Forewarning of Machine Failure via Nonlinear Analysis

V. A. Protopopescu and L. M. Hively

Oak Ridge National Laboratory, P.O. Box 2008, Oak Ridge,TN 37831-6355
protopopesva@ornl.gov ; hivelylm@ornl.gov

Nonlinear processes display rich dynamics under both normal and abnormal conditions. These dynamics typically are extracted from process-indicative data, x_i, via time-serial analysis for monitoring, prediction, and control. Despite decade-long efforts and countless applications, timely, robust, and accurate detection and characterization of condition change remains extremely challenging in large, complex systems for which no suitable or reliable models exist.

We present a new approach to assess condition change within a *model-independent* framework, from *limited, noisy* data. The specific application is forewarning of equipment and machine failures. First, we remove confounding artifacts from the process indicative data, x_i. This is done by using a moving window of length $2w + 1$, with w data points on each side of the current central point. We fit a parabola in the least-squares sense over this window, taking the central point of the fit as the low-frequency artifact, f_i. The residue, $g_i = x_i - f_i$, is essentially artifact-free. Removal of a known low-frequency artifact uses a filter-window width, $w = f_s/(4.4\, f_x)$. Here, f_s the data sampling rate, and f_x is the high-pass cutoff frequency of the noise. Removal of an unknown artifact involves a search over the value of w to determine the best sensitivity for the measures of condition change, as described below. From the artifact-filtered signal, g_i, we construct a d-dimensional time delay vector, whereupon the standard phase space (PS) reconstruction technique [1-2] yields a discrete representation of the distribution function (DF) in the d-dimensional PS. The resulting DF captures the underlying dynamics, in terms of geometry and visitation frequency; (un)altered dynamics lead to an (un)changed DF.

For practical implementation, the DFs are discretized. We denote the DF population of the i-th bin of the PS as Q_i and R_i for the base-case and test-case DFs, respectively. We compare the test and base cases, by using two new measures:

$$\chi^2 = \sum_i (Q_i - R_i)^2 / (Q_i + R_i), \tag{1}$$

$$L = \sum_i |Q_i - R_i|, \tag{2}$$

where the sums run over the populated PS cells. We refer to χ^2 and L *as phase-space dissimilarity measures* (PSDM).

Over the last two decades, various traditional nonlinear measures (TNM) such as correlation dimension (D), Lyapunov exponents, Kolmogorov entropy (K), or mutual information, have been used as nonlinear metrics to detect changes in dynamical systems, but success has remained limited at best [3]. Indeed, while TNM may distinguish between regular and chaotic dynamics, they cannot discriminate between *slightly different* chaotic regimes, especially for limited, noisy data. However, the PSDM turn out to be much more sensitive, even when data is limited and/or noisy [3-6]. The reason for this enhanced performance is clear from the definition: in PSDM, the DFs are first subtracted and then integrated; in TNM, the information in each DF is averaged out and rendered essentially useless for further discrimination.

Direct comparison of PSDM and TNM is meaningless, due to their disparate ranges, variability, and physical interpretation. Thus, we convert both into *renormalized dissimilarity measures* (RDM), defined as: $U(V) = |V_i - \underline{V}|/\sigma$ [3 – 6]. Here, V_i denotes any nonlinear measure from the set, $V = \{D, K, \chi^2, L\}$, over the i-th window of N non-overlapping, contiguous time-serial data points; $\underline{V}$ denotes the mean value of V over a number B of base case windows, with a corresponding sample standard deviation, σ. The parameters (N, S, d, λ, w, and B) depend on the specific data. Distant states have large RDM, which we interpret as forewarning of an abnormal event, such as a machine failure.

We have validated this approach on: (i) the Lorenz [3, 5] and Bondarenko [6] models; (ii) forewarning of epileptic seizures from clinical scalp EEG [3 - 6]; (iii) different drilling conditions from motor current and (un)balanced states in a centrifugal pump from motor power [7]; and (iv) failure forewarning in nuclear-grade equipment [8].

Fig. 1 shows an example [8] of TNM and PSDM for seeded faults in an 800-HP motor, based on electrical power, $P = \Sigma_k I_k V_k$, from the three-phase motor currents, I_k, and voltages, V_k.. State 1 indicates nominal operation. In State 2, one rotor bar was cut 50% at the 11-o'clock position. The same rotor bar was cut completely through in state 3. In state 4, a second rotor bar was cut 100% at the 5-o'clock position. Finally, two more bars were cut on each side of 11-o'clock bar (State 5). Thus, the fault severity doubled from ½ to 1 to 2 to 4. This exponential increase is not reflected by correlation dimension (Fig. 1b) and Kolmogorov entropy (Fig. 1c), but is faithfully mirrored by the linear rise of the logarithm of the two PSDM (Figs. 1d-1e).

In summary, our new method combines several original advances to achieve sensitivity that is at least one order of magnitude larger than that obtained to date by competing methods. A key step is removal of confounding artifacts with a novel nonlinear filter. The crucial point though is the fact that - by using differential as opposed to integral measures of dissimilarity - PSDM contain a much higher amount of dynamical information than TNM.

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References

1 H.D.I. Abarbanel, *Analysis of Observed Chaotic Data*, Springer Publ., New York (1996).

2. J.-P. Eckmann and D. Ruelle, "Ergodic Theory of Chaos and Strange Attractors" *Rev. Mod. Phys.,* **57**, 617 (1985).

3. L. M. Hively, P. C. Gailey, and V. A. Protopopescu, "Detecting condition change in nonlinear time serial data," *Phys. Lett. A*, **258**, 103 (1999).

