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Adaptive filtering techniques for interferometric data preparation : removal of long-term sinusoidal signals and oscillatory transients

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We propose an adaptive denoising scheme for poorly modeled non-Gaussian features in the gravitational wave interferometric data. Preliminary tests on real data show encouraging results.

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1. Motivation

Several large-scale interferometric gravitational wave detectors will come on-line soon, such as LIGO in the U.S., the French/Italian Virgo project, GEO600 the German/British interferometer and TAMA in Japan. Gravitational wave detectors produce an enormous volume of output. Data analysis techniques will have to be developed to optimally extract the weak signature of a gravitational wave from these data. Many of the techniques developed so far are based on matched filtering and assume stationary Gaussian noise.

However, the real data stream from the detectors is not expected to satisfy the stationary and Gaussian assumptions. This disparity between standard Gaussian assumptions and real data characteristics poses a major problem to the direct application of matched filtering techniques in particular for burst sources such as black hole binary quasinormal ringings [1] or inspiral waveforms [2]. In fact, the data from the Caltech 40 meter proto-type interferometer has the expected broadband noise spectrum, but superposed on this are several other noise features: such as long-term sinusoidal disturbances coming from suspensions and electric main harmonics and also ringdown transients occurring occasionally, typically due to servo-controls instabilities or mechanical relaxation in suspension system etc. While no precise model can be given for this noise until the detector is completed and fully tested, matched filtering techniques cannot be used to locate/remove these noisy signals.

We propose a denoising method based on *adaptive linear prediction* techniques which does not require any precise *a priori* information about the noise characteristics. Although our method does not pretend to optimality, we believe that its simplicity makes it useful for data preparation and for the understanding of the first data.

In the following, we present the structure of the proposed algorithm and some results obtained with the data from the Caltech 40 meter proto-type interferometer [3]. For a more detailed presentation, we refer the reader to [4].

2. Adaptive linear prediction

The idea is to predict the current signal sample x_k with a collection of past samples $X_k = (x_{k-d-n}, n = 0, 1, \ldots, N-1)^t$, the delay $d \geq 1$ being fixed arbitrarily. This is possible, only if the target sample shares enough information with (i.e., is sufficiently correlated to) the previous ones. In other words, the only predictable part of the signal is the one whose correlation length is sufficiently large (i.e., long-term sinusoids or ringdowns). On the other hand, the broad band noise cannot be predicted, as it is not possible to guess the next value in this way. The prediction y_k of x_k is obtained through a linear combining of these data samples weighed by the corresponding coefficients w_n, forming the tap-weight vector $W = (w_n, n = 0, 1, \ldots, N-1)^t$, therefore leading to $y_k = W^t X_k$.

The optimal tap-weight vector W^* which leads to the smallest prediction error $e_k = y_k - x_k$ in the mean square sense can be proved to minimize a convex cost function. This minimization can be done using an approach similar to the steepest descent method with the following evolution equation for the tap-weights referred to as Least Mean Square or LMS algorithm [5] :

$$W_{k+1} = W_k + \mu e_k X_k, \tag{1}$$

where the step gain parameter μ is an adjustable parameter. The tap-weight coefficients are renewed iteratively so that to converge and stabilize in a neighborhood of W^* whose size is defined by μ.

Once the filter has converged, we reject the predicted part of the signal (i.e., y_k) corresponding to the long-term sinusoids and the ringdown noise and we send the rest of the signal (i.e., e_k) for further analysis for detection.

This LMS based prediction method is referred to as *adaptive line enhancer (ALE)* [5]. In this context, the term "adaptive" has two different meanings. First, it means that it will auto-adjust to reach for the best setup for a problem which is not initially precisely defined. Second, it is also able to follow changes in the characteristics of the data being processed in case they occur.

Convergence time, frequency tracking ability and frequency resolution are controlled by the three adjustable parameters : the number of tap-weight coefficients N, the step gain parameter μ and the prediction depth d. One can take advantage of certain settings of the ALE to select a family of signals intead of another.

3. The ALE in practice

Structure of the algorithm — We decompose the frequency axis in p disjoint frequency subbands of the same size. In each subbands, we apply twice the ALE with different sets of parameters. In the first step, the adjustable parameters are tuned to best remove long-term sinusoidal components of the noise ; whereas in the second one, the target is the short-time oscillatory transients (see [4] for details about parameter adjustment).

