of the data were generated and examined to identify means, standard deviations, ranges, univariate outliers, and highly correlated variables. Robust analyses of data were performed along with standard analyses to test the specific hypotheses.

Lateralized as well as individual vector length differences between groups were compared using Student's *t*-tests to accept or reject the null hypothesis that the groups' mean vector lengths were equal. Pearson's chi-square tests with Yates's continuity correction were used to analyze differences between groups for incidence of neurological assessment abnormalities.

FIGURE 1. Neuroelectric images based on means for the childhood sexual abuse (CSA) group (top) and the non-CSA (NCSA) group (bottom). *Note.* The figure shows three views of coherence for each band (delta, theta, alpha, beta) as well as the bands collapsed together (cross-correlation) for each group.



Because of small sample size and potential for outliers, there was an increased likelihood the two groups would not meet the assumptions of normality. It has been demonstrated (Wilcox, 1998) that small departures from normality decrease power substantially, which decreases chances for detecting real differences between groups. As has been pointed out in numerous articles and books (Birkes & Dodge, 1993; Hampel, Ronchetti, Rousseeuw, & Stahel, 1986; Hoaglin, Mosteller, & Tukey, 1985; Huber, 1981; Staudte & Sheather, 1990; Wilcox, 1996, 1997), standard and nonparametric methods are insufficient and can lead to erroneous conclusions when even small departures

from normality exist (e.g., outliers, skewness, unequal variances) or when there is an association between random variables. Estimators that perform about as well as the sample mean for normal distributions but continue to perform well under departures from normality are provided with robust estimators. Robust estimators utilize a type of trimming so that extreme values are removed when a measure of location is being estimated. The *t*-test is based on the assumption that *t* has a symmetric distribution around zero. However, for nonnormal distributions (even if large), mean and standard deviation are dependent, which can cause the mean of *t* to differ from zero and result in situations of poor control over the probability of a Type I error and poor probability coverage. Unequal variances also contribute to poor power and inaccurate confidence intervals because this condition results in alteration of the variance of the Student's *t* statistic such that it does not approach 1.0. Robust analyses were therefore implemented to prevent small distribution changes from making large changes in power or probability coverage. Classical analyses were provided as well for comparison purposes; however, only robust results were interpreted. The goal was to avoid missing important discriminations in the data because of low power (Type II error) or unequal variances between groups (Type I error). Specifically, robust mean and robust variance estimates were used to calculate robust effect sizes. The interested reader is referred to Wilcox (1997) for a detailed discussion of robust analysis.

Cohen's *d*, which assumes equal variance, was used in the calculation of standard effect sizes for group differences (Cohen, 1988):

$$d_{Cohen} = \left| \frac{\hat{u}_1 - \hat{u}_2}{\hat{\delta}_{pooled}} \right|$$

where $\hat{u}$ is the estimated population mean, and $\hat{\delta}_p ooled$ is the pooled estimated population standard deviation. Tentative interpretive benchmarks for d_{Cohen} are .10 to .30 is a small effect size, .40 to .60 is a medium effect size, and .70 and beyond is a large effect size when there is no prior research to rely on for effect size estimates (Cohen, 1992). Cohen (1988) emphasized the tentative nature of such definitions in a field of inquiry as diverse as behavioral science. For Cohen's *d*, the amount of variance in the dependent variable by membership in the CSA group for a small effect size is 2 to 2.2%, for a medium effect size is 3.8% to 8.3%, and for a large effect size is 10.9% and beyond.

M-estimators, which do not assume equal variances among groups, were used in the analysis of robust effect sizes to control for inflated sample variance, long confidence intervals, and poor power with the following formula:

$$d_{\text{robust}} = \frac{P_{\text{Mest1}} - P_{\text{Mest2}}}{\hat{\xi}_{\text{bi1}}}$$

where P_{Mest} is the robust M-estimator, and is the square root of the biweight midvariance for group 1. M-estimators remove extreme values when estimating a measure of location and trim to achieve evenly tailed distributions (making possible asymmetric trimming or no trimming). For a more detailed discussion of M-estimators see Wilcox (1997).

Cohen's *r* was used to calculate effect sizes for the descriptive variables and qualitative EEG ratings with the formula described by Rosenthal and DiMatteo (2001):

$$r_{Cohen} = \sqrt{\frac{X^2(1)}{N}}$$

Cohen (1992) reports that using *r*, a value of .05 to .148 can be interpreted as a small effect size, a value of .196 to .287 can be interpreted as a medium effect size, and a value of .330 and higher can be interpreted as a large effect size. For Cohen's *r*, the amount of variance in the dependent variable by membership in the CSA group for a small effect size is 2 to 2.2%, for a medium effect size is 3.8% to 8.3%, and for a large effect size is 10.9% and beyond.

Bootstrapping techniques were used to generate robust *p* values, power, and confidence intervals (Beran, 1986; Herrington,

2001; Wilcox, 1997). Bootstrapping techniques treat the sample as if it were the population, resampling from the mean centered scores with replacement to produce new groups of scores to compare. The critical value of the bootstrap test will be obtained from the sample distribution using 500 bootstrap samples. This technique does not assume normality but does assume symmetry to obtain narrow confidence intervals.

