A major purpose of the Technical Information Center is to provide the broadest dissemination possible of information contained in DOE's Research and Development Reports to business, industry, the academic community, and federal, state and local governments.

Although a small portion of this report is not reproducible, it is being made available to expedite the availability of information on the research discussed herein.

Los Alamos National Laboratory is operated by the University of California for the United States Department of Energy under contract W-7405-ENG-36.

TITLE: PROBLEMS ASSOCIATED WITH DIMENSIONAL ANALYSIS OF ELECTRO-
ENCEPHALOGRAM DATA

AUTHOR(S): Scott Layne, Gottfried Mayer-Kress and Joachim Holzfuss

SUBMITTED TO: CNLS Workshop "Dimensions and Entropies in Chaotic Systems"
Proceedings held Sept. 11-16, 1985 at the Pecos River Conference
Center

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

MASTER

By acceptance of this article, the publisher recognizes that the U.S. Government retains a nonexclusive, royalty-free license to publish or reproduce the published form of this contribution, or to allow others to do so, for U.S. Government purposes.

The Los Alamos National Laboratory requests that the publisher identify this article as work performed under the auspices of the U.S. Department of Energy.

Los Alamos Los Alamos National Laboratory
Los Alamos, New Mexico 87545

Problems Associated With Dimensional Analysis Of Electroencephalogram Data

Scott P. Layne, Gottfried Mayer-Kress & Joachim Holzfuss

Center for Nonlinear Studies
Los Alamos National Laboratory
Los Alamos, New Mexico 87545

We begin with a basic introduction to the electroencephalogram and discuss some of the EEG's clinical uses. Next we introduce a practical application of dimensional analysis to the EEG by asking the question: *How does the "dimension" of the EEG change with general anesthesia?* Finally we discuss major problems associated with dimensional analysis of the EEG.

1. Introduction to the EEG

Electrical activity originating from the brain was first discovered in 1929. In spite of this long history, slow progress has been made in understanding and interpreting the EEG. Currently, there is no ordered atlas of EEG findings versus brain activity -- there are only tendencies for EEG findings versus brain activity. In addition, very few EEG centers are equipped with computers for detailed analysis and so today, EEG interpretation is primarily by skilled visual inspection.

The microscopic genesis of the EEG is not understood. Macroscopically, electric signals appear to originate from collections of dendritic endings on neurons [1]. These collections, in turn, generate signals that are coordinated in space and time near the surface of the brain. Beyond this, there is some attenuation of the brain's electrical activity by the intervening skull and scalp. At the scalp, the EEG is measured as a μ -Volt potential and to record this weak potential, it must be amplified by several orders of magnitude. Generally, EEG signals are recorded by contacting a standard pattern of electrodes, with conductive paste, to rubbed scalp. Pronounced artifacts often originate from slight movements of the electrodes and from contraction of muscles below the electrodes. Since the EEG is a weak signal in a sea of noise, the importance of skilled electrode placement and inspection for artifacts cannot be overestimated [2,3].

The EEG's frequency spectrum ranges from 0.5 to 100 Hz, with most of the power concentrated in the range from 1 to 30 Hz. By visual inspection, the EEG looks like a complex wave that is aperiodic. The appearance of this signal fluctuates throughout the day and changes cyclically with sleep. There are four general classifications of EEG frequencies. They were established primarily by discovery, as

early instrumentation improved, and are of limited intrinsic value: 1 - 3 Hz is termed *delta*, 4 - 7 Hz *theta*, 8 - 14 Hz *alpha*, and >14 Hz *beta*. In addition, the overall appearance of the EEG is modified by drugs. For example:

Cocaine	Increases alpha rhythm
Amphetamines	Decreases amplitude
Thorazine	Decreases alpha rhythm
Barbiturates	Increases beta rhythm

Often, one or more drugs so completely alters the normal pattern of the EEG that it becomes difficult or impossible to interpret. In these instances, diagnostic EEG's are performed only after a period of drug privation.

2. General anesthesia and the EEG

Realizing that drugs alter the EEG, attempts have been made to assess the depth of general anesthesia by analyzing brain waves in real-time. However, two difficult and related questions are involved: 1. *What is the choice for the measure?* and 2. *What is the sensitivity of the measure?* This attempt to assess anesthetic depth by *quantitative* means is important because physicians currently rely on *qualitative* physical signs. Although signs involving flinching, tearing, blood pressure, respiration rate, pupil diameter and heart rate are useful, they do not provide specific information on the well-being of the brain.