The ALE needs to be applied only in the parts of the signal which appears non-Gaussian. Some refinements are adjunct for this purpose : the acceptation (dismissal) of the first cleaning step relies on the detection of a long-term sinusoids of sufficient amplitude in the data. In the second step, the ALE is applied only if the filtered output y_k deviates from Gaussianity. Details about these additional vetos can be found in [4].

Results on Caltech 40m proto-type data — We have applied the algorithm to the Caltech 40meter proto-type data taken in October 1994. Figure 1 illustrates how the algorithm is operating in the fifth frequency subband (from 617 Hz to 771 Hz) among the $p = 32$ ones being processed. Figure 2 shows comparisons between the power spectra and histograms of the signal before and after denoising.

4. Concluding remarks

The originality of the proposed approach lies in the fact that it is possible to treat oscillatory transients. However, it remains that a comparison of the performances achieved by this algorithm on noise features of longer duration with other existing methods need to be done. Finally, although undertaken in [4], this method suffers from the lack of a complete statistical characterization.

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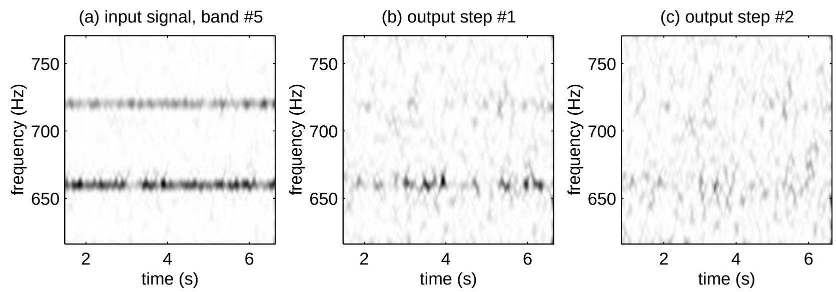

Fig. 1. **Illustration of the denoising procedure on Caltech proto-type data**. In the subband #5 (between 617 Hz and 771 Hz), the signal [6] (the data were taken on the October, 14th 1994, frame #2) contains two power line harmonics (at 660 Hz and 720 Hz), as we see on the spectrogram (**a**) (this is a time-frequency representation of the signal energy. Dark regions are associated to large values of the energy density). We apply the ALE a first time to suppress long-term components (see spectrogram (**b**)) and a second run (**c**) eliminates artefacts of shorter duration (such as fast fluctuations in the harmonic envelope).

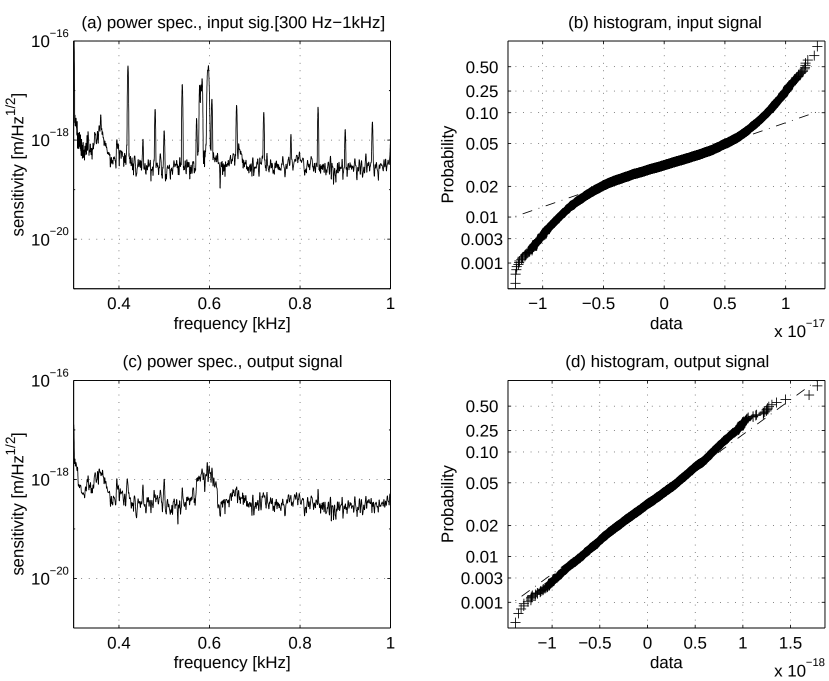

Fig. 2. **Comparison between power spectra and histograms of input/output signals**. The figure depicts power spectra (left column) and histograms (right column) of the Caltech 40 meter signal (top row) in the operating frequency band, between 300 Hz and 1kHz and the same signal after denoising (bottom row). The histograms are displayed in a graph with special axes where a Gaussian bell curve should appeared as a straight line.