RESULTS

Prior to analyzing the data for the separate hypotheses, a Pearson's chi-square analysis was performed on the descriptive variables to assess for differences between the groups. Responses yielded scores of 0 (*no*) or 1 (*yes*) for all but two variables (number of words remembered and reported level of depression) for which Pearson's point biserial correlation was used. Table 3 provides chi-square, degrees of freedom, *p*, and effect size values for the descriptive variables. The groups could be differentiated by large effect sizes on several variables. CSA group membership was associated with having experienced seizures or seizurelike symptoms, past drug abuse, and memory difficulties (as confirmed by remembering fewer words they were asked to remember at the beginning of the interview); experiencing sleep difficulties; experiencing frequent headaches or migraines; and having participated in counseling.

TABLE 3. Chi-square analysis of descriptive variables.

Descriptive Stats	Chi-Square	*df*	*p*	Effect Size
Birth complications	2.509	2	.285	.229
High fevers/Ear infections	2.101	2	.350	.209
Met milestones on time	1.021	2	.600	.146
Repeated a grade in school	2.087	2	.352	.208
Seizure or symptoms of	5.581	2	.061	.341
Prior EEG	1.021	2	.600	.146
Past drug abuse	10.157	2	.006	.460
Past alcohol abuse	2.944	2	.229	.248
Family hx of alcoholism	2.978	2	.226	.249
Memory difficulties	19.664	2	.0001	.64
	point biserial			
Words remembered	−0.4548	6		.207
Episodes of confusion	4.364	2	.113	.300
	point biserial			
Level of reported depression	0.087	12		.008
Family hx of depression	3.136	2	.208	.256
Sleep difficulties	6.047	2	.049	.355
Daytime drowsiness	3.998	2	.136	.288
Bizarre mentation	3.2	2	.202	.258
Headaches/migraines	7.005	2	.030	.382
Past counseling	15.736	2	.0004	.573
Ever arrested	4.639	2	.098	.311
Daily caffeine	1.861	2	.394	.197
Smoker	1.627	2	.443	.184
Use meditation	0.9	2	.638	.137
Exposure to toxic agents	1.282	2	.527	.163
PTSD	4.364	2	.113	.302
High reliability between ec records	4.321	2	.115	.300
Suspected EMG <5 uV incl	2.126	2	.345	.210

Note. EEG = electroencephalogram; hx = history; PTSD = posttraumatic stress disorder; EMG = muscle artifact.

Primary Analyses

The hypotheses addressed differences in right and left hemisphere coherence as defined by average vector length. Specifically, the first hypothesis predicted smaller average vector length distances from the origin in the theta band on the right for the CSA group when compared to the NCSA group. The second hypothesis predicted smaller average vector length distances from the origin in the alpha band on the left for the CSA group when compared to the NCSA group. To test these hypotheses, one-tailed Student's *t* tests were performed. Results did not indicate differences between the groups (Figure 2, Table 4).

Planned Comparisons

To further explore possible differences between the two groups, the pattern of coherence for each of the bands at the level of the individual electrode was examined. Student's *t*-tests were used to accept or reject the null hypothesis that the groups mean vector lengths were equal. Effect sizes in both bands were positive, indicating increased left hemisphere alpha and beta vector length was associated with CSA. Large distances from the origin are indicative of hypocoherence (differentiation).

Figures 3 to 7 provide summaries of the results. Positive effect sizes indicate increased vector length (hypocoherence) for the CSA group in comparison to the NCSA group. Negative effect sizes indicate decreased vector length (hypercoherence) for the CSA group in comparison to the NCSA group. Beginning with the frontal sites shown on Figure 3, it is apparent that a medium positive effect size was obtained for delta at F8, indicating large distances from the origin (hypocoherence) for the CSA group as compared to the NCSA group. Continuing across the head from front to back, Figures 4 and 5 indicate moderate effect sizes in the positive direction (hypocoherence) in the alpha band at F3, F4, T4, and C4. Figure 5 shows moderate effect sizes were also obtained for delta in the negative direction (hypercoherence) at C3, C4, and T5. Continuing toward the posterior sites (Figure 7), results indicate small effect sizes until approaching posterior vertex sites (Figure 8). At PZ, a medium to large effect size in the positive direction for alpha was obtained, indicating large distances from the origin (hypocoherence) for the CSA group as compared to the NCSA group. A medium effect in the positive direction was also seen at PZ for beta and for the cross correlation (all bands collapsed), indicating large distances from the origin (hypocoherence) for the CSA group as compared to the NCSA group.

These results are summarized in Figure 8. The yellow and light orange indicate medium to large effect sizes in the positive direction and light blue indicates medium to large effect sizes in the negative direction. Thus, hypocoherence or decreased connectivity (differentiation) in the CSA group as compared to the NCSA group was apparent on the right frontally in delta, and posteriorly (PZ) in alpha and beta, as well as the cross correlation. Hypercoherence or increased connectivity (redundancy) in the CSA group as compared to the NCSA group was apparent centrally across the motor strip and on the left temporally in delta. Statistical tables containing t statistics, confidence intervals, *p* values, power, means, and effect sizes are available from the first author.

