ROBUST DETECTION OF DYNAMICAL CHANGE IN EEG

by

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OUTLINE

Nonlinear time series and nonlinear measures
Previous work on condition change
New Methodology
Application to condition change in the model system
Application to condition change in EEG data
Conclusions

NONLINEAR TIME SERIES

One variable from (possibly high) d-dimensional system:

$$x(i),\ x(i+\tau),\ x(i+2\tau),\ \ldots$$

Reconstruction in d-dimensional phase space:

$$y(i) = [x(i),\ x(i+\lambda),\ \ldots,\ x(i+(d-1)\lambda)]$$

Essential features of dynamics in evolution of y(i)

NONLINEAR MEASURES

Traditional nonlinear measures

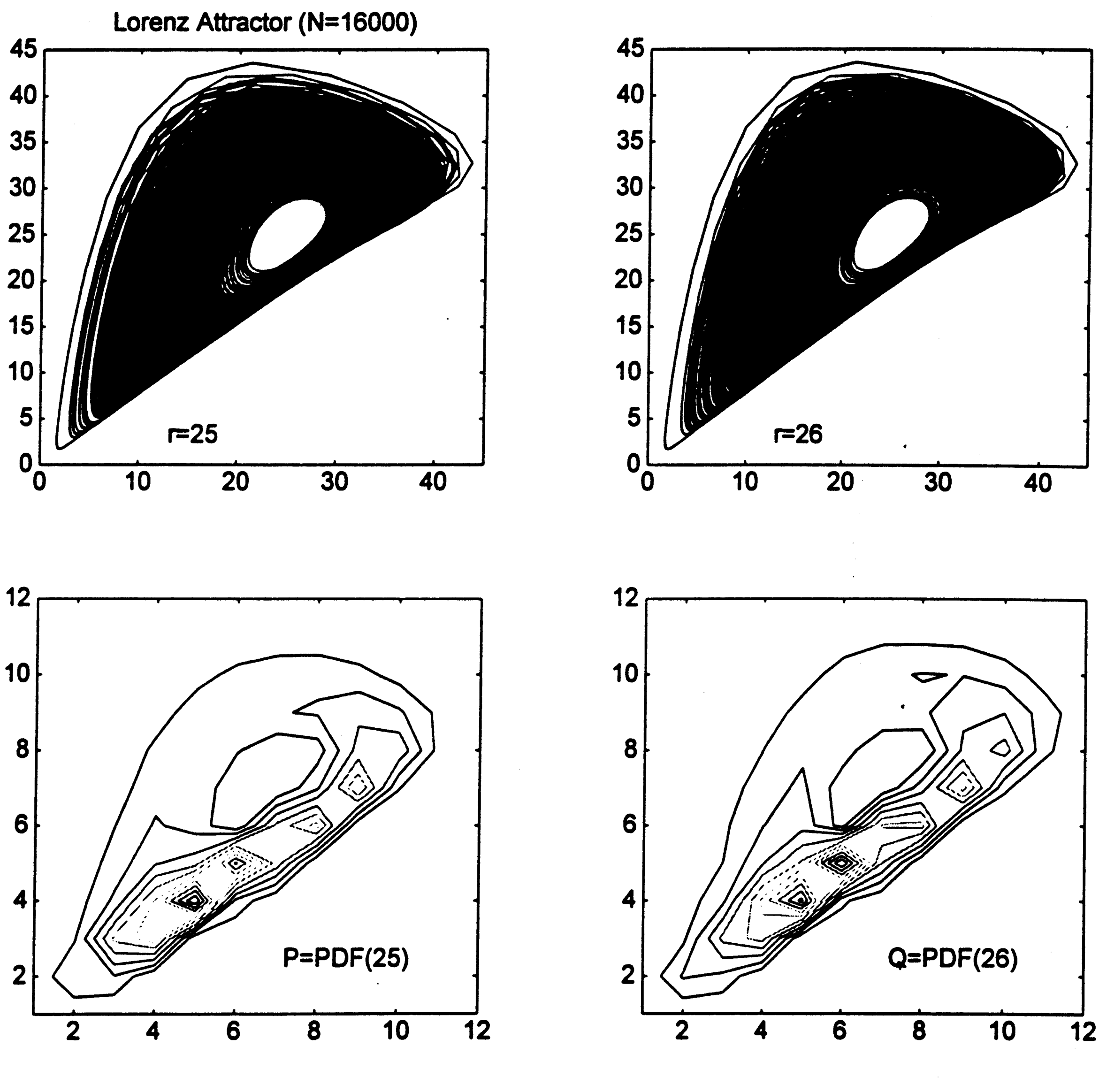
- Mutual information function (decorrelation time)
- Kolmogorov entropy (information loss rate)
- Correlation dimension (complexity)

Integrated measures characterize dynamics by one number
Hard to capture condition change
Especially hard to capture changes among chaotic states

PHASE-SPACE DISTRIBUTION FUNCTION

Capture dynamics as # visits to PS regions

Lorenz system: r=25 versus r=26



Condition change difficult to capture directly

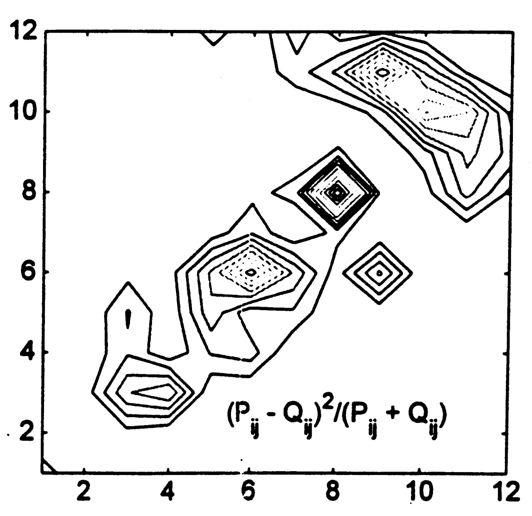
NEW MEASURES

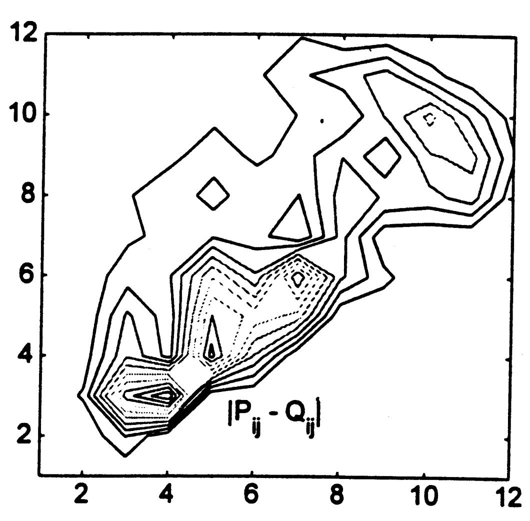
Define base case (R) and test case (S)
Change: new visitation frequency, locations
Measure difference between R and S as

