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Some Methods for Dynamic Analysis of the Scalp Recorded EEG

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Summary: This paper describes methods for quantifying the spatiotemporal dynamics of EEG. Development of these methods was motivated watching computer-generated animations of EEG voltage records. These animations contain a wealth of information about the pattern of cha across time in the voltages observed across the surface of the scalp. In an effort to quantify this pattern of changing voltages, we elected to extra single quantifiable feature from each measurement epoch, the highest squared voltage among the various electrode sites. Nineteen channels of were collected from subjects using an electrode cap with standard 10-20 system placements. Two minute records were obtained. Each record sampled at a rate of 200 per second. Thirty seconds of artifact-free data were extracted from each 2 minute record. An algorithm then determ the location of the channel with the greatest amplitude for each 5 msec sampling epoch. We quantified these spatio-temporal dynamics as scal vectors and cluster analytic plots of EEG activity for finger tapping, cognitive effort (counting backwards) and relaxation to illustrate the utility techniques.

Key words: EEG; Cluster analysis; Vector; Scalar; MATLAB.

Introduction

In recent years some of the most promising advances in the study of brain/behavior relationships have come from an increase in the power of imaging techniques (e.g., PET, MRI, EEG) that can be used to correlate human brain activity with cognitive, emotional and behavioral processes. Of these, the recording of brain electrical activity (EEG or event-related potentials), though the oldest method, has benefitted as much as the others form the availability of powerful computational platforms. For example, Paul Nunez and others, reviewed by Nunez (1995), have been able to increase the spatial resolution and determine phase relationships among EEG placements by using Laplacian mappings. Furthermore, Nunez has related EEG mappings to linear and non-linear systems. Similar advances have been made for ERP analyses by Alan Gevins, who has developed covariance patterns among experimentally isolated ERP events (Gevins and Cu 1995). Such mappings, produced by lines conne covariant ERPs, were shown to differ systematicall a function of fatigue during performance orl memory task.

At present, the major measures of brain elect activity have one advantage over other im niques -- that is, their potential for temporal resolut This potential is just beginning to be realized. Tucker, also using ERPs, has shown that a visual evokes a positive occipital response (at approximat 100 msec) and then a second occipital wave form "reprise" (at approximately 300 msec) (Tucker et al. 1 Tucker et al. 1995). Using EEG recordings, That (1994) has traced the development of coherence pat in children, and Lehmann (1990) showed that, in absence of external stimulation, patterns of brain ele cal activity appear to remain stable, on the average about 200 msec and then change fairly abrupt to a w pattern. Such dynamical analyses of successi of b electrical microstates open a whole new vista ing brain/behavior relationships. Bressler (1994) taken advantage of these new possibilities in deline portraits of intracerebral synchronization and h synchronizations vary over 80 and 240 msec perio activity.

Advances in computer technology have enab our laboratory and others (e.g., Tucker et al. 1994) generate animations of changing voltages acros array of electrodes over time. However, as not

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Tucker et al. (1994) these "animations tax computational resources and pose new challenges for scientific communication" (p. 151). Currently, the only technique available for reporting findings based on these animations is to present a series of static images of the scalp surface which represent the locations of peak activity at different points in time. However, this method does not provide a quantifiable means by which data obtained under different task conditions can be compared. Therefore, we have attempted to develop a way of quantifying the spatiotemporal dynamics of the EEG. The approach reported in this paper is based on mapping changes in the location of a single feature of each measurement epoch across time, the highest squared voltage. This approach retains the excellent temporal resolution available in EEG, while focusing attention in the spatial domain on one electrode location per measurement epoch.

Initial representations of the "path" of the highest squared voltage indicated that the location of this feature changed rapidly (over 50 times per second). Our term for a change in the location of the highest squared voltage was a "switch". The "path" of the highest squared voltage over time was thus called the "switching" pattern, and the number of changes in location per second became known as the "switching rate". However, it quickly became clear that our use of the term switching was misleading, because it carried the clear implication that a change in location of the highest squared voltage reflected the controlled movement of a signal from one location within the brain to another. Other laboratories have noted this problem in interpreting information regarding changes in EEG activity over time. For example, Tucker et al. (1994) state that "Interpreting the shift in the N1 as actual movement of the electrical field could of course be misleading; sequential negativities over different regions could produce apparent motion" (pp 141-142).

In order to avoid the implication that changes in the location of the single highest squared voltage reflect the presence of a continuous wave across the scalp, we chose the term recrudescence as a label for changes in the location of the highest squared voltage, rather than the term "switching". The term recrudescence, of medical origin, describes a sequence of phenomena in which a phenomenon "pops up" but does not directly "cause" the phenomenon to appear at another location at a later point in time. Our use of this term emphasizes the "pop up" aspect of its meaning.

This paper describes two methods by which patterns of recrudescence can be depicted graphically. We also demonstrate the use of a statistical technique known as Cluster Analysis in representing the spatiotemporal dynamics of the EEG. The goal of all three methods is to provide measures of changing EEG voltage patterns that can be used in comparisons of different groups of subjects and different task conditions as well as in replications of work done in other laboratories.

Methods

Data Acquisition

EEG data were collected using 20 Grass M[illegible] P5 A.C. preamplifiers feeding into a pc 486 computer by way of two 16-channel A/D converters. Ten channels of each converter were involved in data acquisition. EEG data were sampled at a rate of 200 per second for 120 seconds. Data acquisition and processing are controlled by BrainScope, an in-house software package. Electrodes were placed on the scalp using a standard 10-20 system with an EEG cap (Electro-Cap International, Eaton, Ohio) referred to both ears. Channel 20 is used to monitor eye movements for later artifact identification and removal and does not enter further into the data analysis. Data sets are 30 second portions of the original 2 minute record, converted from binary to ASCII format and transferred to a Silicon Graphics workstation for analysis. Data sets are arranged in a matrix in which each of the 19 channels is represented by a different row. Each of the 200 per second sample epochs is represented as a column in the data matrix. All algorithms used to calculate rate of change and to complete the graphical representations are written as MATLAB functions.