FIGURE 2. Left and right hemisphere effect sizes based on mean distance from the origin for the alpha and theta bands. *Note.* The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.

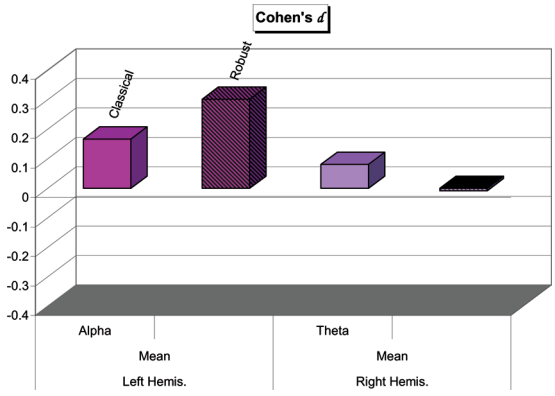


TABLE 4. Classical and robust analyses of mean distance from the origin for NeuroRep NEI's for the left and right hemispheres.

Location	Contrast	Band	Type	One-Tailed	LowerConf	UpperConf	*p*	Power	Mean CSA	Mean NCSA	Cohen's *d*
Left hemisphere	*M*	Alpha	Classical	0.579	−0.034	0.061	.566	0.089	0.534	0.52	0.167
			Robust		−0.02	0.066	.302	0.234	0.544	0.52	0.302
Right hemisphere	*M*	Theta	Classical	0.28	−0.022	0.029	.781	0.059	0.572	0.569	0.081
			Robust		−0.019	0.02	.978	0.076	0.577	0.577	−0.008

Note. Conf = confidence level; CSA = childhood sexual abuse; NCSA = no childhood sexual abuse.

FIGURE 3. Effect sizes based on mean distance from the origin for each band as well as the bands collapsed together (cross-correlation) for sites F1, F2, F7, and F8. *Note*. The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.

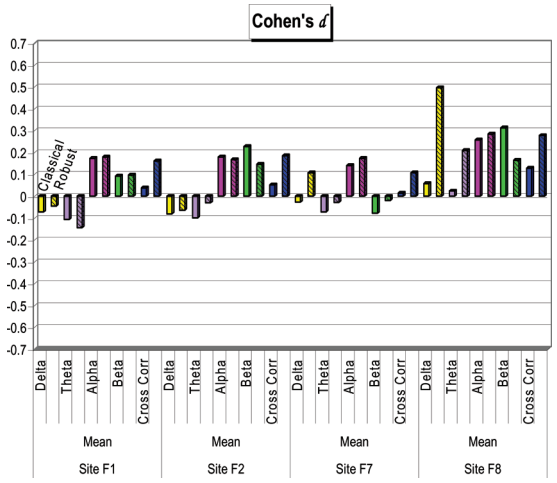
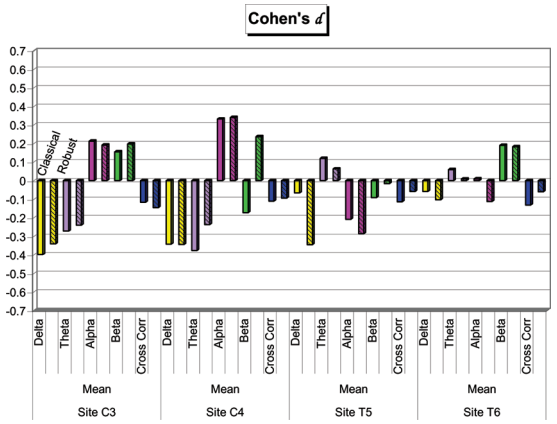


FIGURE 5. Effect sizes based on mean distance from the origin for each band as well as the bands collapsed together (cross-correlation) for sites C3, C4, T5, and T6. *Note*. The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.



DISCUSSION

Earlier research uncovered evidence of damage to subcortical structures of the brain affecting cortical function (Bremner et al., 1997;1993), but no previous studies had NEI methodology to closely identify cortical–cortical intercommunication dysfunction. Our results show a pattern and degree of functional differences between the NCSA group and CSA group across all bands. Despite statistical error ramifications for making more comparisons rather than averaging cortical regions, greater clinical importance was given to gain information related

FIGURE 4. Effect sizes based on mean distance from the origin for each band as well as the bands collapsed together (cross-correlation) for sites F3, F4, T3, and T4. *Note*. The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.