$$\chi^2 = \sum_i (R_i - S_i)^2/(R_i + S_i)$$

$$L = \sum_i |R_i - S_i|$$

Lorenz system: r=25 versus r=26





High sensitivity: subtract, then integrate
Low sensitivity: integrate, then subtract

ONE STEP FURTHER

Vector in one-step connected phase-space:

$$Y(i) = [y(i), y(i+1)]$$

More dynamics in “connected” measures:

$$\chi_c^2 = \sum_{ij} (R_{ij} - S_{ij})^2/(R_{ij} + S_{ij})$$

$$L_c = \sum_{ij} |R_{ij} - S_{ij}|$$

Greater magnification of differences, since:

$$\chi_c^2 \geq \chi^2$$

$$L_c \geq L$$

GENERAL METHODOLOGY

Acquire windows of process-indicative data

↓

Remove artifact with zero-phase, quadratic filter

↓

Construct (connected) phase-space representation

↓

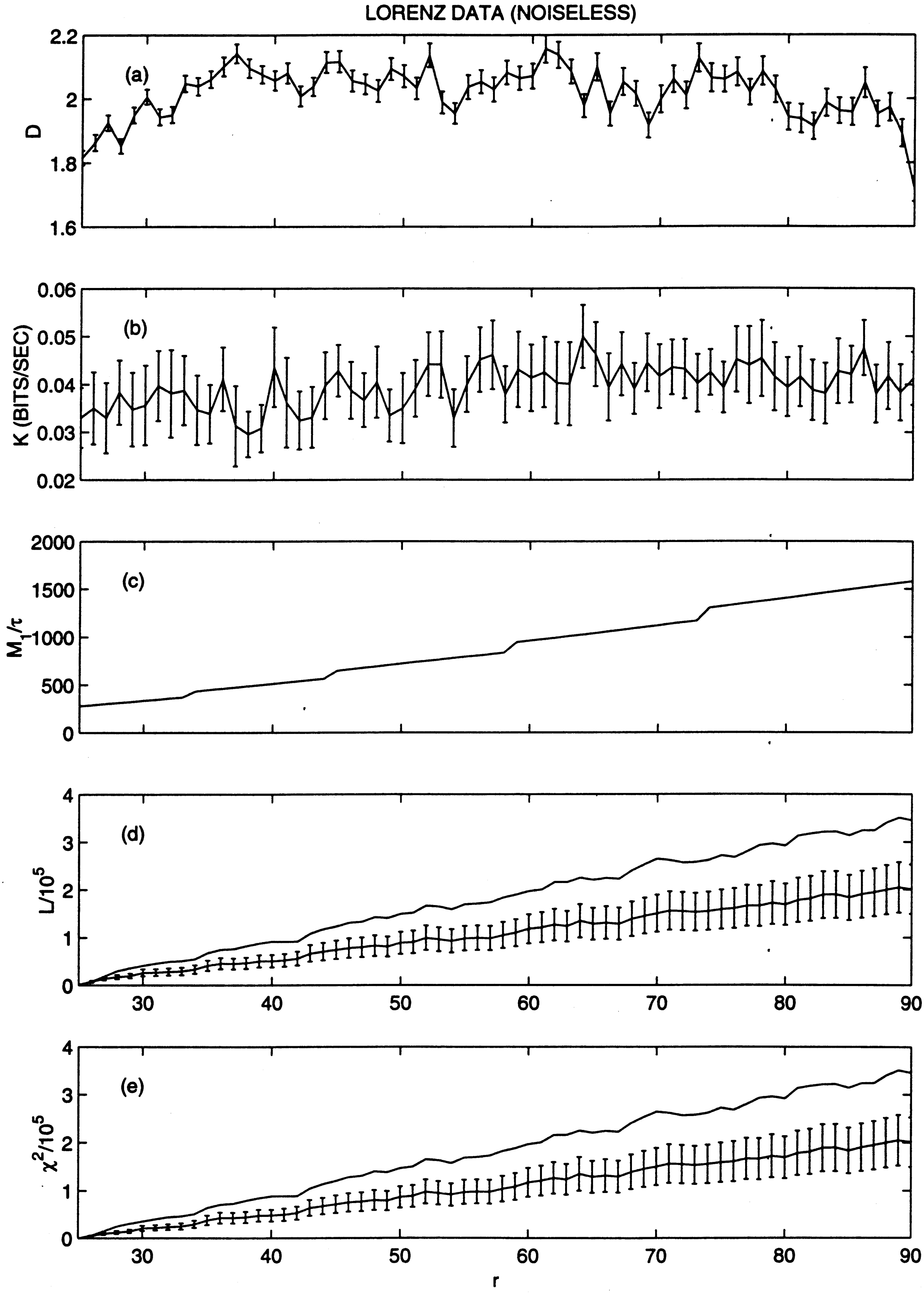
Construct (C)PS-PDF: natural measure of the attractor

