



Information Redundancy as an Information Theoretic Criterion for Onset Detection

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Abstract

We propose a criterion, called ‘maximal redundancy’, for onset detection in time series. The concept redundancy is inspired from information theory and indicates how well a signal locally can be explained by an underlying model exploiting past observations. It is shown that a local maximum in the redundancy is a good indicator for an onset. It is proven that ‘maximal redundancy’ detection is a statistical asymptotically optimal detector for AR processes. Moreover, the detector accounts for non-Gaussianity of the innovations in the AR processes, using negentropy. Several applications are shown where the new criterion has been successfully applied.

Introduction

Previous research often started from the assumption that an onset is characterized by a change in the variance profile of a signal (see [1] for an overview). This assumption was made either heuristically (see the Hodges and Bui, Bonato et al., Lidierth, Abbink et al. references in [1]) or explicitly by means of a statistical model (*EstOpt*, *AGLRstep* and *AGLRramp* in [1]).

Here, we assume that the onset of a ‘signal of interest’ can be determined as a change in the information redundancy profile. In fact, it was shown ([2]) that the proposed *MaxRed* criterion is not contradictory to *EstOpt*, but rather is complementary to it. Both *EstOpt* and *MaxRed* are based on a log-likelihood ratio; however *EstOpt* assumes identical and independently distributed (i.i.d.) Gaussian variables whereas our *MaxRed* can handle dependent and non-Gaussian variables, by establishing the link with information theoretic concepts.

Information Theoretic Equivalent for Onset Detection

Given 2 hypotheses H_1 and H_0 , the optimal statistical decision is determined by the Neyman-Pearson criterion [3]:

$$\ln \frac{p(y_j, y_{j+1}, \dots, y_k | H_1)}{p(y_j, y_{j+1}, \dots, y_k | H_0)} \underset{H_0}{\overset{H_1}{>}} \gamma \quad (1)$$

We then assume H_1 is a model, where the current observation is a function of past observations, while H_0 contains i.i.d. observations:

$$\begin{aligned} y_n &= f(y_{n-1}, y_{n-2}, \dots, y_{n-p}) + \varepsilon_n \\ H_0 : p &= 0 \\ H_1 : p &> 0 \end{aligned} \quad (2)$$

Note that the model in (2) contains the autoregressive model (AR) as a special case. We can further prove, by transforming the y_i into the ε_i variables, and making use of causality, that (2) is equivalent to (see [2]):

$$\sum_{i=j}^k (\ln p(\varepsilon_i) - \ln p(y_i)) \underset{k-j+1 \text{ large}}{\approx} (k-j+1)(-H(\varepsilon) + H(y)) \quad (3)$$

In (3), we used the *Shannon-McMillan-Breiman* theorem (see [4]) to establish the asymptotic result, where $H(\cdot)$ is the Shannon entropy. It can be proven further [2], that (3) is equivalent to the *marginal information redundancy* [5]. Hence, we can state (1) combined with (2) intuitively as:

“We choose in favour of H_1 if there is a significant decrease in the number of bits needed to encode a sequence of observations, when we take into account the past observations”.

Applications

We show 2 applications, where the ‘maximal redundancy’ criterion has been successfully applied as an onset detection criterion.

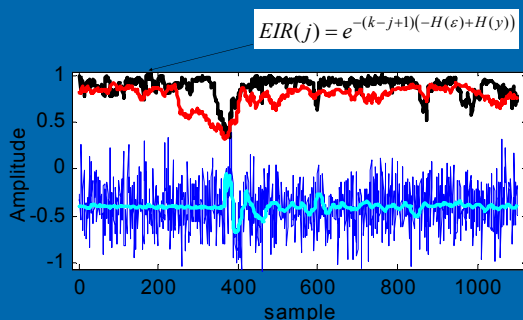


Figure 1. Burst onset detection. The oscillating burst (in cyan) is an example of an acoustic event due to pitting. Detection of the burst occurs by detecting a minimum in the inverse redundancy profiles on top of the figure. The noisy signal was created from the burst signal by adding WGN until -14 dB SNR.

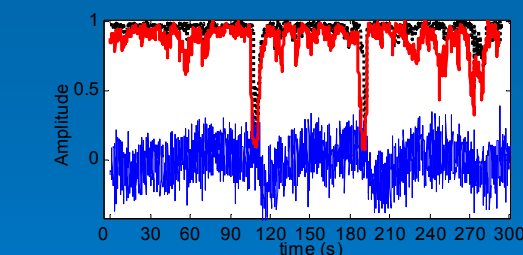


Figure 2. Voltage jumps onset detection. The electrochemical noise signal is shown on the bottom. The jumps are related to stress corrosion cracking (SCC) events. On top 2 exponential inverse redundancy profiles corresponding with 2 different parameter settings are shown. Note that at the onset of the jumps, about 110 s and 190 s, 2 distinctive minima (or maxima in redundancy) are obtained.

References

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