The methods presented in this paper are based on an algorithm which detects and records the maximum value and location (row) of the squared voltages for each 5 msec epoch within the data matrix. The program then tracks the changes in the location of maximum amplitude between EEG channels and between successive sampling epochs. Finally, the changes in location are drawn onto a circular figure, which represents a simulated scalp EEG mapping surface. Data were collected during three conditions, all with eyes closed. The conditions were: Relaxation (baseline), Counting backwards fro[illegible] by threes, and right and left Finger tapping. Relax[illegible]n and Counting backwards resulted in the most in[illegible]rmative use of our analyses, so only results from these conditions are presented in this report. In general, we have found other techniques, such as coherence plots, to [illegible] more useful in plotting brain electrical activity coordinate with behavior, while our dynamic analyses show promise in plotting brain electrical activity in subjectively experienced states.

We examined our records over the whole range of frequencies and separately for the theta, alpha, beta and gamma ranges. When we checked the gamma (40 Hz) range plots against plots of 50-70 Hz and even against the 70-90 Hz range, we were unable to discern any difference. Therefore, these plots are not presented, as we could not comfortably assume that our gamma range recordings were free from muscle artifact.

Rates of Recrudescence

Rates of change of maximum amplitude between various electrode locations were obtained using an algorithm that searches and detects the maximum value of the voltage for each epoch in the data set. As this value is detected, the channel number containing that voltage is stored. The rate of recrudescence (appearance or reappearance of maximum amplitude in a different location) is then calculated as the number of changes in location of maximal voltage across successive epochs, divided by the total duration (in seconds) of the recording. As an example, assume that the data set contains 5000 sampling epochs. The algorithm would, therefore, record the maximum squared voltage and its location for each of the 5000 epochs. It would then count the number of successive epochs for which the location of the maximum squared voltage changed. Suppose that this was 300. Since 5000 samples at 200 samples per second represents 30 seconds of recording, the rate of recrudescence would be 300 divided by 30 seconds for a recrudescence rate of 100 per second.

Scalar Representation of the Distribution of Recrudescence

Changes in location of peak amplitude across successive 5 msec samples taken during a 30 sec record are represented by lines (scalars) connecting any two electrode locations. These locations are plotted on a circular diagram representing the approximate locations of the electrodes on the scalp. As the maximum amplitude recurs between two locations, the line between those locations is drawn thicker. Thus the lines connecting electrode locations show that the most frequent joint sequence of maximum amplitude activity becomes denser.

Vectorial Representation of the Spatial Distribution of Recrudescence

The scalar lines connecting the points of maximum amplitude depict the successive points of maximum EEG amplitude, but do not provide information regarding the direction in which recrudescence is operating. For example, frequent recrudescence between F2 and T4 does not distinguish between a voltage peak at F2 followed by one at T4 and the reverse, a voltage peak at T4 followed by a peak at F2. As the utility of the dynamic analysis is explored, we hope that an underlying process that directs the rapid changes in the location of amplitude will be discovered. As a first step in such an exploration, a vector representation is constructed which provides a surface view of the direction of movement of recrudescent maximum amplitude points. The purpose of the vectorial display is to provide a graphic depiction of quantitative indices of directionality in recrudescence between electrode sites.

The display is based on a 19x19 matrix in which rows are the 19 locations at any one epoch, and the columns are the same 19 locations at the next recorded epoch. Cells along the diagonal indicate no change in location of maximal voltage between successive 5 msec epochs. Within this matrix, we simply count the number of successive epochs in which maximum voltage changed from one electrode to another. The total number of such occurrences are tabulated in each cell of the matrix. Therefore, the matrix constitutes a frequency distribution of directionally specific recrudescent activity between electrode locations. This frequency distribution is represented as a contour diagram, which accompanies each frequency matrix.

Statistical Analysis of Changing Voltage Patterns

Cluster analysis is a statistical technique that groups cases together on the basis of similar profiles of variables. Cluster analysis has been used in the context of EEG research to assign individual subjects to clusters on the basis of variables derived from one or more EEG sessions (e.g., John et al. 1992) or to assign segments of EEG to clusters (e.g., Friedman and Jones 1984). In this paper, we use cluster analysis to assign each "measurement epoch" to one of two clusters or profiles on the basis of the pattern of 19 voltages obtained at each epoch. The goal of these analyses was simultaneously to take information from all electrodes into account and to categorize the patterns of voltage changes over time. We chose two clusters to represent the pattern of unsquared voltage change -- that is, maxima and minima -- over time not just the voltage of a single electrode (highest squared voltage) that was used to describe recrudescence. This allowed the analysis to determine differences between two clusters with regard to the sign of the voltage (that is, positive or negative deflection from baseline). The pattern of changes from one cluster assignment to another over time could thus provide information about the type of psychological activity (e.g., relaxation versus cognitive effort) during those portions of the record.

Two separate cluster analyses were conducted, with twenty second records of unfiltered EEG obtained from