↓

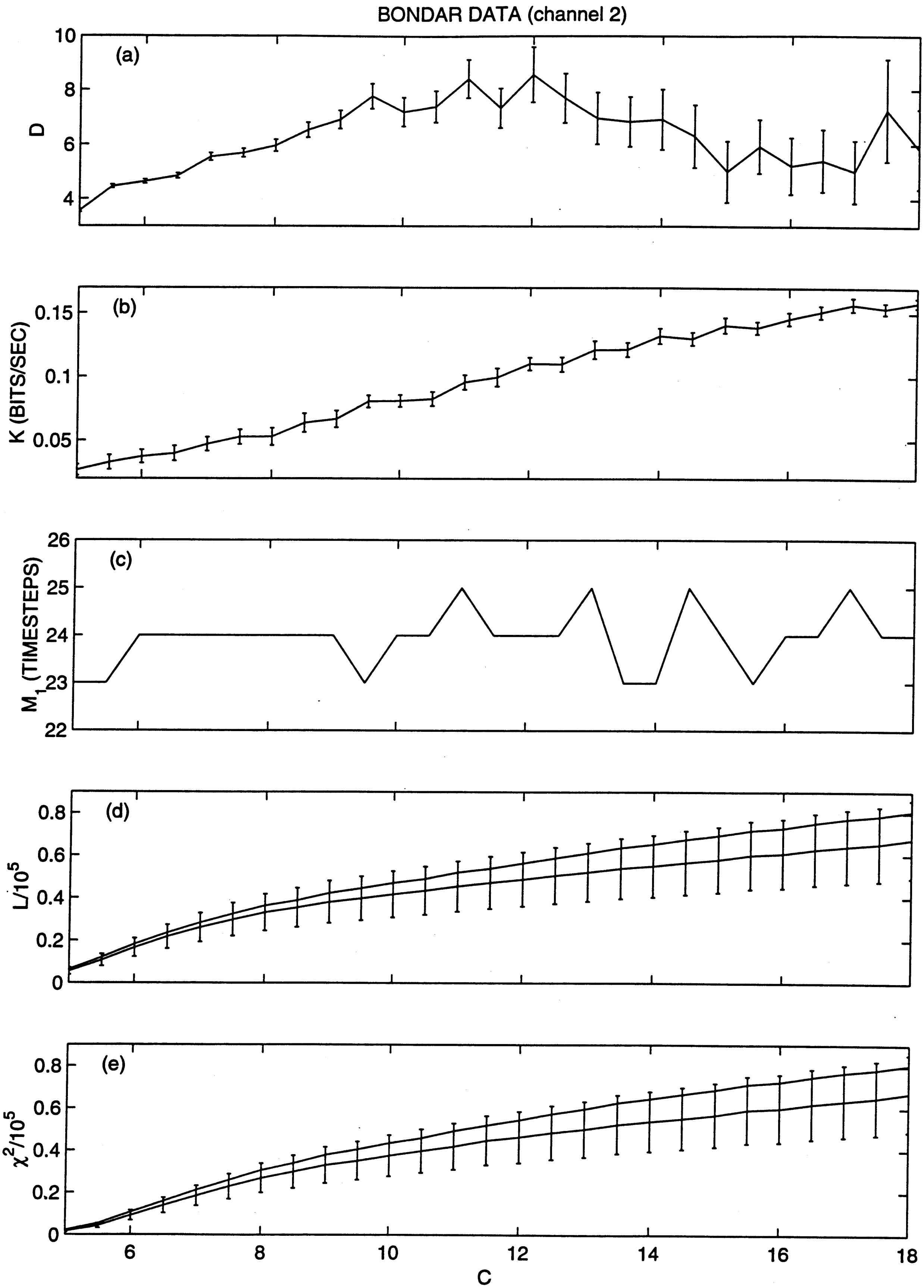
Compare of base case dataset(s) to test case dataset

↓

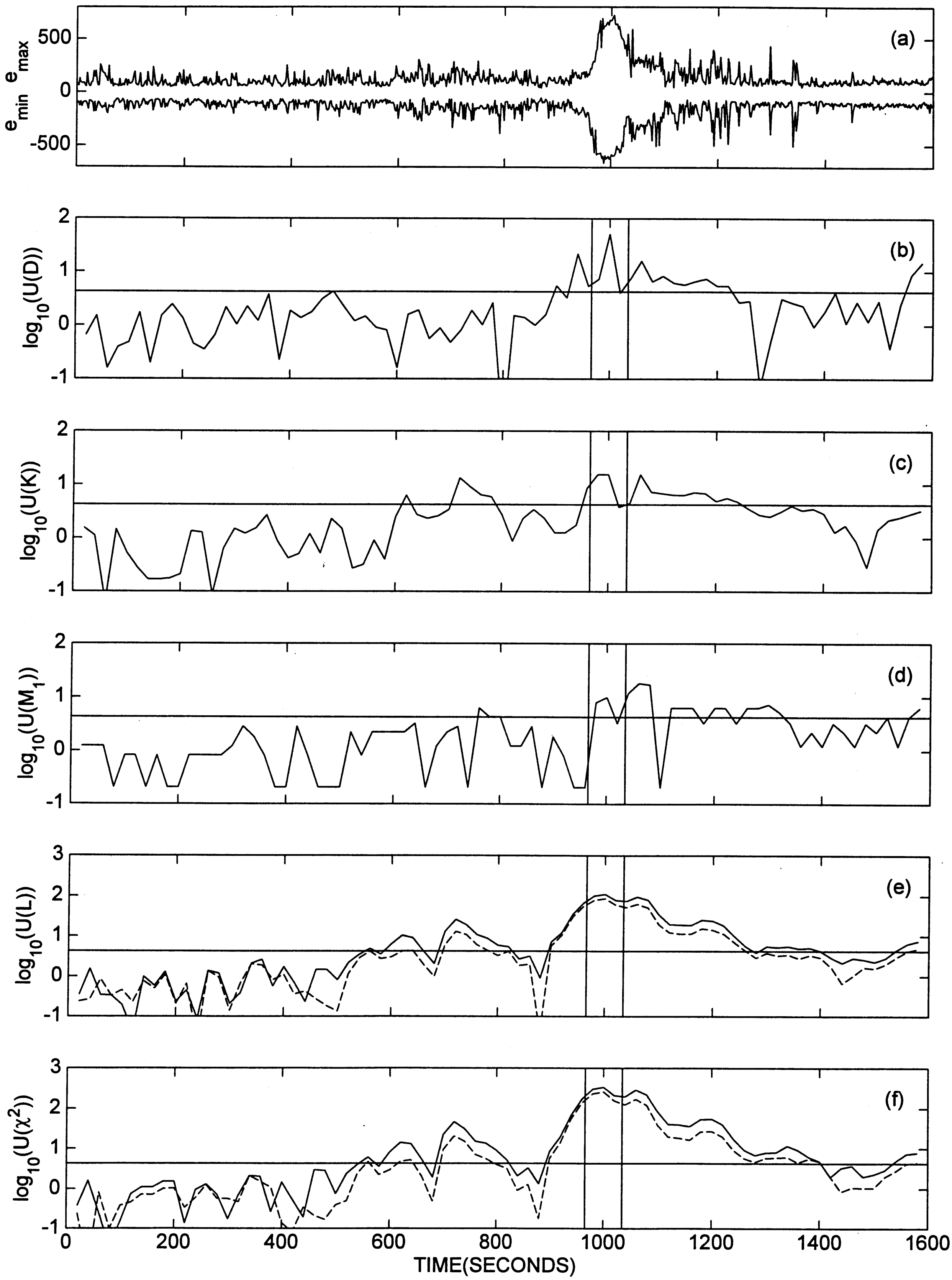
Renormalize difference measures to detect condition change