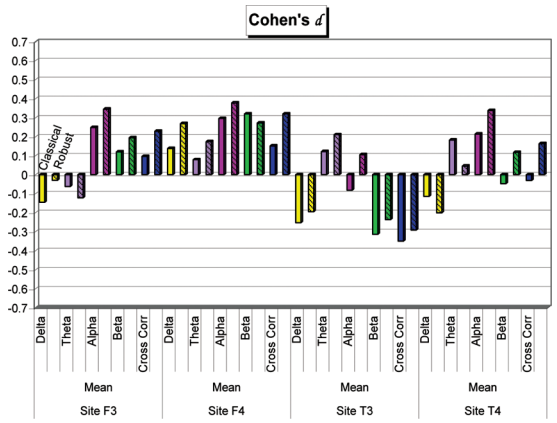


FIGURE 6. Effect sizes based on mean distance from the origin for each band as well as the bands collapsed together (cross-correlation) for sites P3, P4, O1, and O2. *Note*. The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.

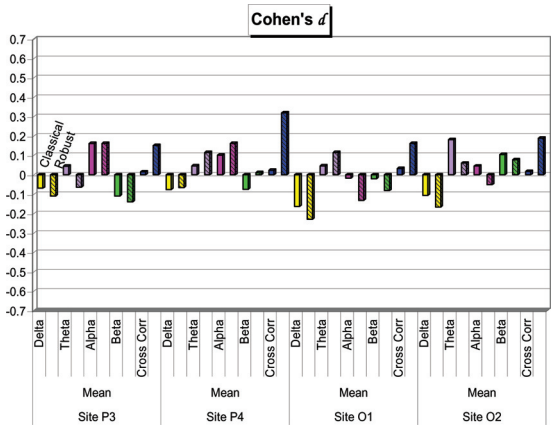
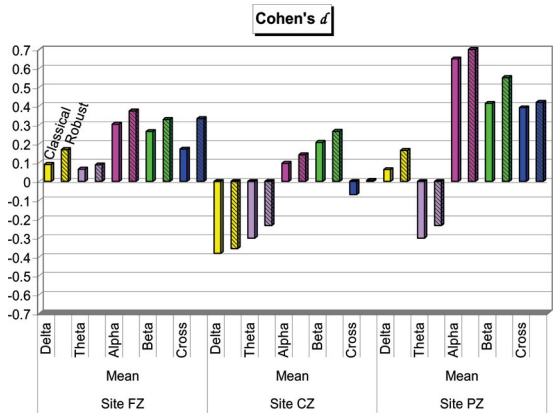


FIGURE 7. Effect sizes based on mean distance from the origin for each band as well as the bands collapsed together (cross-correlation) for sites FZ, CZ, and PZ. *Note*. The plain bars represent classical effect sizes and the hatched bars represent robust effect sizes.

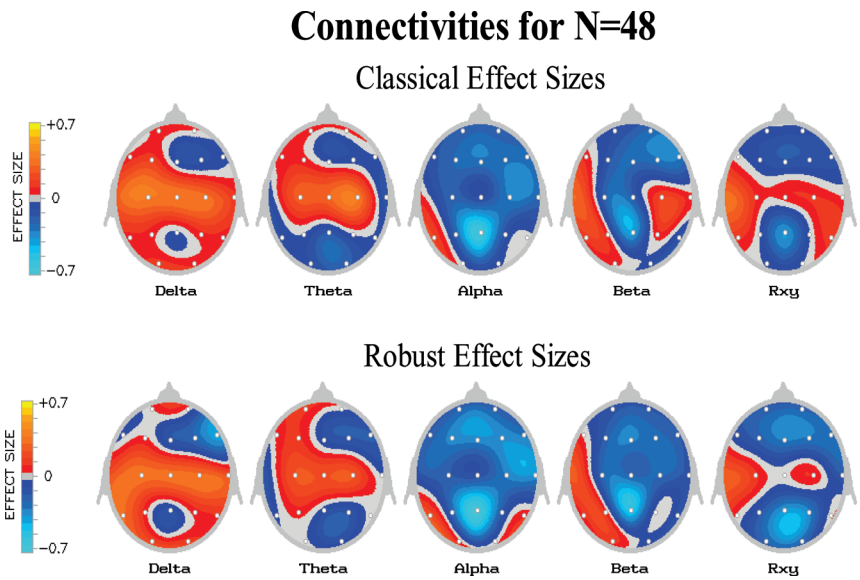


to integration across brain regions as high functioning samples have not before been considered in the CSA QEEG literature. Priority was therefore given to examining whether important differences were missed by limiting evaluation to only one band per hemisphere. This required lenience with regard to Type I/Type II error balance. A fuller evaluation and consideration of medium effect sizes made it possible to see decreased connectivity on the right frontally (F8) in the delta band, frontally (F3, FZ, F4) and centro-temporally on the right (T4, C4) in the alpha band, and posteriorly (PZ) in the alpha and beta bands, as well as in the cross-correlation. Increased connectivity was also evidenced centrally across the motor strip (C3, C4, and CZ) and on the left temporally (T5) in the delta band.

These findings are in contrast to prior findings by Black et al. (2002) of decreased connectivity in left frontal regions in the theta and beta bands and increased connectivity in posterior central regions across all bands in the CSA group as compared to the NCSA group. Thus, a very different picture arises for the nonclinical groups than was obtained for the clinical groups. It may be the obtained differences in results relate to medication effects and lower functionality in the Black et al. findings. Perhaps these findings were derived by chance because of multiple comparisons. It is also possible that our findings describe the functional brain characteristics of resilience in the face of CSA.