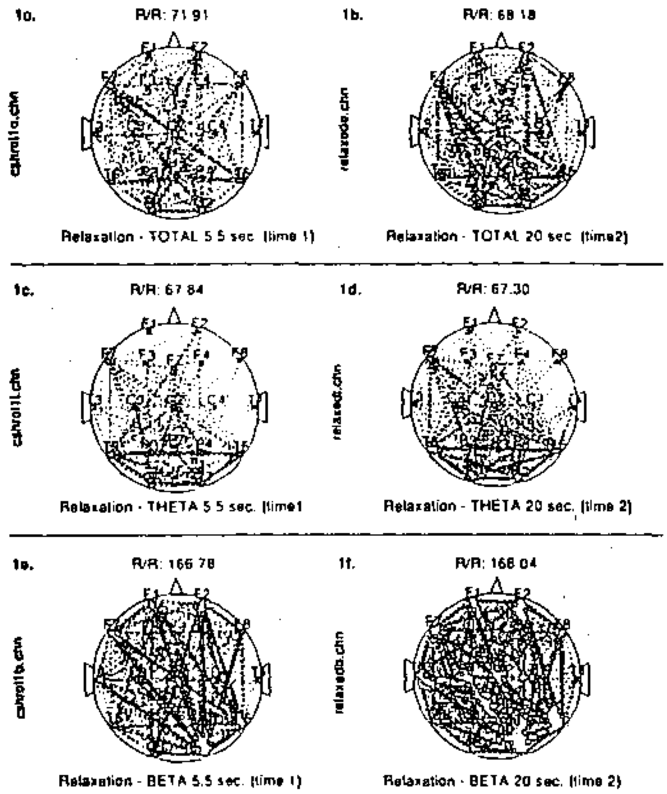

Figure 1. Scalar representation of two different portions (early and late) and two data set lengths (5.5 and 20.0 secs.) of the baseline condition: Figure 1a and 1b, total; 1c and 1d, theta; and 1e and 1f, beta.

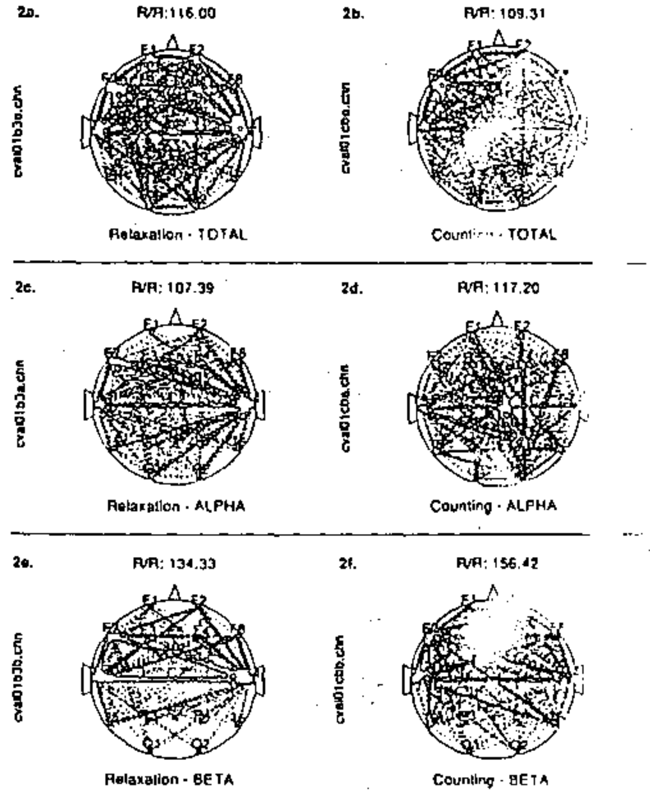

Figure 2 (a-f). Scalar representations of recrudesce Total, alpha and beta EEG during resting and co backwards.

both the Counting and Baseline conditions using the cluster procedure available from SPSS (Statistical Package for the Social Sciences). Epochs in both conditions were assigned to one of two clusters.

Results

Within-Record Replication

The stability of our scalar and vector representations with respect to the location of the epochs is presented in figure 1, which shows scalar representations of one subject's data from different portions (early and late) and two data set lengths (5.5 and 20.0 sec) of the resting (baseline) condition. Figures 1a and 1b represent total EEG; figures 1c and 1d represent theta; and figures 1e and 1f represent beta activity. Alpha activity gave identical results, emphasizing the occipital region and is not presented to conserve space. Note the consistency in the overall pattern of scalar representation as well as the similarity in recrudescence rate as both data set length and position in the record are changed. The only noticeable differ that, as expected, the tracings are darker in the records. Vector plots also showed this stability samples taken at different times and within fre bands.

Scalar Plots of Counting Experiment

Representations of the location and amount o descence during relaxation and counting backwar ditions are presented in figure 2 (a-f). For to recrudescence rates for relaxation and countin wards conditions were 116 and 109 per second, tively.

Of interest in these plots are differenes betw relaxation and counting conditions in the overall of recrudescence among electrode locations. N ticularly the "triangular" pattern among F7, T3 total EEG. In the alpha band, the pattern ch more scattered recrudescence with a strong pat