4. L. M. Hively, V. Protopopescu, and P. Gailey, "Timely Detection of Dynamical Change in Scalp EEG Signals," *Chaos*, **10**, 864 (2000).

5. V. Protopopescu, L. M. Hively, and P. C. Gailey, "Epileptic event forewarning from scalp EEG," *J. Clin. Neurophys*., **18**, 223 (2001).

6. L. M. Hively and V. A. Protopopescu, "Channel-consistent forewarning of epileptic events from scalp EEG," to be published in *IEEE Trans. Biomed. Engr.* (2003).

7. L. M. Hively, "Data-Driven Nonlinear Technique for Condition Monitoring," in *Proc. Maintenance and Reliability Conf*, edited by T.E. Shannon et al. (Univ. of Tennessee, Knoxville), **1**, 16.01 (1997).

8. L. M. Hively and V. Protopopescu, "Forewarning of Failure in Critical Equipment at Next Generation Nuclear Power Plants," *ORNL/TM-183* (Oak Ridge National Laboratory) 2002.

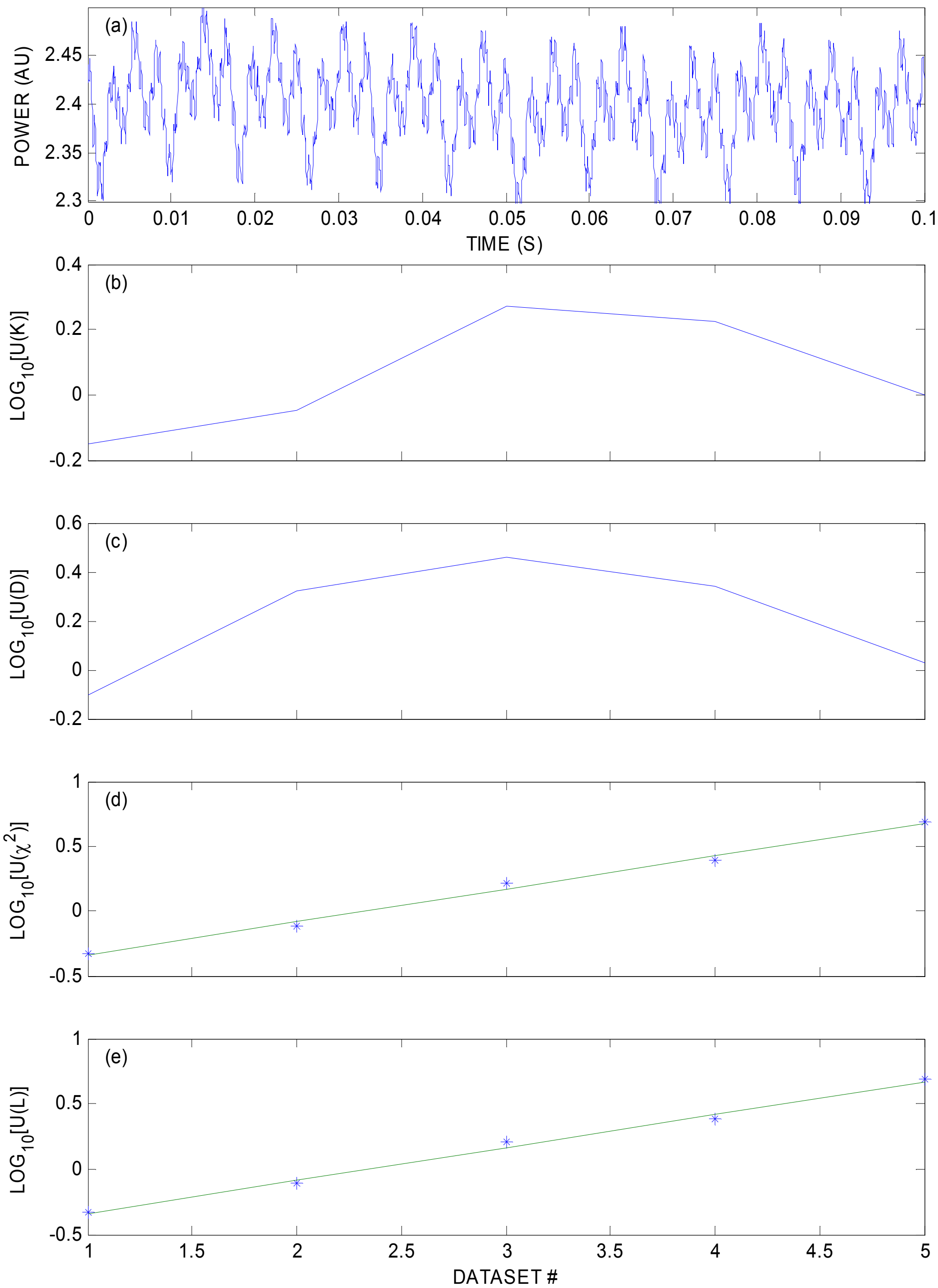

Figure 1: Motor power data vs. time (a), and four RDM vs. dataset number as discussed in the text for (b) Kolmogorov entropy, (c) correlation dimension, (d) χ^2, and (e) L. The PS reconstruction parameters are as follows: $d = 4$, $S = 88$ (equiprobable symbols), $\lambda = 31$, w=550, $N = 12000$, and $B = 5$.