LORENZ DATA (NOISELESS)
(a)
D
2.2
2
1.8
1.6
(b)
K (BITS/SEC)
0.06
0.05
0.04
0.03
0.02
(c)
M_1/τ
2000
1500
1000
500
0
(d)
L/10^5
4
3
2
1
0
30
40
50
60
70
80
90
(e)
χ^2/10^5
4
3
2
1
0
30
40
50
60
70
80
90
r

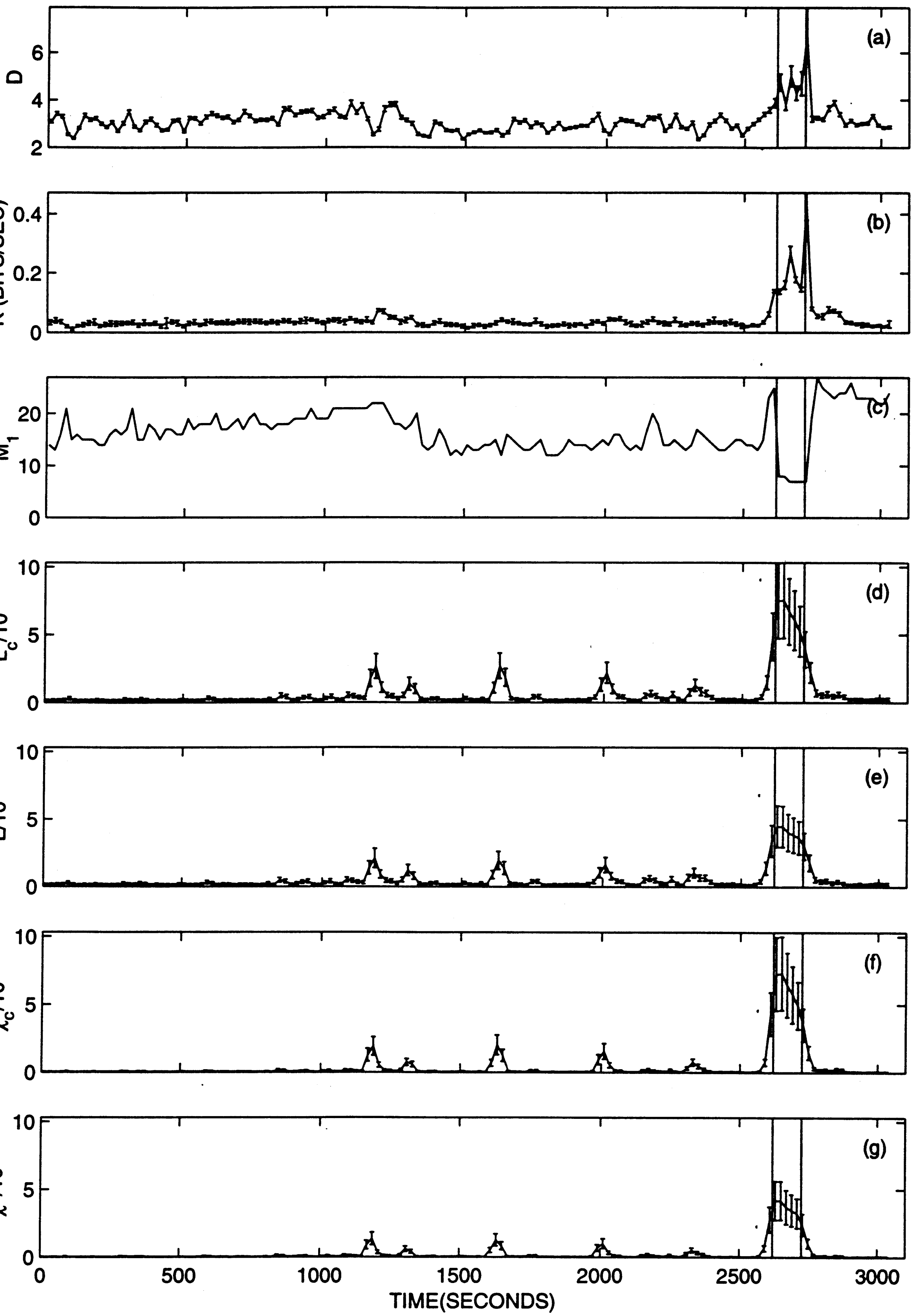


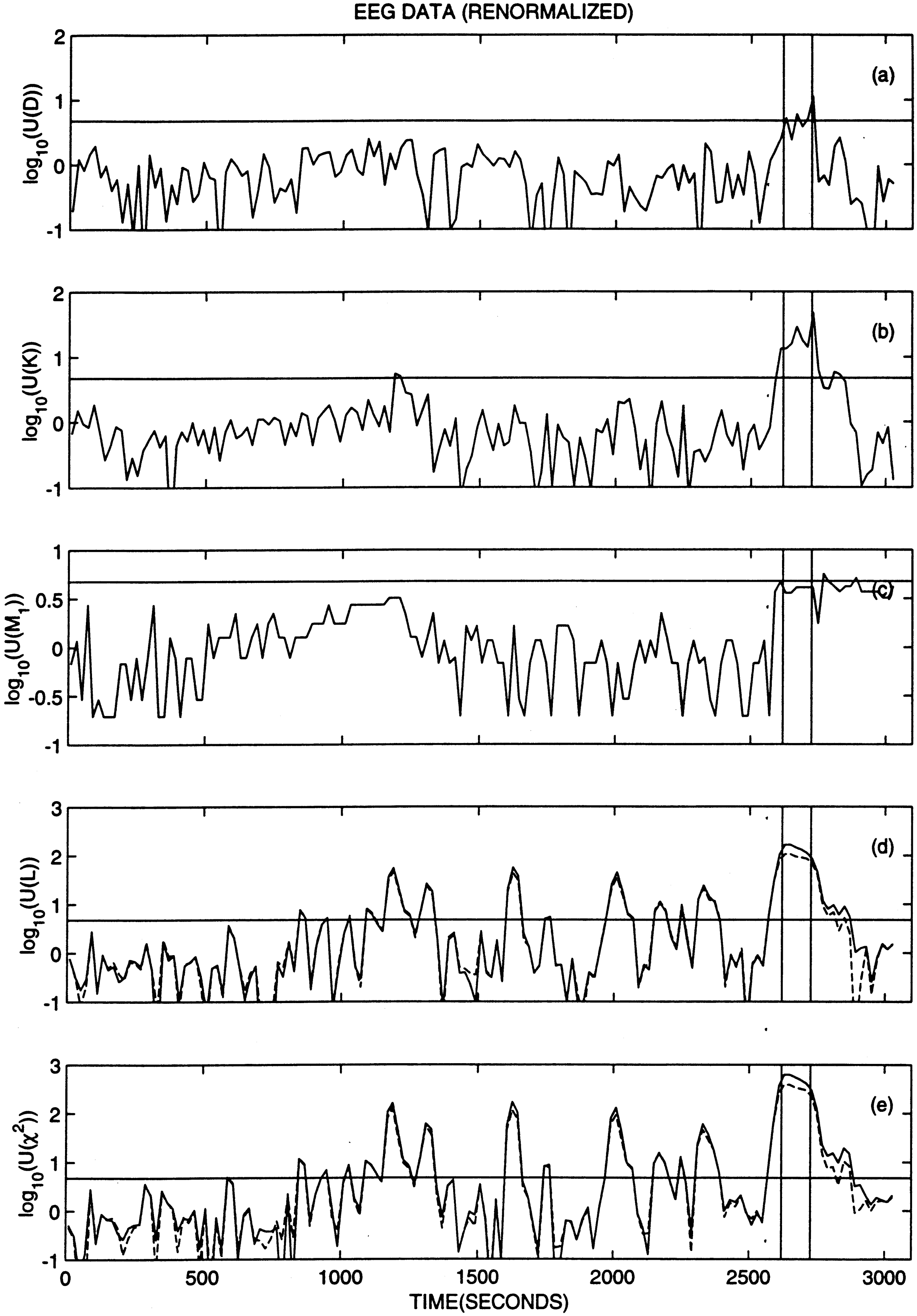
BONDAR DATA (channel 2)
(a)
D
(b)
K (BITS/SEC)
(c)
M1 (TIMESTEPS)
(d)
L/10^5
(e)
χ^2/10^5
C



(a)
(b)
(c)
(d)
(e)
(f)
e_{min} e_{max}
$\log_{10}(U(D))$
$\log_{10}(U(K))$
$\log_{10}(U(M_1))$
$\log_{10}(U(L))$
$\log_{10}(U(\chi^2))$
TIME(SECONDS)

EEG DATA (NOISY)




EEG DATA (RENORMALIZED)
(a)
(b)
(c)
(d)
(e)
$\log_{10}(U(D))$
$\log_{10}(U(K))$
$\log_{10}(U(M_1))$
$\log_{10}(U(L))$
$\log_{10}(U(\chi^2))$
TIME(SECONDS)
0
500
1000
1500
2000
2500
3000

CONCLUSIONS

- PS-DF and CPS-DF are more sensitive measures of condition change than traditional nonlinear measures
- Successful demonstration for other physical processes
- Unambiguous change detection of model *chaotic* regimes
- Preseizure warning of 500 - 2200s in nine EEG datasets

BACKUPS

BONDARENKO MODEL

Coupled set of time-delayed ordinary differential equations:

$$du_i/dt = -u_i(t) + \sum_{j=1}^{M} a_{ij}\, f(u_j(t - \tau_j))$$

Ten coupled neurons: $1 \leq i\ ,\ j \leq M=10$

Uniformly random coupling coefficients: $-2 \leq a_{ij} \leq 2$.

Time delay: $\tau_j = 10$ (constant)

Nonlinear neural response: $f(x) = c \tanh(x)$, $5 \leq c \leq 18$

Fourth-order Runge-Kutta integration ($h=0.05$)