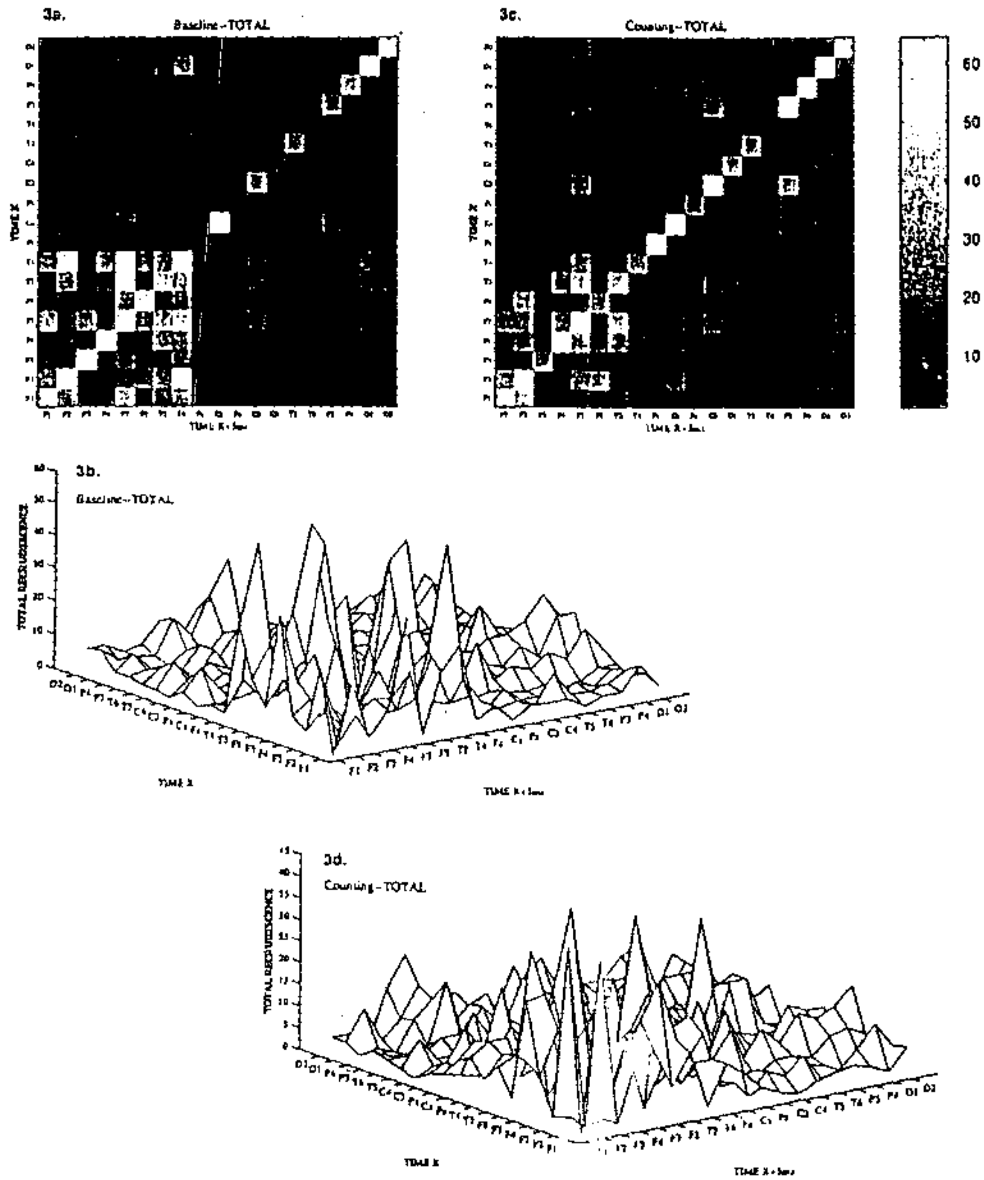

Figure 3. Matrix and mean vector (contour) plots of recrudescence corresponding to the scalar representations of fi… 2a and 2b. Baseline, 3a and 3b; Counting, 3c and 3d.

tween right posterior and frontal areas (for example, between O2 and F1). In the beta frequency band, the original triangular pattern in the resting condition spreads to include other frontal locations during counting.

Vector Representations of Counting Experiment

Matrix and mesh vector (contour) plots of recrudescence corresponding to the scalar representations of figure 2 are presented in figures 3 and 4. The highest values in the matrix are often on the diagonal formed from the lower left to the upper right of the matrix representations of recrudescence. This indicates that most frequently there is no recrudescence between adjacent 5 msec … occurs. For the contour plots the diagonals have … suppressed (set to zero) so that patterns created by recrudescence will be more apparent.

Figure 3 (a-d) presents graphs of total EEG d… baseline and counting conditions and transforms th… in figure 2 to represent the direction of change in … mum amplitude between pairs of electrode loc… The representation on the top is the matrix di… whereas the one on the bottom represents a two-… sional frequency histogram (contour plot) of the … data. The diagonal which runs from the lower left … to the upper right corner serves as a reference for … the matrix representations. Symmetry about t…