If the functions of the regions of the brain are taken into consideration, the CSA

FIGURE 8. Classical and robust effect size topographic maps; Dependent measure—distance from the origin for NeuroRep (Hudspeth, 1999a) neuroelectric images. *Note*. Based on means and standard deviation.



group exhibited decreased connectivity (disconnection) in regions important for communication in combination with increased connectivity (rigidity) in regions important in level of body arousal. The nonclinical CSA group exhibited decreased connectivity (disconnection) in regions important for emotional expression and body arousal. Based on connectivity patterns, we would expect that the NCSA group would have difficulty with emotional expression and/or communication and intact general communication. In contrast, based on connectivity patterns in the clinical group, we would expect some impairment in overall communication. Based on decreased connectivity patterns, we would expect body arousal to be low for the nonclinical group but heightened for the clinical group because of increased connectivity patterns. Thus, resilience in the high-functioning, nonclinical group may relate to the ability to avoid or disconnect from emotionally laden expression and to maintain a low level of body arousal.

This functional description of the clinical CSA group based on connectivity patterns is consistent with the neuropsychological literature that shows poorer verbal than performance IQ scores (Ito et al., 1993) for a clinical CSA group, and heightened physical (heart rate responses) and emotional arousal for a CSA group with PTSD versus CSA without PTSD during the recall of sexual trauma (Shin et al., 1999).

A concern in this data analysis is that of *p* value significance. In reaction to much debate over the past decade about overreliance on statistical significance (Borenstein, 1997; Kirk, 1996)as well as recommendations issued by the American Psychological Association Task Force on Statistical Inference (see Thompson, 2002, for review), statistical significance was not relied on as the determining factor for the interpretations made in this study. Instead, effect sizes were used to characterize the degree to which the CSA group diverged from the NCSA group to highlight clinical significance. Because effect sizes have not been reported in prior coherence research with CSA, it was not known how best to interpret these effects, so Cohen's benchmarks for effect size interpretation were used (e.g., for d_{Cohen} .4–.6 = a medium effect size, for r_{Cohen} .196–.287 = medium effect size). It is hoped the effect sizes reported here will serve as a starting point for future research to provide meaningful understandings of these effect sizes as they relate to CSA.

Beyond effect sizes, power was taken into account in interpretation of results. Low power served to prevent statistically significant *p* values despite moderate effect sizes. However, this was a time intensive study (6–8 hr of testing with each participant) with a small number of participants because of rigid exclusion criteria. Although power was compromised because of low total sample size, the value of gaining a purer look at physiological and psychological underpinnings of CSA without the mask of medications was gained. The rigid exclusion criteria used may have biased the sample toward CSA participants who have developed resilience. A methodological study by Clark-Carter (1997) found that researchers typically do not consider power in their analyses and run a high risk of Type II error, resulting in decreased recognition of interesting effects. In addition, given the low power evident partly as a result of the small sample size, it did not make sense to adjust for multiple contrasts. Therefore, effect sizes are considered a summarization of the data providing information about the degree to which CSA impacted the variable.

In addition, a model has been presented for working with coherence data in a statistically modern and parsimonious way. As this study is one of the first attempts to examine the impact of CSA on cortical integration in high-functioning adults, it provides a starting point for future research, suggesting important differences exist. A representative sample of the statistical code required to run these coherence analyses can be requested from the first author for the purpose of future replication. Finally, values representing distance from the origin were used in this analysis as this was determined to provide the most comparable way to view the data with prior research. However, the data could be analyzed in terms of interelectrode differences with some minor changes in the

statistical code. A representative sample of the statistical code required to run such a comparison can also be requested from the first author.

The first aim of this study was to describe in detail the methodology behind the QEEG-based neuroelectric coherence measure developed by Hudspeth (1994–2004a).The challenge for the clinician utilizing QEEG measures and interventions is how to interpret findings when different measures produce differing results. Research suggests increased accuracy for EEG bivariate coherence estimates of near neighbor sites but increased chance for erroneous conclusions when comparing more distant sites (Kus et al., 2004; Liberati et al., 1997) and increased overall accuracy for multivariate estimates of coherence in comparison to bivariate estimates of coherence (Kus et al., 2004). Hudspeth's (1999–2004a) NEIs in the NeuroRep QEEG analysis software, provide a multivariate measure of EEG coherence that takes into account the full spatio-temporal nature of continuous time series brain data. The clinician should consider the QEEG analysis as part of an evaluation that also includes background information, behavioral observation, other psychological testing, symptom checklists, and an understanding of the limits of the results obtained by the various measures. Future research could compare the various coherence measurement techniques in a human sample with behavioral validation provided from a functional brain region symptom checklist and neuropsychological testing.

REFERENCES

Anderson, C. W., Stolz, E. A., & Shamsunder, S. (1998). Multivariate autoregressive models for classification of spontaneous electroencephalogram during mental tasks. *IEEE Transactions on Bio-Medical Engineering*, *45*(3), 277–286.