To our knowledge, Hanley and Waltz [4] have done the most successful work to assess anesthetic depth by computer analysis of the EEG. In this study, a variety of auto-spectral and cross-spectral relationships were correlated: 1. Power density, mean frequency, and band width of selected frequencies for a given lead, and 2. Phase relationships and shared electrical activities between different leads. Anesthesia was induced by a single agent and depth was evaluated by measuring blood concentrations of drug with a mass spectrometer. In order to establish self-controls and dose-related effects, the EEG was analyzed before anesthesia, during light anesthesia, and during medium anesthesia.

The above quantitative analysis involving the EEG is promising because: 1. The EEG is an overall measure of brain activity and general anesthetics globally affect the brain, 2. Certain drugs induce dose-related and frequency-related changes in the EEG, and 3. Overwhelming doses of some general anesthetics diminish the EEG to a flat line. During routine surgery, however, general anesthetics are not given in sufficient amounts to reduce the EEG to a flat line. Only in special cases involving prolonged anoxia, such as drowning, are drug comas induced to minimize brain damage. In these instances, sufficient anesthetic is administered so that the EEG is not active for several days.

Attempts to assess brain function and depth have been most successful when one

drug is used to induce general anesthesia. In most surgical cases, however, several drugs are used to induce anesthesia which results in complex and unpredictable EEG changes. In these instances, numerical analysis of the EEG has been less accurate and rather difficult to interpret. These limitations have motivated us to consider a different approach.

3. Rationale for dimensional analysis of the EEG

In this section, we use "dimension" as a qualitative term. In this regard, "dimension" corresponds to the number of independent variables needed to specify the activity of a system at a given instant. It also corresponds to a measure for the number of active modes modulating a physical process and therefore, it is a measure of complexity. In the next section, we will describe dimension by outlining our numerical procedures.

Dimensional analysis of the EEG during general anesthesia is an interesting approach for several reasons: 1. Large doses of some anesthetics reduce the EEG to a flat line, therefore the dimension of the EEG may decline with anesthesia, 2. It provides a single number rather than a series of correlations for assessing depth, 3. The dimension provides information about the complexity of the EEG signal which cannot be extracted from the power spectrum, 4. Dimension may be calculated before anesthesia and during anesthesia for the same person, which provides a method of standardization, and 5. The EEG may be more than "noise" in cerebral tissue; it may play a causal role in information processing and storage [5]. In this regard, there has been conjecture that the brain's electrical activity reflects a complex dynamical system which may be evaluated by the tools of nonlinear dynamics [6,7].

Our original goal was to evaluate anesthetic depth for a series of 5 to 10 patients by dimensional analysis. This goal turned out to be more ambitious than we thought. It has been very difficult to obtain clean EEG records from the operating room. Noise is prominent due to electrocautery and to movement of the patient's head by operating room personnel. In addition, specialized EEG equipment must be used to reduce noise and to accommodate limited space in the room.

In the following section, we discuss the problems associated with dimensional analysis of the EEG. We choose one EEG record from a single patient, in order to study the method but not to draw general conclusions. For simplicity, we consider only two states: awake but quiet, and medium anesthesia. The EEG data we use comes from Hanley and Walts [4]. It was selected because anesthesia was induced by a single agent, and because of its uninterrupted length and lack of artifacts [8].

4. Dimensional analysis of the EEG

We analyze data that was derived from two standard EEG leads, as shown in Fig. 1. Lead T3-C3 records activity primarily from the motor cortex, and lead P3-O1 records activity primarily from the occipital cortex of the brain.

Fig. 1. Two standard EEG leads from the International 10-20 system

In order to convey a feeling for the appearance of the EEG, Fig. 2 shows three time-series of different lengths. All three time-series start from the same location in time and were recorded from lead P3-O1, while the patient was awake but quiet. In most people, the optical cortex generates a strong alpha-rhythm in states of quiet consciousness. This rhythm appears as cycles of large amplitude waves that come and go with time. Longer time-series (not shown) demonstrate that this overall "cyclic" activity is aperiodic. At the same time, lead T3-C3 does not demonstrate a prominent alpha-rhythm.