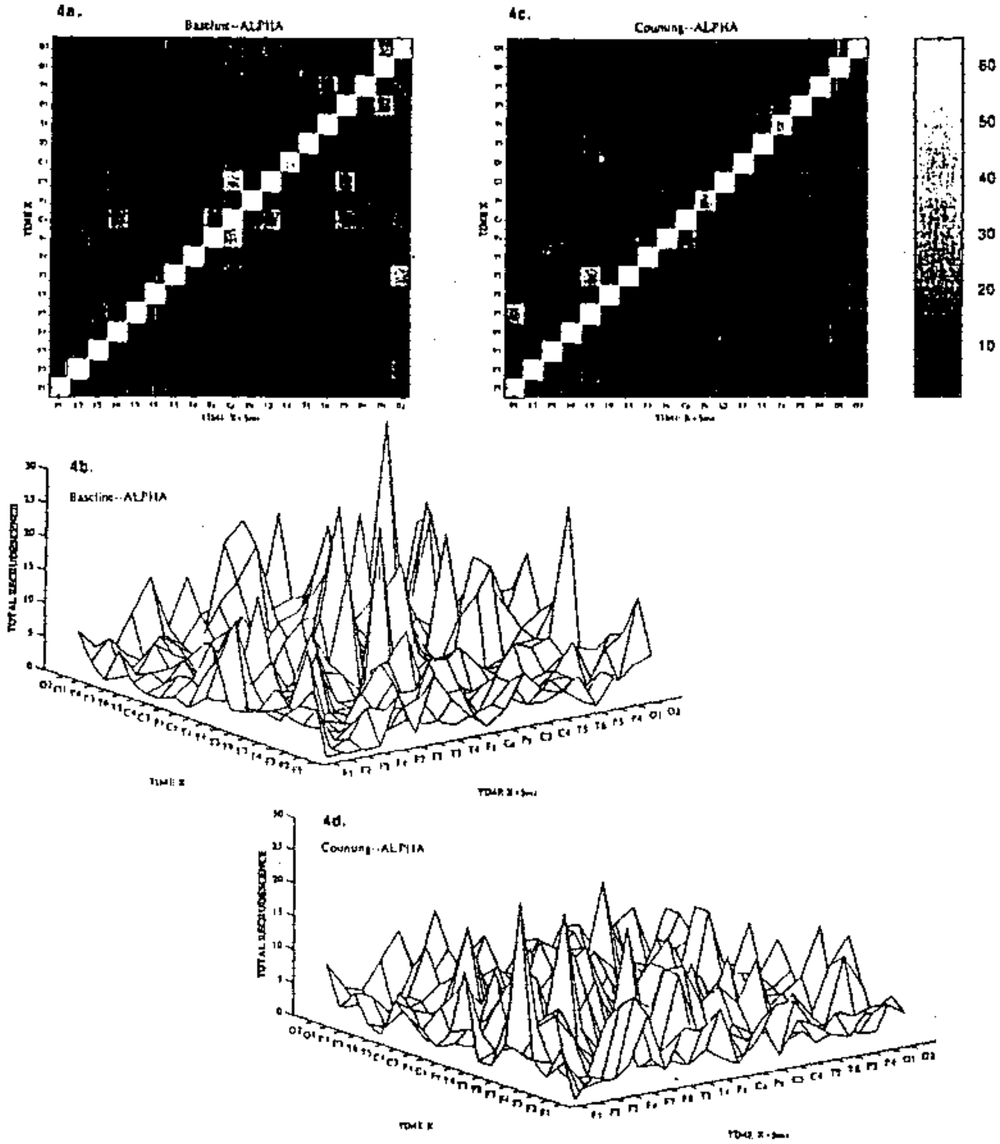

Figure 4. Matrix and mean vector contour plots of recrudescence for alpha activity corresponding to scalar r... sentations of figure 2c and 2d. Baseline, 4a and 4b; Counting, 4c and 4d.

nal indicates an equal amount of recrudescence from successive epochs between pairs of electrodes. The lower left quadrant of the matrix represents recrudescence among more frontal electrode locations, whereas the upper right quadrant represents recrudescence among more posterior electrode locations. Note the frontal recrudescence (denoted by the light areas) in total EEG during relaxation, baseline conditions in figure 3a. This pattern (frontal recrudescence) persists during counting, but it is somewhat less concentrated within frontal areas. Similarly, in figure 4a and 4b, concentrated recrudescence among occipital areas in the alpha band during baseline spreads out to other locations during counting. Finally (figure 5a and 5b) shows concentrated recrudescence among temporal lobe leads in the beta band ... rest, which changes to a more distributed pattern ... counting.

Cluster Representations of Counting Experim...

When measurement epochs using unsquar... ages were classified as belonging to either a fi... second cluster, descriptive statistics indicated ... two clusters differed from each other in terms of ... of the mean voltages over time at each electro... Epochs assigned to Cluster 1 have mean voltag... nineteen electrode sites that are positive. Clust... mean voltages at all nineteen electrode sites ...

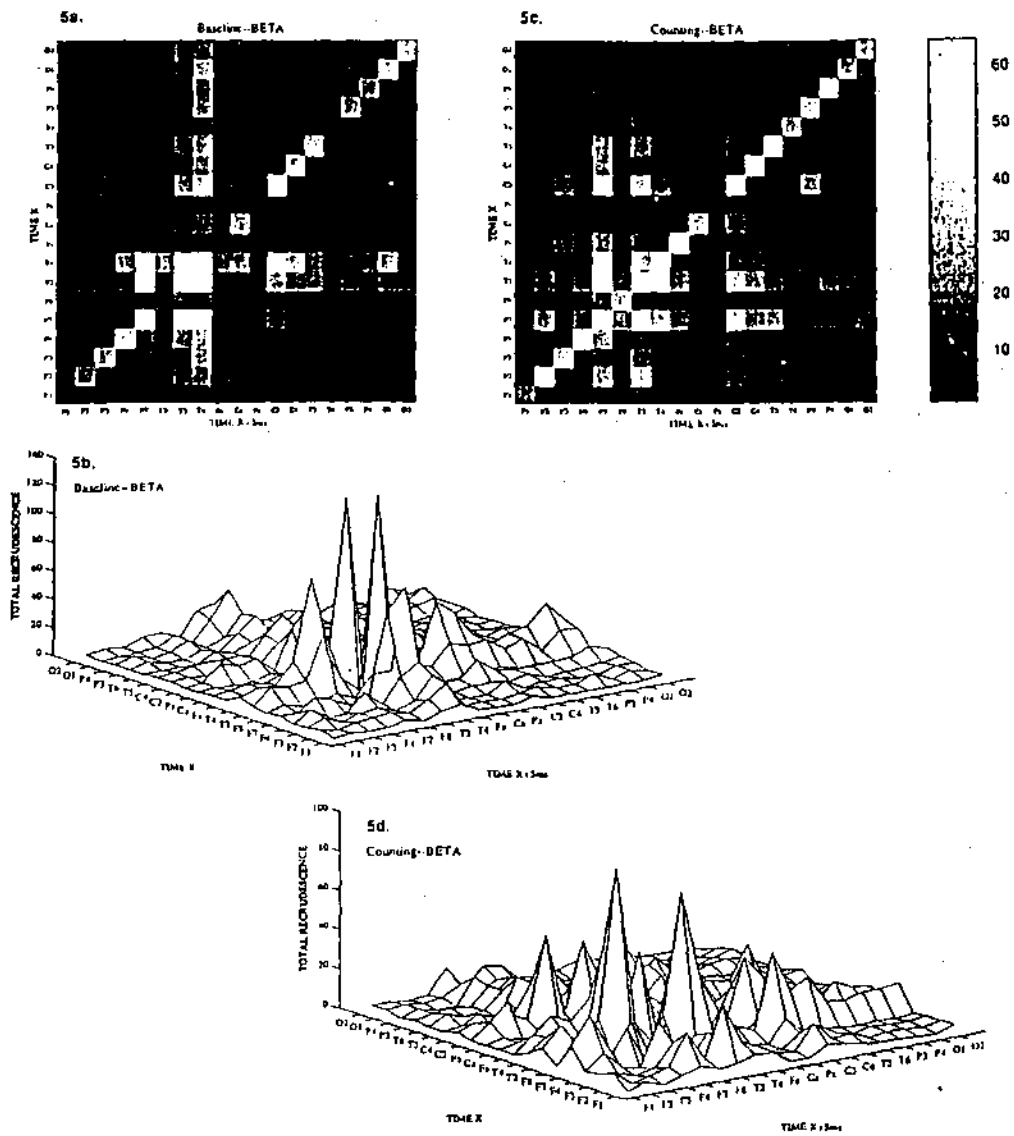

Figure 5. Matrix and mean vector (contour) plots of recrudescence for beta activity corresponding to scalar representations of figures 2c and 2f. Baseline, 5a and 5b; Counting 5c and 5d.

negative. No differences in the pattern of mean voltages across electrode sites were observed between EEG records obtained in the Counting and Baseline conditions.