Arnold, M., Miltner, W. H. R., Bauer, R., & Braun, C. (1998). Adaptive AR modeling of nonstationary time series by means of Kalman filtering. *IEEE Transactions on Bio-Medical Engineering*, *45*(5), 553–562.

Barry, R. J., Clarke, A. R., McCarthy, R., & Selikowitz, M. (2005). Adjusting EEG coherence for inter-electrode distance effects: An exploration in normal children. *International Journal of Psychophysiology*, *55*, 313–321.

Beran, R. (1986). Simulated power functions. *The Annals of Statistics*, *14*(1), 151–173.

Birkes, D. & Dodge, Y. (1993). *Alternative methods of regression*. New York: Wiley.

Black, L. M., Hudspeth, W. J., Townsend, A. L., & Bodenhamer-Davis, E. (2002, October). *Effects of childhood sexual abuse on adult brain plasticity as measured by quantitative electroencephalogram*. Oral presentation at the Society for Neuronal Regulation Annual Conference, Scottsdale, AZ.

Blake, D., Weathers, F., Nagy, L., Kaloupek, D., Klauminzer, G., Charney, D., et al. (2000). *Instruction manual: National Center for PTSD Clinician-Administered PTSD Scale (CAPS)*. Boston: National Center for Posttraumatic Stress Disorder.

Borenstein, M. (1997). Hypothesis testing and effect size estimation in clinical trials. *Annals of Allergy, Asthma, and Immunology*, *78*, 5–16.

Brazier, M. A. B. & Casby, J. U. (1951). An application of the M.I.T. digital electronic correlator to a problem in EEG: The EEG during mental calculation. *Electroencephalograpy and Clinical Neurophysiology*, *3*, 375.

Bremner, J. D., Scott, T. M., Delaney, R. C., Southwick, S. M., Mason, J. W., Johnson, D. R., Innis, R. B., McCarthy, G., & Charney, D. S. (1993). Deficits in short-term memory in post-traumatic stress disorder. *American Journal of Psychiatry*, *150*, 1015–1019.

Bremner, J. D., Randall, P., Vermetten, E., Staib, L., Bronen, R. A., Mazure, C., Capelli, S., McCarthy, G., Innis, R. B., & Charney, D. S. (1997). Magnetic resonance imaging-based measurement of hippocampal volume in posttraumatic stress disorder related to childhood physical and sexual abuse—A preliminary report. *Biological Psychiatry*, *41*, 23–32.

Butcher, J. N., Dahlstrom, W. G., Graham, J. R., Tellegen, A., & Kaemmer, B. (1989). *MMPI-2 (Minnesota Multiphasic Inventory-2): Manual for administration and scoring*. Minneapolis: University of Minnesota Press.

Clark-Carter, D. (1997). The account taken of statistical power in research published in the British Journal of Psychology. *British Journal of Psychology*, *88*, 71–83.

Clarke, A. R., Barry, R. J., McCarthy, R., Johnstone, S. J., Abbott, I., Croft, R. J., et al. (2005). Effects of methylphenidate on EEG coherence in Attention-Deficit/Hyperactivity Disorder. *International Journal of Psychophysiology*, *58*(1), 4–11.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences,* (2nd ed). Hillsdale, NJ: Erlbaum.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*, 155–159.

Fisch, B. J. (1999). *Fisch and Spehlmann's EEG primer: Basic principles of digital and analog EEG* (3rd ed.). Amsterdam: Elsevier.

Friston, K. J., Frith, C. D., Liddle, P. F., & Frackowiak, R. S. J. (1993). Functional connectivity: The principal component analysis of large (PET) data sets. *Journal of Cerebral Blood Flow Metaboism*, *13*, 5–14.

Gallot, S., Hulin, D., & Lafontaine, J. (2004). *Riemannian geometry (*3rd ed.*)*. Berlin: Universitext, Springer-Verlag.

Guevara, M. A. & Corsi-Cabrera, M. (1996). EEG coherence or EEG correlation?. *International Journal of Psychophysiology*, *23*, 145–153.

Hammond, D. C. & Gunkelman, J. (2001) *The art of artifacting*. (Available from the International Society for Neurofeedback & Research Web site: http://www.isnr.org/cart/Details.cfm?ProdID=97&category=4)

Hampel, F. R., Ronchetti, E. M., Rousseeuw, P. J., & Stahel, W. A. (1986). *Robust statistics: The approach based on influence functions*. New York: Wiley.

Harmony, T., Fernandez, T., Rodriguez, M., Reyes, A., Marosi, E., & Bernal, J. (1993). Test-retest reliability of EEG spectral parameters during cognitive tasks: II coherence. *International Journal of Neuroscience*, *68*, 263–271.

Harner, R. N. (1990). Singular value decomposition—A general linear model for analysis of multivariate structure in the electroencephalogram. *Brain Topography*, *3*, 43–47.

Harner, R. N. & Riggio, S. (1989). Application of singular value decomposition to topographic analysis of flash-evoked potentials. *Brain Topography*, *2*, 91–98.

Herrington, R. S. (2001). *Simulating statistical power curves using robust estimation and the Bootstrap*. Unpublished doctoral dissertation, University of North Texas, Denton.