Fig. 2. Awake but quiet EEG data from P3-O1. The length of each time-series is indicated above

Fourier transform reveals several additional characteristics, see Fig. 3. The EEG is composed of multiple frequencies that vary with time, and a time-average over several minutes shows no dominant bands. Even the prominent alpha-rhythm of lead P3-O1, Fig. 3c, is a broad band that varies in width and intensity. Each lead has a different and somewhat characteristic power spectrum that depends on the state of consciousness (note the lack of alpha-rhythm in C3-T3). With medium (fluroxene) anesthesia, the power spectrum reveals more energy at higher (15 to 25 Hz) frequencies, and with deeper anesthesia (not shown) the power spectrum shifts to lower (1 to 8 Hz) frequencies.

Fig. 3. Time-resolved Fourier spectra of the EEG. Each track (or spectrum) transforms 2.05 seconds of EEG data at a resolution of 0.5 Hz. Time (in minutes) indicated the position in the EEG record.

In order to calculate the "dimension" of the EEG, it is first necessary to reconstruct an "attractor" from the time-series data. The usual procedure for this is to construct vectors $V(t_k)$ in an m -dimensional phase-space by taking time-delayed samples of scalar data $x(t_k)$. In our case, phase portraits of dimension m are constructed such that: $V(t_k) = \{x(t_k), x(t_k + \Delta T), x(t_k + 2\Delta T), \dots, x(t_k + (m-1)\Delta T)\}$, where t_k is discrete time with k running from 1 to the number of data points and ΔT is a

constant time-delay [9]. For an ideal data set, the size of ΔT is essentially arbitrary. For a realistic data set, however, the quality of the phase portrait depends strongly on ΔT . We have chosen values for ΔT that correspond to the first minimum in mutual information. This procedure selects time-delay coordinates that are generally independent and therefore aids in the construction of an "attractor" from limited time-series data [10]. From a number of mutual information calculations, we find different values for ΔT at each lead: 40 ms for C3-T3, and 20 ms for P3-O1. These values are used for subsequent phase portrait construction and dimensional analysis.

Conventional two-dimensional phase portraits ($m=2$) of the EEG are shown in Fig. 4. These phase portraits reveal chaotic orbits with diverging trajectories. With time, the EEG changes its average position and on occasion makes large excursions in the phase-space. Such complex trajectories are related to the multiple and variable frequencies of the EEG. The dominant alpha-rhythm of lead P3-O1 yields a more regular looking structure but again with diverging trajectories. Such behavior implies a non-stationary system of high dimension. In such instances, the notions of "attractor" and "fractal dimension" (which refer to stationary or asymptotic properties) do not apply.

C3-T3 Awake but quiet

P3-O1 Awake but quiet

0 - 6 sec.

6 - 12 sec.

12 - 18 sec.

C3-T3 Medium anesthesia

P3-O1 Medium anesthesia

0 - 6 sec.

6 - 12 sec.

12 - 18 sec.

Fig. 4. Two-dimensional phase portraits, $V(t_k + \Delta T)$ vs $V(t_k)$, of EEG data. Each portrait is generated by 3000 data points and consecutive portraits (in time) appear from left to right. The top two portraits are from "awake but quiet" EEG data; the bottom two portraits are from "medium anesthesia" EEG data

To compute the "dimension" of the EEG, we use the method of Grassberger and Procaccia [11]. This method is now in standard use, since it requires modest computer time and storage. For a sufficiently large embedding dimension m , the dimension d of an attractor behaves as a power of r for small distances r such that

$$\log C(r) \approx d \log r \quad \text{and} \quad C(r) = \lim_{k \rightarrow \infty} \frac{1}{n_{\text{ref}}} \sum_{j=1}^{n_{\text{ref}}} \frac{1}{k} \sum_{i=1}^k \Theta(r - |V_i - V_j|),$$

where Θ equals 1 for positive and 0 for negative arguments, and n_{ref} equals the number of reference points in the calculation. For all our calculations, we follow two procedures: 1. Reconstruct sets of phase-space vectors such that $\{V\} = \{V(t_k)\}$ for each embedding dimension m ranging from 1 to 20, and 2. Calculate the dimension d for

each embedding dimension m by averaging over 200 equally spaced reference points in the "attractor". We average over that many reference points because $C(r)$ is sensitive to the local structure of the "attractor". Certain regions of the attractor are more "important" in the sense that they are visited more often than others. By using 200 reference points, an average for the various regions is calculated. The details of this procedure and our codes are described in reference [12].