$u_j(t = -\tau) = \rho_j$ for uniformly random values, $-2 \leq \rho_j \leq 2$

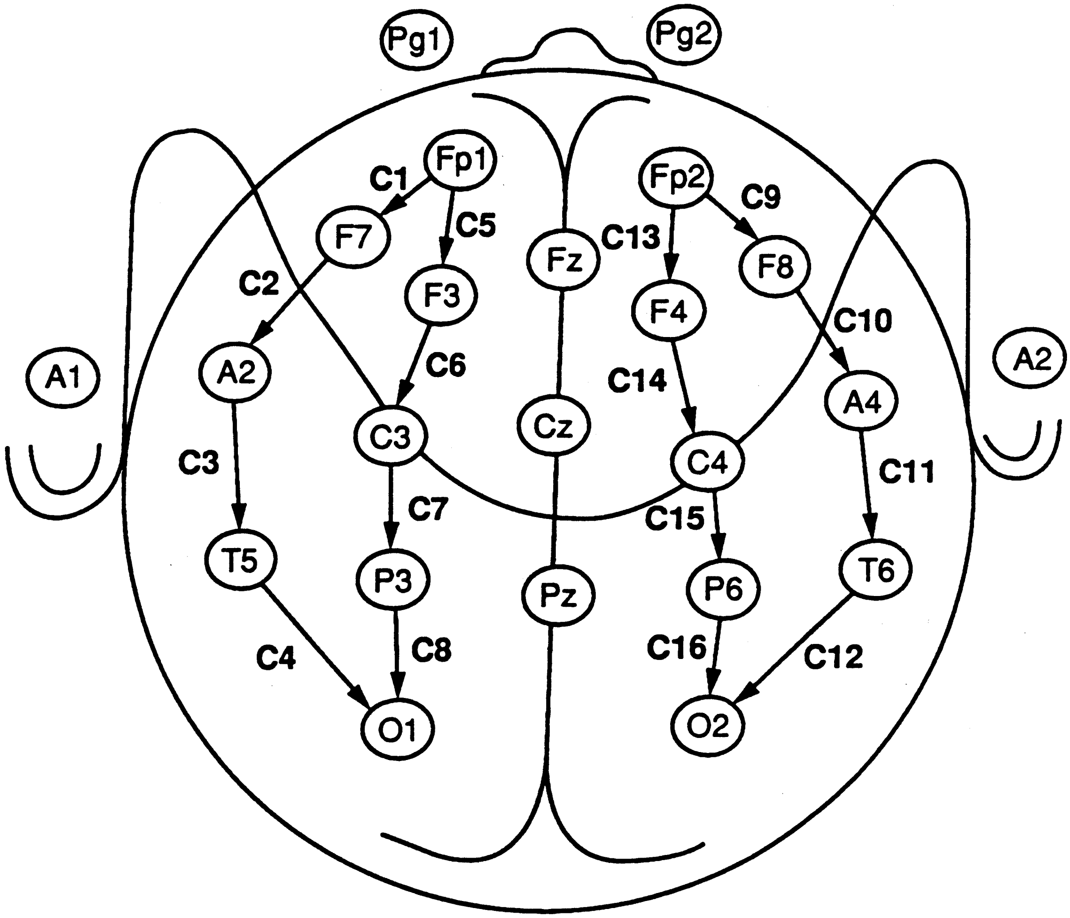
Transient time = $400M\tau h$

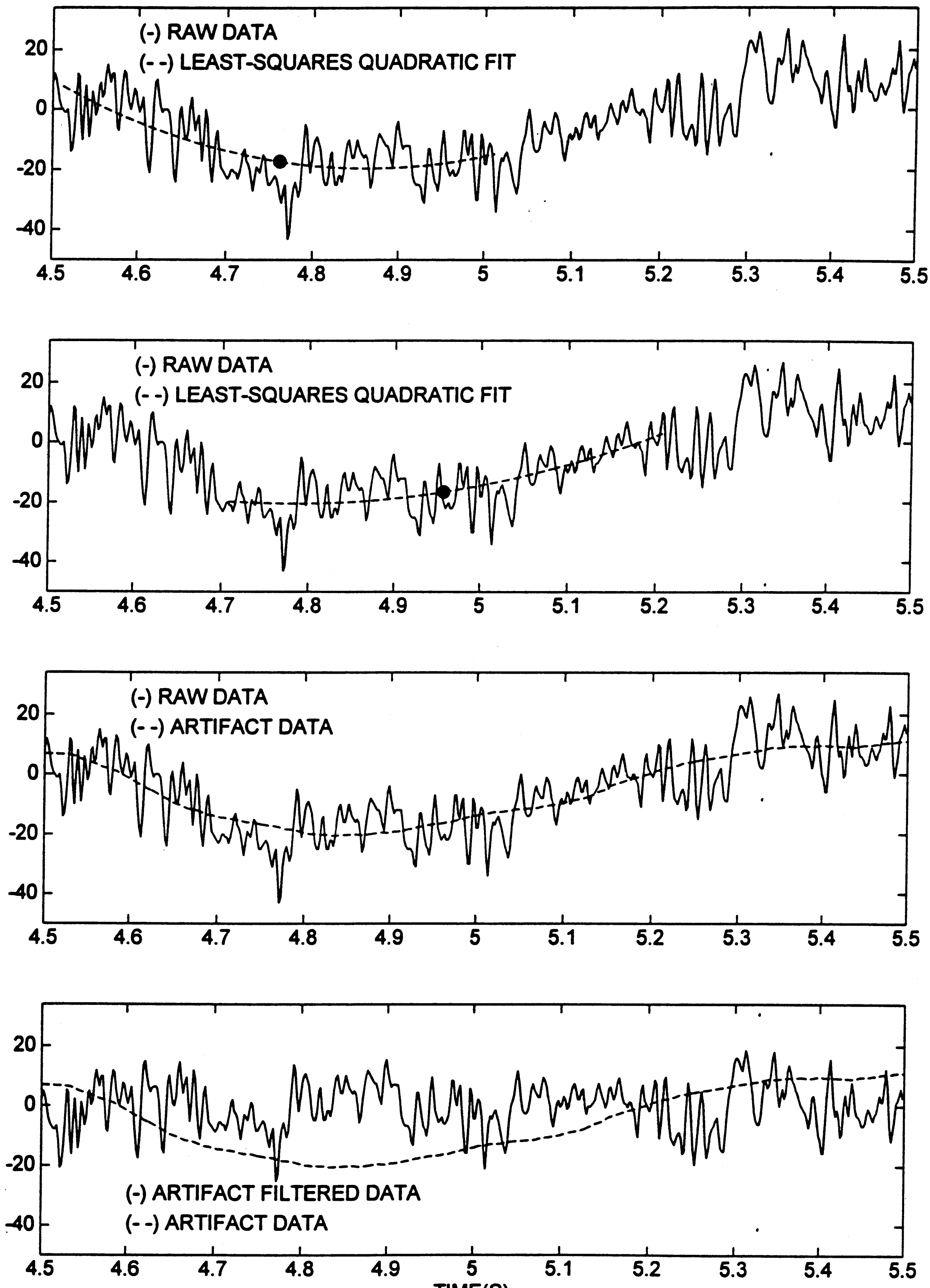
Ref: Bondarenko, *Int'l J Bifur. Chaos* 7 (1997) 1133-1140

BRAIN WAVE DATA FOR EPILEPSY MONITORING

- Analog signal from VHS tape
- 12 bit digitization precision (-2048 to +2047)
- Sample frequency of 512 Hz
- Only channel 13 (over right eye) in bipolar montage
- Nine datasets with lengths of 23 - 50 minutes
- Eyeblink artifact removal with zero-phase, quadratic filter
- Nonlinear analysis of artifact-filtered data
- PS-DF for d=3 and S=34 (bins over signal amplitude)