After each measurement epoch was assigned to either Cluster 1 or Cluster 2, plots of cluster assignment for each measurement epoch were obtained for both the Baseline and Counting conditions. Figure 6 displays the cluster assignment for each epoch in a 500 msec sample of the complete record during the baseline condition for the same subject. Figure 7 displays the cluster assignment (1 or 2) for each measurement epoch in a 500 msec sample of the full 20 second record while one subject was counting. Visual inspection of both figures clearly shows that periods of time in which the rate of switching from one cluster assignment to the other is slow (e.g., Epochs 1-70 in figure 6 and Epochs 1-39 in figure 7) are interrupted by periods in the record where the rate of cluster switching is rapid (e.g., Epochs 75-93 in figure 6 and Epochs 39-45 in figure 7). Visual inspection of the rates of cluster switching in the baseline and counting records indicated that the frequency of very short cluster segments (i.e., portions of the record where less than five consecutive epochs re assigned to the same cluster) was higher in the Counting condition than in the Baseline condition. This hypothesis generated by visual inspection was submitted to statistical analysis using the Chi-Square test as reported below.

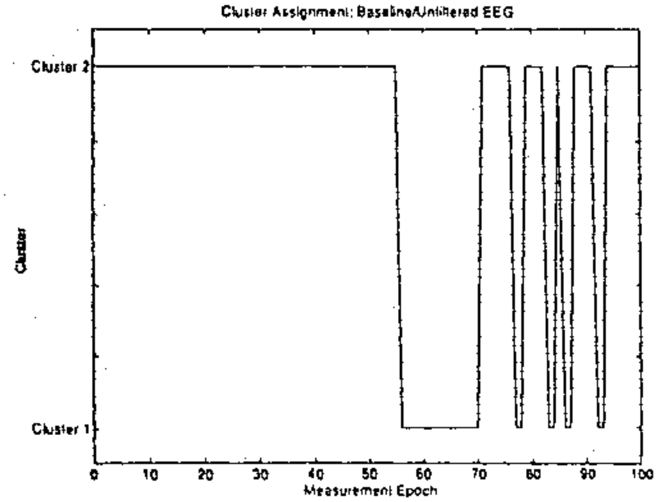

Figure 6. Cluster Assignment of 100 Consecutive Measurement Epochs (500 msecs) for Unfiltered EEG During the Baseline Condition.

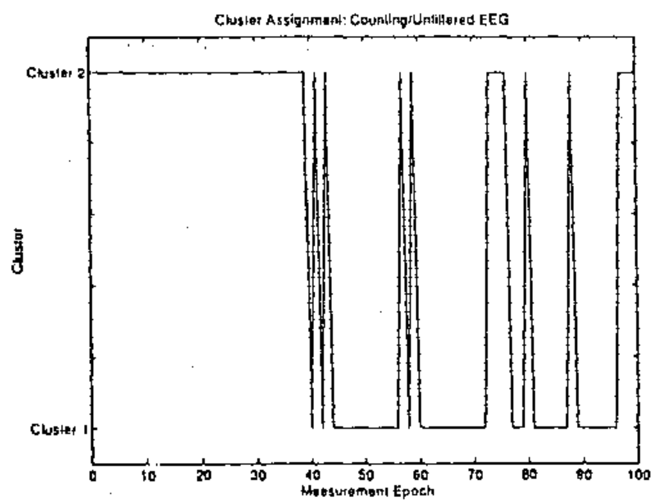

Figure 7. Cluster Assignment of 100 Consecutive Measurement Epochs (500 msecs) for Unfiltered EEG During the Counting Condition.

Rate of Cluster Switching

A program written in C++ counted the number of cluster segments at each possible length of a segment (i.e., the number of consecutive epochs assigned to a single cluster). Figures 8 and 9 display the percentages of the time in which each cluster Segment Length was encountered for the Baseline and Counting conditions, respectively. A higher percentage of short cluster segments (i.e., representing fast cluster switching) was present in the Counting condition than in the Baseline condition. This observation was confirmed by a Chi-Square analysis that indicated that the percentage of short cl er se ment lengths (between 1 and 5 epochs in each clust segment) in the Counting condition was significantl higher than the percentage of short cluster segments ir the Baseline condition (X^2 (1,32) = 5.2, $p<.05$). One quantitative difference in the dynamical pattern of EEG vol age changes between two cognitive task conditions ha thus been established.