Fig. 5 shows the result of such procedures. It plots the logarithm of the average number of vectors n (which are separated by a distance $< r$) versus the logarithm of the distance r . The value of the "dimension" d is obtained by fitting a straight line to an interval of this "dimension" curve that shows the relevant scaling behavior. In Fig. 5, this interval occurs over the region $-2 \leq \log r \leq -1$.

Fig. 6 shows the "dimension" (or local slope) of Fig. 5 versus $\log r$. We obtain this local slope by a weighted least squares fit of length $L = 7$ unit distances in $\log r$. The maximum "dimension" occurs for $\log r = -1.8$ and is equal to 7.7 ± 7.4 . Note, however, that the error is of the same magnitude as the dimension itself. For short distances ($\log r \leq -3$) we see that the local slope $d = 1$. This artifact is due to an excessive digitalization rate of 500 Hz for the EEG. Such a rapid rate generates large numbers of vectors along a short segment of the trajectory. For large distances ($\log r \geq 0.5$) we see that the local slope $d = 0$, which reflects the finite size of the "attractor".

Fig. 5

Fig. 6

Fig. 5. Dimension curve, with embedding dimension $m=20$, for typical EEG data. This calculation is based on 15000 data points t (30 seconds of data) and 200 reference points. Error bars indicate standard deviations in the distribution of the average number of vectors n at distance r . Figs. 5 through 8 are from the same awake but quite EEG data (lead T3-C3)

Fig. 6. Local slope d of the "dimension" curve vs $\log r$. Note the asymptotic values of $d = 1$ for $r \rightarrow 0$ and $d = 0$ for $r \rightarrow \infty$

We also investigated the question: *How does "dimension" depend on the length of a line segment L that is fit to the "dimension" curve?* In Fig. 7, we see a decrease in the observed dimension d as L increases. At the same time, the size of the uncertainty in d decreases which indicates a systematic error in the procedure. This error occurs because the weighted least square fit is constrained to shorter ranges of slope by line segments of longer length. For EEG calculations, dimension and error estimates were obtained by limiting the maximum error in the weighted fit, see reference [11]. In all cases, a maximum error of 10% appeared to be reasonable constraint. This constraint determined the length L over which the dimension curves scale and generally, we found relevant scaling over a range that is close to a factor of 2 [13].

When a complex time-series is generated by a low-dimensional chaotic dynamical system, one expects that dimension d (as a function of embedding dimension m) should level off at a finite value. In Fig. 8, we see that this behavior is not observed for the EEG data. This lack of saturation at $m = 20$ indicates that low-dimensional models cannot account for the dynamics of the EEG.

Fig. 7

Fig. 8

Fig. 7. Dimension and error-estimate as a function of length L . The result is generated by a weighted least squares fit to Fig. 5. A scaling factor of 2 corresponds to 8 unit divisions in r on the horizontal axis

Fig. 8. Observed "dimension" as a function of embedding dimension m . Dimension values at each m were calculated by a weighted least squares fit. The length of the line segments L for each fit ranged from 7 to 9 unit divisions in $\log r$ on the "dimension curve"

5. Summary of calculations for the EEG

The table below summarizes the results of our "dimension" calculations for the EEG. In addition to calculating "dimension" for longer data sets of 15000 points, we also calculated "dimension" for shorter subsets of 4000 data points. We considered these shorter subsets in order to see how the "dimension" of the EEG changes with time and number of data points. The data for the shorter subsets were taken from the beginning and the end of the longer sets.

To our surprise, the "dimension" of the EEG appears to increase with fluroxene anesthesia. The most prominent increase is seen in lead P3-O1, while the increase in lead T3-C3 is less convincing. In all cases, the shorter data subsets reveal smaller values for the "dimension" of the EEG. The shorter subsets also reveal fluctuations with time, that could easily account for increases seen in lead C3-T3 during anesthesia.

