SENSITIVE MEASURES OF CONDITION CHANGE IN EEG DATA

by

P.C. Gailey, L.M. Hively, V.A. Protopopescu
Oak Ridge National Laboratory
Oak Ridge, Tennessee, USA

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OUTLINE

Nonlinear time series and nonlinear measures
Previous work on condition change
New Methodology
Application to condition change in the Lorenz 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

\[ \chi^2 = \sum (R_i - S_i)^2 / (R_i + S_i) \]

\[ L = \sum |R_i - S_i| \]

Lorenz system: r=25 versus r=26

High sensitivity: subtract, then integrate
Low sensitivity: integrate, then subtract
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) $D$

(b) $K$ (BITS/SEC)

(c) $N_{H/F}$

(d) $L/10^5$

(e) $\chi^2/10^5$

$r$
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 Lorenz chaotic regimes
- Preseizure warning of 500 - 2200s in nine EEG datasets
BACKUPS
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)
### TIME (SECONDS) OF EEG CONDITION CHANGE

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| 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 \(\propto R^d\)
\(\delta_{ij} = \max_{0 \leq k \leq m-1} |x_{i+k} - x_{j+k}| = \) maximum-norm distance

\(m = \) average number of points per cycle
\(\delta = \) representative length scale in data (multiple of a)

\[a = \frac{1}{N} \sum_{i=1}^{N} |x_i - \bar{x}|, \quad \text{and} \quad \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i\]

\(\delta_n = \) length scale associated with noise in the data
\(M = \) number of randomly sampled point pairs
\(D = \left\{\frac{-1}{M} \sum_{i,j} \ln \left[ \frac{(\delta_{ij} - \delta_n)/(\delta - \delta_n)}{\delta_n} \right] \right\}^{-1}\)
Kolmogorov entropy (K)

\[ K = -f_s \ln \left(1 - \frac{1}{b}\right) = \text{bits of information lost per second} \]

\[ f_s = \text{digital sampling rate (e.g., 512 Hz)} \]

\[ b = \frac{1}{M} \sum_{i,j}^M b_{ij} \]

\[ b_{ij} = \text{number of timesteps for two points to diverge from } |x_i - x_j| \leq \delta, \text{ to } |x_i - x_j| > \delta \]
Mutual information function \( (I) \)

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

\[ = I(S,R) = H(R) + H(S) - H(R,S) \]

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

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

\[ R,S = \text{all possible measurements of } r_i \text{ and } s_j \]

\[ P_R = \text{probability associated with } r_j \]

\[ P_S = \text{probability associated with } s_j \]

\[ P_{RS} = \text{joint probability of both } r_j \text{ and } s_j \text{ occurring} \]

\[ M = \text{lag at first minimum in } I \]
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 ($V$) with corresponding standard deviation of the mean ($\sigma_v$)

- Define renormalized measure: $U(V) = |V_i - \bar{V}|/\sigma_v$
  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