Hoaglin, D. C., Mosteller, F., & Tukey, J. W. (1985). *Exploring data tables, trends, and shapes*. New York: Wiley.

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology*, *24*, 417–441.

Huber, P. (1981). *Robust statistics*. New York: Wiley.

Hudspeth, W. J. (1985). Developmental neuropsychology: Functional implications of quantitative EEG maturation [Abstract]. *Journal of Clinical and Experimental Neuropsychology*, *7*, 606.

Hudspeth, W. J. (1993). Neuroelectric eigenstructures of mental representation. In D. S. Levine & M. Aparicio IV (Eds.), *Neural networks for knowledge representation and inference* (pp. 420–446). Hillsdale, NJ: Erlbaum.

Hudspeth, W. J. (1994–2004a). *NeuroRep: The qEEG analysis and report system* [Computer software]. Los Osos, CA: Grey Matter.

Hudspeth, W. J. (1994–2004b). *Adult qEEG reference database*. Los Osos, CA: Grey Matter.

Hughes, J. R. & John, E. R. (1999). Conventional and quantitative electroencephalography in psychiatry. *Journal of Neuropsychiatry & Clinical Neuroscience*, *11*(2), 190–208.

Ito, Y., Teicher, M. H., Glod, C. A., & Ackerman, E. (1998). Preliminary evidence for aberrant cortical development in abused children: A quantitative EEG study. *The Journal of Neuropsychiatry and Clinical Neurosciences*, *10*, 298–307.

Ito, Y., Teicher, M. H., Glod, C. A., Harper, D., Magnus, E., & Gelbard, H. A. (1993). Increased prevalence of electrophysiological abnormalities in children with psychological, physical, and sexual abuse. *The Journal of Neuropsychiatry and Clinical Neurosciences*, *5*, 401–408.

Jasper, H. H. (1958). The ten-twenty electrode system of the International Federation. *Electroencephalography and Clinical Neurophysiology*, *10*, 371–375.

John, E. R., Ahn, H., Prichep, L., Trepetin, M., Brown, D., & Kaye, H. (1980). Developmental equations for the electroencephalogram. *Science*, *210*, 1255–1258.

John, E. R., Prichep, L. S., Fridman, J., & Easton, P. (1988). Neurometrics: Computer-assisted differential diagnosis of brain dysfunctions. *Science*, *239*, 162–169.

John, E. R., Ruchkin, K. S., & Villegas, J. (1964). Experimental background: Signal analysis and behavioral correlates of evoked potential configuration in cats. *Annals of the New York Academy of Sciences*, *112*, 362–420.

Keane, T. M., Malloy, P. F., & Fairbank, J. A. (1984). Empirical development of an MMPI subscale for the assessment of combat-related post-traumatic stress disorder. *Journal of Consulting and Clinical Psychology*, *52*, 888–891.

Kirk, R. E. (1996). Practical significance: A concept whose time has come. *Educational and Psychological Measurement*, *56*(5), 746–759.

Knott, V. J., LaBelle, A., Jones, B., & Mahoney, C. (2002). EEG coherence following acute and chronic clozapine in treatment-resistant schizophrenics. *Experimental and Clinical Psychopharmacology*, *10*(4), 435–444.

Kus, R., Kaminski, M., & Blinowska, K. J. (2004). Determination of EEG activity propagation: Pair-wise versus multichannel estimate. *IEEE Transactions on Bio-Medical Engineering*, *51*(9), 1501–1510.

Liberati, D., Cursi, M., Locatelli, T., Comi, G., & Cerutti, S. (1997). Total and partial coherence

analysis of spontaneous and evoked EEG by mean of multi-variable autoregressive processing. *Medical and Biological Engineering and Computing*, *35*, 124–130.

Marosi, E., Harmony, T., Sanchez, L., Becker, J., Bernal, J., Reyes, A., et al. (1992). Maturation of the coherence of EEG activity in normal and learning-disabled children. *Electroencephalography and Clinical Neurophysiology*, *83*, 350–357.

Martin, J. H., Brust, J. C., & Hilal, S. (1991). Imaging the living brain. In E. R. Kandel, J. H. Schwartz, & T. M. Jessell (Eds.), *Principles of neural science* 3rd ed., (pp. 309–324). New York: Elsevier.

Moller, E., Schack, B., Arnold, M., & Witte, H. (2001). Instantaneous multivariate EEG coherence analysis by means of adaptive high-dimensional autoregressive models. *Journal of Neuroscience Methods*, *105*(2), 143–158.

Nagy, L. M., Blake, D. D., Schnurr, P., Southwick, S. M., Charney, D., Weathers, F., et al. (1999). *The Clinician-Administered PTSD Scale—Weekly Version (CAPS-2): Reliability and validity*. Manuscript submitted for publication.

Nunez, P. L., Srinivasan, R., Westdorp, A. F. F., Wijesinghe, R. S., Tucker, D. M., Silberstein, R. B., et al. (1997). EEG coherency I: Statistics, reference electrode, volume conduction, laplacians, cortical imaging and interpretation at multiple scales. *Electroencephalography and Clinical Neurophysiology*, *103*, 499–515.