Figures 10 and 11 display values of the highes squared voltage over the same 250 msec samples of re cord used in displays of the Cluster Switching rates fc the Baseline (figure 6) and Counting (figure 7) condition: Visual inspection of these and other portions of the com plete records for Baseline and Counting conditions ind cates that slow rates of cluster switching are associat with higher squared voltages (e.g., Epochs 75-9? for tl Baseline condition and Epochs 39-45 for the Countir

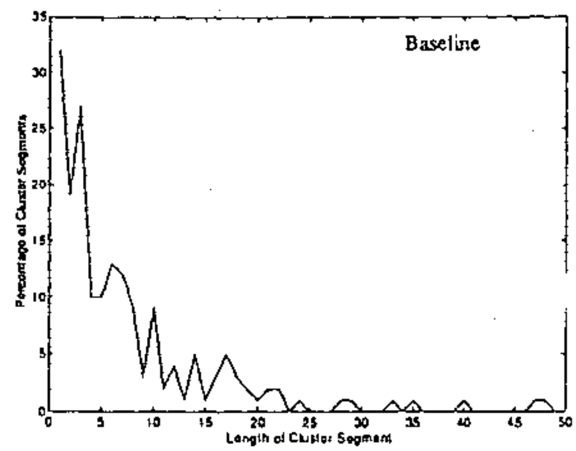

Figure 8. Percentage of Segments at Each Possi le Clu Segment Length for Unfiltered EEG During the Ba el Condition.

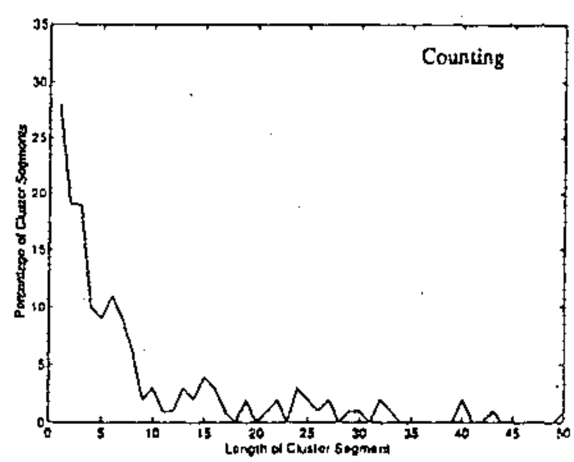

Figure 9. Percentage of Segments at Each Possible Clus Segment Length for Unfiltered EEG During the Counti Condition.

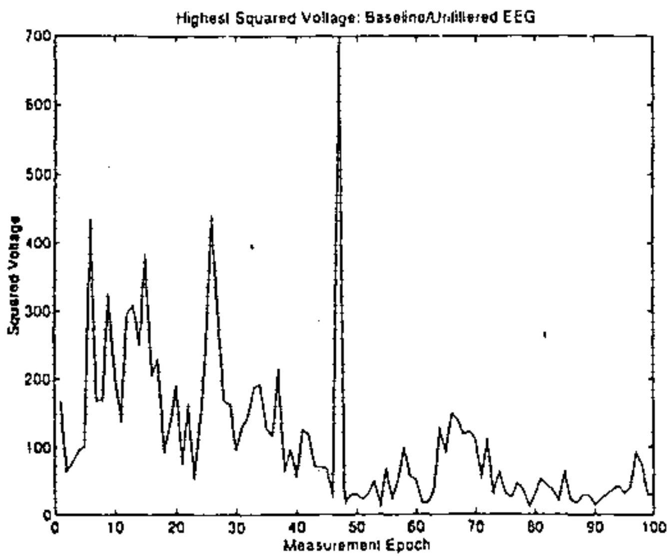

Figure 10. Highest Squared Voltage at 100 Consecutive Measurement Epochs for Unfiltered EEG During the Baseline Condition.

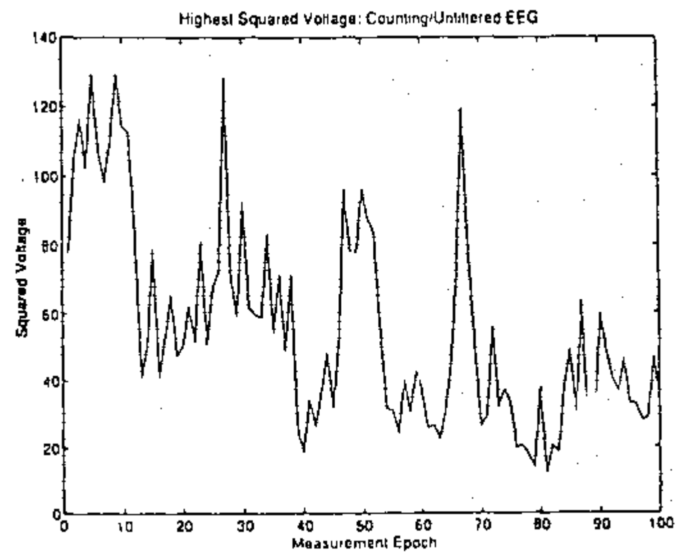

Figure 11. Highest Squared Voltage at 100 Consecutive Measurement Epochs for Unfiltered EEG During the Counting Condition.

condition). These visual observations were addressed through statistical analyses using ANOVA, as reported below.

One-way ANOVAs were used to compare the mean highest squared voltages for short cluster segments (one to five consecutive epochs in each segment) and long cluster segments (30 or more consecutive epochs assigned to the same cluster). Separate ANOVAs were conducted on data from the Baseline and Counting conditions. When data from both the Baseline and Counting conditions were examined, epochs in short cluster segments were found to have significantly lower highest squared voltages $\underline{M} = 64.04$, $\underline{SD} = 67.44$ for Baseline; ($\underline{M} = 42.20$, $\underline{SD} = 24.26$ for Counting) than epochs in long cluster segments ($\underline{M} = 118.76$, $\underline{SD} = 87.22$ / $\underline{F}(1,1893) = 151.62$, $\underline{p}<.05$ for Baseline; $\underline{M} = 104.40$, $\underline{SD} = 68.64$ / $\underline{F}(1,2718) = 362.14$., $\underline{p}<.05$ for Counting).

Discussion

The foregoing data illustrate the possible utility of some methods of dynamic analysis of the EEG made possible by recent advances in both hardware and software computer technology. The various depictions not only provide spatiotemporal images of EEG dynamics but also provide the bases for quantification and subsequent statistical analysis of the temporal course of EEG dynamics.