From these results, it is clear that neither 4000 nor 15000 data points sample the full complexity of the EEG. Therefore, the "dimension" of the EEG has potential relevance only in a comparative sense. Moreover, this comparison must be made for each lead and not between leads. We feel that reports which try to explain EEG dynamics by low-dimensional chaotic attractors are too optimistic [14].

EEG LEAD	LEVEL OF AWARENES	SET OF DATA POINTS		
		<u>1 to 4000</u>	<u>11000 to 15000</u>	<u>1 to 15000</u>
T ₃ - C ₃	AWAKE BUT QUIET	6.5 ± 4.5	6.9 ± 6.7	7.7 ± 7.4
	MEDIUM ANESTHESIA	6.8 ± 5.0	7.8 ± 5.0	8.4 ± 6.4
P ₃ - O ₁	AWAKE BUT QUIET	5.5 ± 5.1	6.3 ± 3.6	6.6 ± 5.0
	MEDIUM ANESTHESIA	7.4 ± 4.5	7.4 ± 4.4	8.6 ± 5.6

6. Conclusions

1. The EEG is both non-stationary and high-dimensional. Therefore, we cannot speak of dimensions in the strict sense. Our calculations of "dimension" have meaning only in a comparative sense.
2. Our use of the word "dimension" is not strictly accurate. More appropriate terms might be "apparent dimension" or "dimensional complexity".
3. Our findings do not conclusively show whether the "dimension" of the EEG is a sensitive tool for measuring anesthetic depth. For fluroxene anesthesia, the "dimension" appears to increase but there is significant uncertainty in our calculations. Further work on representative EEG records is necessary.

4. In general, new approaches to the EEG hold promise since limited progress has been made in finding new methods for analysis and diagnosis.

7. Acknowledgement

We thank Alwyn C. Scott for first suggesting the idea of anesthetic monitoring. We also thank John Hanley for providing the EEG data and for valuable discussion. One of us (G.M.-K.) acknowledges expanding conversations with Cindy Ehlers and Arnold Mandell. Finally, we thank Andrew Fraser for the mutual information code, and Erica Jen for early versions of the dimension codes.

8. References and Notes

1. R. Elul: *Int. Rev. Neurobiol.* **15**, 227 (1972)
2. J. Hanley: "Electroencephalography in Psychiatric Disorders: Part I", in *Directions in Psychiatry* vol. 4, lesson 7, pp. 1-8 (1984)
3. J. Hanley: "Electroencephalography in Psychiatric Disorders: Part II", in *Directions in Psychiatry* vol. 4, lesson 8, pp. 1-8 (1984)
4. J. Hanley & L. Walts: Unpublished results form a series of clinical trials with gaseous anesthetic agents at UCLA from 1974 - 1976 (Private communication: April 12, 1985)
5. W. R. Adey: "The Influences of Impressed Electrical Fields at EEG Frequencies on Brain Behavior", in *Behavior and Brain Electrical Activity*, N. Burch & H. Altshuler eds., Plenum, pp. 363-390 (1974)
6. J. D. Farmer: "Dimension, Fractal Measures, and Chaotic Dynamics", in *Evolution of Order and Chaos in Physics, Chemistry and Biology*, H. Haken ed., Springer-Verlag, pp. 228-246 (1982)
7. A. Mandell: private communication
8. The patient was a 45 year old female. No premedication was prior to surgery. Anesthesia was induced by inhalation of fluroxene. The EEG record lasts for 17 minutes: 5 min. awake but quiet, 5 min. light anesthesia, and 5 min. medium anesthesia. Analog data from the EEG was digitalized at 500 Hz.
9. N. H. Packard, J. P. Crutchfield, J. D. Farmer & R. S. Shaw: *Phys. Rev. Lett.* **45**, 712 (1980)
10. A. M. Fraser & H. L. Swinney: *Phys. Rev. A* **33** (1986); A.M. Fraser: this volume
11. P. Grassberger & I. Procaccia: *Phys. Rev. Lett.* **50**, 346 (1983)
12. J. Holzfuss & G. Mayer-Kress: this volume
13. One might argue that "attractors" which look similar over a scaling factor of ~ 2 are not really self-similar. Since we are operating in 20-dimensional space, a scaling factor of ~ 2 is rather large and denotes similarity.
14. A. Babloyantz, C. Nicolis & M. Salazar: *Phys. Lett.* **111A**, 152 (1985); A. Babloyantz: this volume