Otnes, R. K. & Enochson, L. (1972). *Digital time series analysis*. New York: Wiley & Sons.

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 559–572.

Prichep, L. S. & John, E. R. (1992). QEEG profiles of psychiatric disorders. *Brain Topography*, *4*(4), 249–257.

Reiterer, S., Hemmelmann, C., Rappelsberger, P., & Berger, M. (2005). Characteristic functional networks in high- versus low-proficiency second language speakers detected also during native language processing: An explorative EEG coherence study in 6 frequency bands. *Cognitive Brain Research*, *25*(2), 566–578.

Rosenthal, R. & DiMatteo, M. R. (2001). Meta-analysis: Recent developments in quantitative methods for literature reviews. *Annual Review of Psychology*, *52*, 59–82.

Sauseng, P., Klimesch, W., Schabus, M., & Doppelmayr, M. (2005). Fronto-parietal EEG coherence in theta and upper alpha reflect central executive functions of working memory. *International Journal of Psychophysiology*, *57*(2), 97–103.

Schack, B., Chen, A. C. N., Mescha, S., & Witte, H. (1999). Instantaneous EEG coherence analysis during the Stroop task. *Clinical Neurophysiology*, *110*, 1410–1426.

Schlenger, W. E., & Kulka, R. A. (1989). *PTSD scale development for the MMPI–2*. Research Triangle Park, N.C.: Research Triangle Institute.

Shin, L. M., McNally, R. J., Kosslyn, S. M., Thompson, W. L., Rauch, S. L., Alpert, N. M., et al. (1999). Regional cerebral blood flow during script-driven imagery in childhood sexual abuse-related PTSD: A PET investigation. *American Journal of Psychiatry*, *156*(4), 575–584.

Sritharan, A., Sergejew, A., Silberstin, R., Egan, G., & Copolov, D. (2005). EEG coherence measures during auditory hallucinations in schizophrenia. *Psychiatry Research*, *132*(2–3), 189–200.

Staudte, R. G. & Sheather, S. J. (1990). *Robust estimation and testing*. New York: Wiley.

Suffin, S. C. & Emory, W. H. (1995). Neurometric subgroups in attentional and affective disorders and teir association with pharmacotherapeutic outcome. *Clinical Electroencephalography*, *26*(2), 76–84.

Suffin, S. C. & Emory, W. H. (1996). Neurometric classifiers and response to medicine. *Syllabus and Proceedings Summary, American Psychiatric Association 1996 Annual Meeting*, 87–88.

Teicher, M. H., Glod, C. A., Surrey, J., & Swett, C. (1993). Early childhood abuse and limbic system ratings in adult psychiatric outpatients. *The Journal of Neuropsychiatry and Clinical Neurosciences*, *5*, 301–306.

Thatcher, R. W. (1992). Cyclic cortical reorganization during early childhood. *Brain and Cognition*, *20*, 24–50.

Thatcher, R. W., Krause, P. J., & Hrybyk, M. (1987). Cortico-cortical associations and EEG coherence: A two-compartmental model. *Electroencephalography and Clinical Neurophysiology*, *64*, 123–143.

Thompson, B. (2002). What future quantitative social science research could look like: Confidence intervals for effect sizes. *Educational Research*, 25–32.

Thornton, K. (2003). The electrophysiological effects of a brain injury on auditory memory functioning: The QEEG correlates of impaired memory. *Archives of Clinical Neuropsychology*, *18*(4), 363–378.

Townsend, A. L., Black, L. M., & Bodenhamer-Davis, E. M. (2001, October). *qEEG and MMPI-2 patterns of adults with a history of childhood sexual abuse*. Poster presented at the Society for Neuronal Regulation annual conference, Monterrey, CA.

Valdes-Sosa, P. A. (2004). Spatio-temporal autoregressive models deined over brain manifolds. *Neuroinformatics*, *2*(2), 239–250.

van Ball, G. C. M., van Beijsterveldt, C. E. M., Molenaar, P. C. M., Boomsma, D. I., & de Geus, E. J. C. (2001). A genetic perspective on the developing brain: Electrophysiological indices of neural functioning in young and adolescent twins. *European Psychologist*, *6*(4), 254–263.

Weathers, F. W., Ruscio, A. M., & Keane, T. M. (1999). Psychometric properties of nine scoring rules for the Clinician-Administered Posttraumatic Stress Disorder Scale. *Psychological Assessment*, *11*, 124–133.

Wechsler, D. (1999). *Wechsler Abbreviated Scale of Intelligence*. San Antonio, TX: Psychological Corporation.

Wilcox, R. R. (1996). *Statistics for the social sciences*. San Diego, CA: Academic Press.

Wilcox, R. R. (1997). *Introduction to robust estimation and hypothesis testing*. San Diego, CA: Academic Press.

Wilcox, R. R. (1998). How many discoveries have been lost by ignoring modern statistical methods? *American Psychologist*, *53*(3), 300–314.