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SENSITIVE MEASURES OF CONDITION CHANGE IN EEG DATA

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We present a new, robust, model-independent technique for measuring condition change in nonlinear data. We define indicators of condition change by comparing distribution functions (DF) defined on the attractor for time windowed data sets via L_1 -distance and χ^2 statistics. The new measures are applied to EEG data with the objective of detecting the transition between non-seizure and epileptic brain activity in an accurate and timely manner. We find a clear superiority of the new metrics in comparison to traditional nonlinear measures as discriminators of condition change.

The aim of this paper is twofold: (i) we present a new, robust, model-independent technique for measuring condition change in nonlinear data and (ii) we apply it to clinical EEG data. Our technique focuses on discriminating between different and possibly close *chaotic* regimes.

Based on the phase space (PS) reconstruction of the dynamics from delayed time series ¹ various nonlinear measures have been defined to characterize process dynamics. We choose three of these nonlinear measures, against which to compare the new metrics. In particular, we use ¹: (i) the first minimum in the mutual information function, M_1 , as a measure of decorrelation time, (ii) the correlation dimension, D , as a measure of dynamic complexity, and (iii) the Kolmogorov entropy, K , as a measure of predictability.

While describing certain global features of the nonlinear dynamics, these traditional nonlinear measures do not capture the host of finer details that could be responsible for condition change. The same is true for other global indicators such as fractal dimension, Lyapunov exponents, etc. The main reason for this insufficient discriminating power is the fact that in the definition of these indicators most dynamical details cancel each other out by averaging over many cycles. In order to capture these minute details, more refined indicators are needed. We define two such new indicators starting from the invariant measure of the dynamics on the attractor. We represent the distribution function (DF) on the attractor by using N discrete cells. We denote the population in the i -th PS-DF state as Q_i for the basecase and R_i for the unknown and we measure the difference between Q_i with R_i by the χ^2 statistics and L_1 distance:

$$\chi^2 = \sum_{i=1}^N (Q_i - R_i)^2 / (Q_i + R_i), \quad (1)$$

$$L = \sum_{i=1}^N |Q_i - R_i|. \quad (2)$$

The choice of these measures is dictated by the following considerations. The χ^2 statistics is one of the most powerful, robust, and widely-used statistical tests to measure discrepancies between observed and expected frequencies. The L_1 distance is the natural metric for DFs since it is directly related to the total invariant measure on the attractor. To apply these measures properly we have to scale the total population of the unknown DF (sum over all the domain populations in R_i) to be the same as the total population of the basecase.

By connecting successive PS points as indicated by the dynamics, $y(i) \rightarrow y(i+1)$, one obtains a discrete representation of the process flow¹. This approach motivates the extension of the PS method to capture even more dynamical information using pair-wise connectivity between successive d -dimensional PS states, thus forming a $2d$ -dimensional vector, $Y(i) = [y(i), y(i+1)]$, in the connected-PS (CPS). The connected distribution functions (CDF) are Q_{ij} and R_{ij} for the basecase and unknown processes, respectively. The index, i , denotes the beginning (i -th) PS state, and $j = i + 1$ denotes the ending (j -th) PS state. We define the connected χ^2 statistic, χ_c^2 , and the connected L_1 distance, L_c , by expressions similar to Eqs. (1)-(2) in which we replace Q_i, R_i by Q_{ij}, R_{ij} and sum over both indices, $i, j = 1, \dots, N$. These measures satisfy the following inequalities: (i) $\chi^2 \leq L$; (ii) $\chi_c^2 \leq L_c$; (iii) $L \leq L_c$; and (iv) $\chi^2 \leq \chi_c^2$, which show that, as expected, the measures of condition change for the CPS are stronger than those for the PS representation.

We applied these measures to brain wave data, which have often been described in terms of nonlinear dynamics². Nonlinear EEG measures are not stationary, displaying marked transitions between normal and epileptic states. EEG data display clear PS structure and low-dimensional features^{2,3} with at least one positive Lyapunov exponent^{2,4} and hence positive Kolmogorov entropy. Thus, use of the new L_1 and χ^2 PS and CPS measures seems warranted for detection of nonlinear condition changes in brain wave data. Since brain dynamics in EEG are obscured by muscular activity due to eye blinks, facial twitches, etc., we eliminated by using a zero-phase quadratic filter.^{5,6}

Figure 1 shows a typical plot of nonlinear EEG measures versus time. For the first 800 seconds, variability in all of the measures is modest, representing the dynamics of normal brain activity. The clinical seizure occurs at 2620-2726 seconds, as indicated by the vertical bars at these times in this (and the subsequent) figure. A pre-seizure indication in D occurs as a small decrease at 1150 seconds (Fig. 1a). Likewise, a pre-seizure indication in K is a small peak at 1150 seconds (Fig. 1b). Later variations in D and K provide no clear pre-seizure indication in Fig. 1. The value of M_1 rises slowly from 12 to 20 during the non-seizure period (0 - 1100 seconds), then falls gradually to an average value of 14 (range: 11-20) during the pre-seizure period (Fig. 1c). During the seizure, D and K show clear peaks, while M_1 falls abruptly. In sharp contrast to these weak pre-seizure indications, clear peaks occur in the PS measures (Figs. 1d-g) at 1150, 1300, 1600, and 2350 seconds.

Our approach differs markedly from earlier work^{3,4} in several respects. First, previous investigations used data from subdural and depth electrodes, while we use scalp EEG data that allows non-invasive, ambulatory, long-term monitoring. Second, those studies obtained EEG data from the epileptogenic area, while we used data only from channel 13 in the bipolar montage, showing the robustness of

our method, and allowing easy electrode placement by a patient for non-clinical monitoring. Third, prior effort used invasive monitoring to avoid low-frequency artifacts, which we removed from scalp data with a zero-phase quadratic filter, dramatically improving the data quality and the nonlinear measures. Fourth, previous investigations focused only on temporal lobe epilepsy, while we earlier determined no consistent trends in D and K for various seizure types and instead focused on these new measures of condition changes for any seizure. These advantages will facilitate routine use by patients in a non-clinical setting.

Practical use of this method for forewarning epileptic events will require characterization of several seizures for each patient, and detailed determination of detection criteria. Future work will involve: (i) statistical evaluation of false positives and negatives in epileptic patients, and of false positives in normal patients and (ii) clinical monitoring of each patient to determine optimal (C)PS construction parameters, which subsequently would be fixed for ambulatory monitoring.

We presented two new model-independent measures to detect non-stationarity (condition change) in nonlinear time series. These indicators integrate (and magnify) the *differences* between the process dynamics, and avoid the inner cancellation effects due to averaging over many orbits. The new measures also indicate significant pre-seizure changes in all nine analyzed EEG datasets 521 – 2200 seconds before the clinical seizure while correlation dimension, Kolmogorov entropy, and mutual information fail to detect any change at all in three, two, and five EEG datasets, respectively ⁶. These results show that the new measures are superior to traditional nonlinear measures for detection of condition change.

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Figure 1. Nonlinear measures versus time for dataset #62723t: (a) correlation dimension, D , (b) Kolmogorov entropy, K , (c) first minimum in the MIF M_1 , (in timesteps), (d) L_c , (e) L , (f) χ_c^2 , and (g) χ^2 .