ORNL-DWG 95M-8764




(-) RAW DATA
(- -) LEAST-SQUARES QUADRATIC FIT
(-) RAW DATA
(- -) LEAST-SQUARES QUADRATIC FIT
(-) RAW DATA
(- -) ARTIFACT DATA
(-) ARTIFACT FILTERED DATA
(- -) ARTIFACT DATA
20
0
-20
-40
4.5
4.6
4.7
4.8
4.9
5
5.1
5.2
5.3
5.4
5.5
TIME(S)

TIME (SECONDS) OF EEG CONDITION CHANGE

Dataset #	D	K	M	L_c	L	χ_c^2	χ^2	best
109310	**2455**	1155	*	1155	835	1175	-45	2455
109314	1100	1940	**2200**	**2200**	**2200**	1960	**2200**	2200
119230	**2051**	491	*	911	911	911	911	2051
119234	2060	2060	**2120**	**2120**	**2120**	**2120**	**2120**	2120
62723t	-140	1380	*	**1720**	**1720**	**1720**	**1720**	1720
69212	716	**996**	696	736	736	736	736	996
73305D	*	*	*	765	**785**	665	**785**	785
c8492D	*	206	166	386	**586**	386	**586**	586
wm12sD	*	*	*	41	41	41	**521**	521
Max time	2455	2060	2200	2200	2200	2120	2200	
Min time	-140	206	166	41	41	41	-45	
Avg time	1374	1175	1296	1115	1104	1079	1059	

Entries denoted by an asterisk (*) show no indication of condition change.
For each dataset, bold entries denote the earliest time of change indication.

Correlation dimension (D)

d = dimensionality

R = radius about some central point = $|x_i - x_0|$

n = number of points from data within that radius $\propto R^d$

$\delta_{ij} = \max\limits_{0 \leq k \leq m-1} |x_{i+k} - x_{j+k}|$ = maximum-norm distance

m = average number of points per cycle

δ = representative length scale in data (multiple of a)

$a = (1/N)\sum_{i=1}^{N} |x_i - \underline{x}|$, and $\underline{x} = (1/N)\sum_{i=1}^{N} x_i$

δ_n = length scale associated with noise in the data

M = number of randomly sampled point pairs

$D = \{(-1/M)\sum_{i,j} \ln [(\delta_{ij} - \delta_n)/(\delta - \delta_n)]\}^{-1}$

Kolmogorov entropy (K)

$K = -f_s \ln(1 - 1/\underline{b})$ = bits of information lost per second

f_s = digital sampling rate (e.g., 512 Hz)

$$\underline{b} = (1/M) \sum_{i,j}^{M} b_{ij}$$

b_{ij} = number of timesteps for two points to diverge from $|x_i - x_j| \leq \delta$, to $|x_i - x_j| > \delta$

Mutual information function ($\mathcal{I}$)

$\mathcal{I}(R,S) =$ bits of information inferred from measurement now about second measurement at some time lag later

$= \mathcal{I}(S,R) = H(R) + H(S) - H(R,S)$

$$H(R) = -\sum_i P_R(r_i)\log_2[P_R(r_i)]$$

$$H(R,S) = -\sum_{i,j} P_{RS}(r_i, s_j)\log_2[P_{RS}(r_i, s_j)]$$

R,S = all possible measurements of r_i and s_j
P_R = probability associated with r_j
P_S = probability associated with s_j
P_{RS} = joint probability of both r_j and s_j occurring
M = lag at first minimum in $\mathcal{I}$

RENORMALIZATION

- For meaningful comparison, renormalization is needed for each of the nonlinear measures $V = \{D, K, M, \chi^2, L\}$

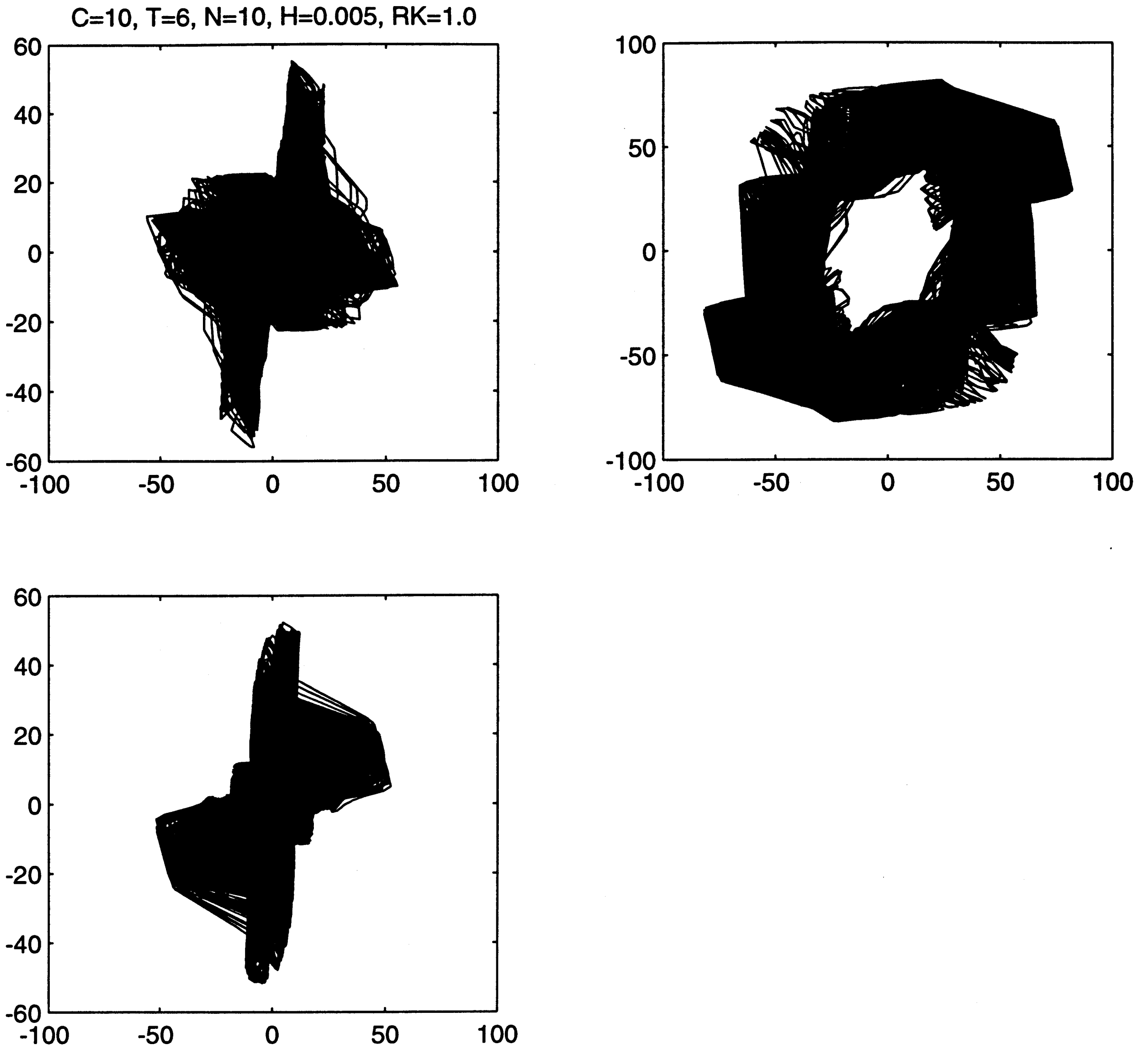
- Average over base case windows ($\underline{V}$) with corresponding standard deviation of the mean (σ_v)