To us, the most important and surprising finding of this study is the rapidity of change in electrical pattern. Recrudescence rates ranged from 60 to 170 per second. Next, the technique showed that under the conditions of the investigation, there were no clear cut sweeps of wavefronts across expanses of scalp. Rather the maximum squared potential "popped up" in one location and then in another totally different location over time. Recrudescence rates and the scalar diagrams thus provided an initial quantification of the speed of change and spatial distribution of EEG activity, respectively. The patterns so generated allow for quick and accurate (as accurate as the particular recording technique will allow) comparisons of spatial dynamics between individuals or between experimental conditions.

The vectorial representations provide information on the directionality of recrudescence between all pairs of electrode locations. It is informative that most often for the sample rate of 5 msec used in our studies the location of highest squared voltage does not change across successive sampling epochs. With the diagonal formed by this lack of change in the record as a baseline, we can also obtain a picture of directional relationships between all electrode locations. Sample rates at 100 samples/sec (i.e., one each 100 msec) demonstrated no appreciable difference in the pattern of recrudescen[illegible]

To assess the duration between stable ep[illegible]chs, [illegible] statistical analyses that we undertook and their [illegible]comp[illegible]nying graphics allow a more inclusive look at the tempo[illegible] dynamics of recrudescence among spatial locatio[illegible] Lehmann (1990) had demonstrated that standard dev[illegible]tions across successive measurement samples of alp[illegible] EEG (64-128 samples per second) exhibited a cyclic pat[illegible]tern corresponding to approximately 20 peaks per secon[illegible] He then showed that during periods when the standar[illegible] deviation of successive epochs was highest, that the loca-

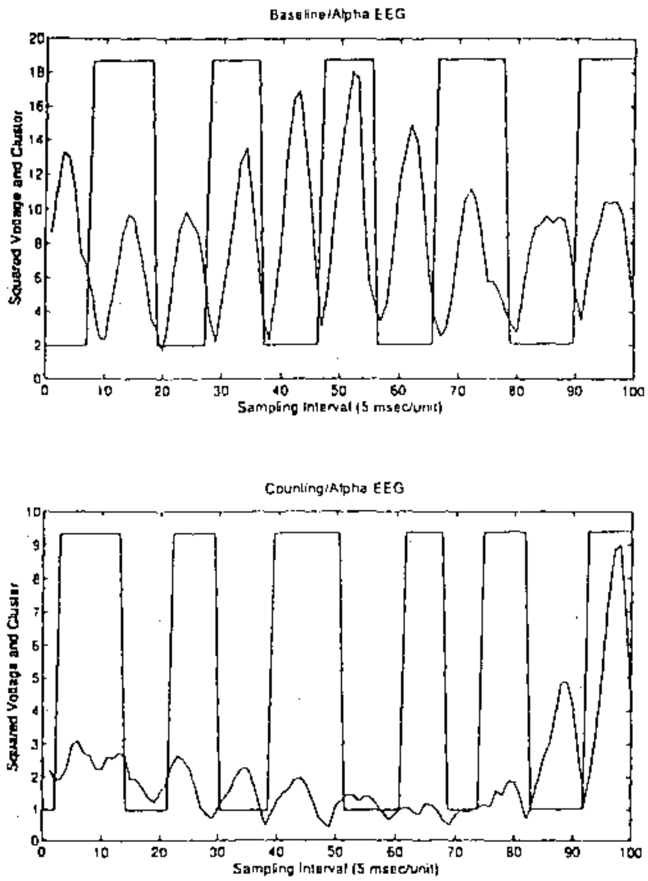

Figure 12. Overlay of Squared Voltage and Cluster Assignment for Baseline and counting for alpha activity.

tion of the highest and lowest voltages remained stable for approximately 200 msecs. In order to replicate and extend these findings, we filtered (IIR digital filter) our EEG data for two conditions in the experiment (baseline and counting) for alpha (8-12 Hz) activity. We plotted the highest squared voltage at each of 100 successive measurement intervals. A cluster analysis was conducted, as described earlier, on the unsquared voltages, separating each measurement interval into one of two clusters. We then plotted the pattern of these clusters over the same 100 successive intervals (sample rate 200 Hz) as was used to plot the highest squared voltages. The results of this analysis are illustrated in figure 12 A and B.

Consistent with Lehmann's results, we found that the highest squared voltage (solid line in figure 12 A and B) cycles at a rate of about 20 Hz. Lehmann found this same cycle rate in standard deviations across successive sample intervals. When viewed in concert with our cluster analyses, however, an interesting relationship emerges. Note that whenever the highest squared voltage is at its peak, the pattern across the 19 electrodes remains on a single cluster (dashed line in figure 12A and B). Changes in cluster assignment are associated with the trough of the highest squared voltage. Note also the regularity of the changes in cluster assignment, particularly in the baseline sample. This regularity is consistent with the regularity in the alpha EEG.

However, contrary to Lehmann's analysis, we found that the pattern across 19 electrodes remains stable for an average of only 50 msecs during rest, as opposed to an average of 210 msecs in his data. Perhaps this difference is due to his lower sample rate (64-128 samples per second), or the fact that he used only two electrodes (those with the highest and lowest voltage). Analyses involving cluster segment length thus appear to be especially promising. This is borne out not only in the comparison we can make with Lehmann's work, but in the ability of frequency distribution of cluster segment length to discriminate between the Baseline and Counting conditions. As did Lehmann, we are currently examining the relationship between EEG measures and behavioral reaction time. We are also using time series techniques to quantification of the pattern of cluster switching displayed in figures 6 and 7.

We ourselves plan to explore the utility of using a Laplacian correction to enhance localization of recorded voltages across the scalp. However, a 19-electrode array most likely provides insufficient samples for such a correction. A 128-electrode net provides the opportunity for accurate reference-independent voltage correction at each electrode site. The application of both voltage and Laplacian (current density) data as used by Tucker (1993) in developing programs used with the geodesic net holds promise for future studies of the spatiotemporal dynamics of EEG.

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