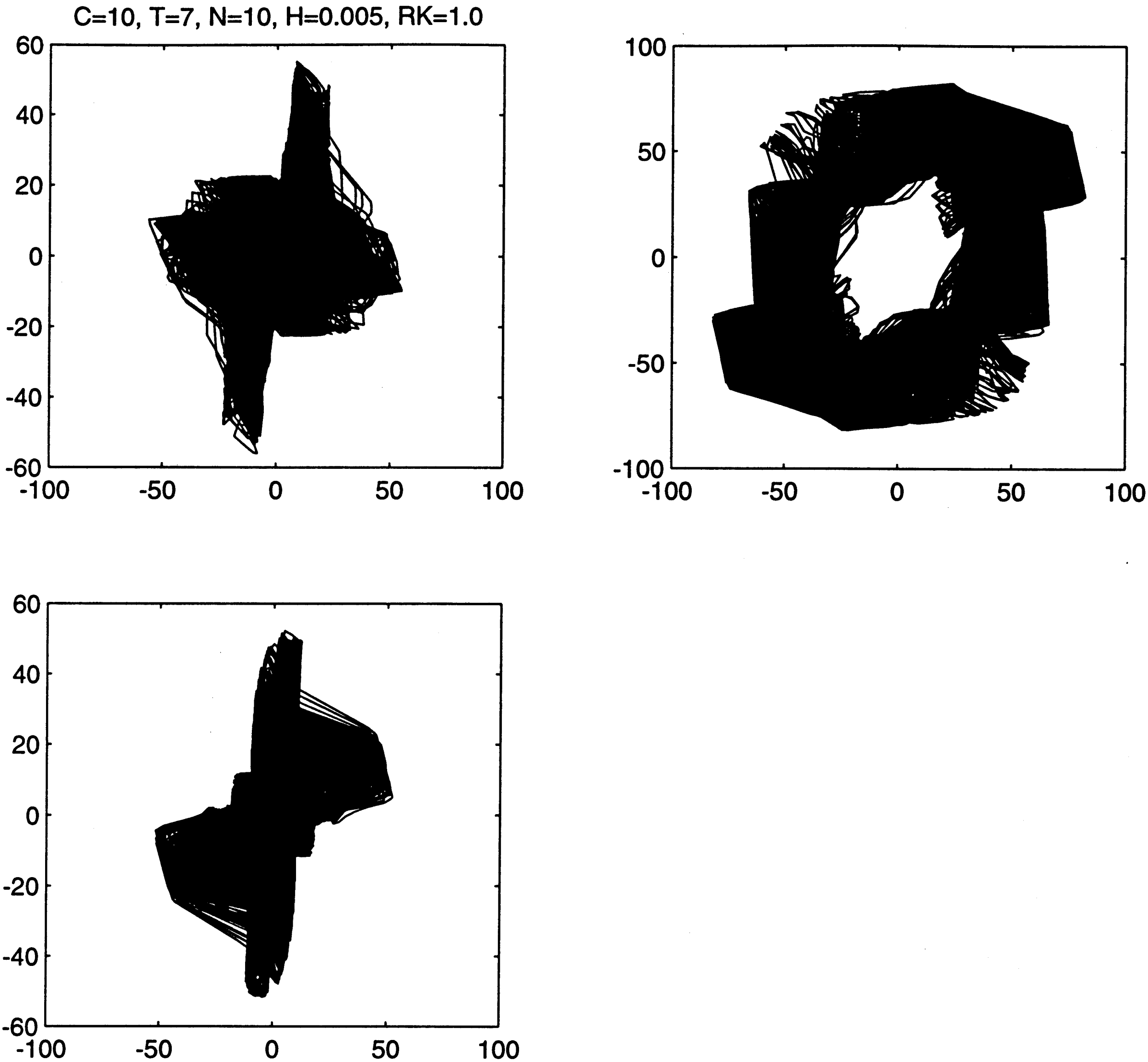
- Define renormalized measure: $U(V) = |V_i - \underline{V}|/\sigma_v$ where V_i = value of nonlinear measure for i-th time interval

- Renormalized measure provides unified basis for comparison

DEMONSTRATION FOR OTHER PHYSICAL PROCESSES

- motor current for pre-failure indications
- motor current to distinguish drilling conditions
- motor power to distinguish (un)balanced conditions
- microcantilever vibrations to distinguish sensor state


C=10, T=6, N=10, H=0.005, RK=1.0
60
40
20
0
-20
-40
-60
-100
-50
0
50
100
100
50
0
-50
-100
-100
-50
0
50
100
60
40
20
0
-20
-40
-60
-100
-50
0
50
100


C=10, T=7, N=10, H=0.005, RK=1.0
60
40
20
0
-20
-40
-60
-100
-50
0
50
100
100
50
0
-50
-100
-100
-50
0
50
100
60
40
20
0
-20
-40
-60
-100
-50
0
50
100